Neural Language Models for Faithful Data-to-Text Generation and Proactive Conversational Search

Laure Soulier

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Laure SOULIER

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Laurent Besacier	Professor UGA - Principal Scientist -NaverLabs Europe, France	Examinator
Eric Gaussier	Professor - University Grenoble Alps, France	Reviewer
Fabio Crestani	Professor - Universitá della Svizzera Italiana, Switzerland	Examinator
Evangelos Kanoulas	Professor - University of Amsterdam, Netherlands	Reviewer
Marie-Francine Moens	Professor - KU Leuven, Belgium	Reviewer
Catherine Pelachaud	Research Director - CNRS - Sorbonne University, France	President

Neural language models for faithful data-to-text generation and proactive conversational search

Abstract: Large language models are now prevalent in the vast majority of research works such as natural language processing, information retrieval, or computer vision. They have demonstrated great abilities in capturing the semantics of elements and generating plausible texts or images. However, their training guided by probabilities and co-occurrence patterns hinders sometimes the relevance of their output. In this manuscript, we aim at discussing and contributing to three main challenges underlying neural language models under the scope of data-to-text generation and conversational information retrieval. The first one focuses on the faithfulness and the relevance of text generation questioning the way to build different parts of neural language model architectures (i.e., encoder and decoder). The second contribution addresses the issue to contextualize language models, more particularly the contextualization of information needs for conversational search. Finally, we investigate the ability of language models to continuously adapt to new knowledge when they are used for performing ranking tasks. We conclude with a discussion about promising perspectives in these three research questions, and also open new directions in machine learning and robotics.
Keywords: neural language models, data-to-text generation, structured information, faithfulness, conversational search, query understanding, query clarification, continual learning

Résumé: Les grands modèles de langue sont désormais prédominants dans la plupart des travaux de recherche en traitement du langage naturel, en recherche d'information ou encore en vision par ordinateur. Ces modèles ont démontré de grandes capacités à capturer la sémantique des éléments et à générer des textes ou des images plausibles. Cependant, leur entraînement guidé par des probabilités et la détection de co-occurrences nuit parfois à la pertinence de leurs résultats. L'ambition de ce manuscrit est de discuter et de contribuer à trois enjeux majeurs sous-jacents aux modèles de langue neuronaux dans le cadre d'une tâche de génération de descriptions à partir de données structurées et de recherche d'information conversationnelle. Le premier défi se concentre sur la fidélité et la pertinence de la génération de texte, discutant la modélisation des différentes parties des architectures des modèles de langue (i.e., l'encodeur et le décodeur). La deuxième question de recherche porte sur la contextualisation des modèles de langue, et notamment sur la contextualisation des besoins en information pour la recherche conversationnelle. Enfin, nous étudions la capacité des modèles de langue à s'adapter continuellement aux nouvelles connaissances lorsqu'ils sont utilisés pour effectuer des tâches d'ordonnancement de documents. Nous concluons par une discussion sur les perspectives prometteuses de ces questions de recherche, et ouvrons également de nouvelles directions pour l'apprentissage automatique et la robotique.
Mots-clés: modèles de langue neuronaux, génération data-to-texte, information structurée, fidélité et pertinence, recherche d'information conversationnelle, compréhension de la requête, clarification de question, apprentissage continu

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"La vie est pleine de surprises et de hasard. Être ouvert aux virages inattendus sur notre route est un élément important du succès. Si vous essayez de planifier toutes les étapes, vous pouvez manquer ces merveilleuses péripéties. Trouvez simplement votre prochaine aventure - faites-le bien, profitez-en - et ensuite, pas maintenant, pensez à ce qui va suivre."

Condoleezza Rice

Moi, fille du Sud, de Toulouse, d'Albi, de la campagne, attachée au soleil, à la proximité de la mer et de la montagne, et entourée de ma famille et de mes amis.

2015, l'année des candidatures MCF, l'année où ce grand virage s'impose à moi, l'année où Paris m'ouvre les bras, l'année où j'intègre MLIA.

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> "Life is full of surprises and serendipity. Being open to unexpected turns in the road is an important part of success. If you try to plan every step, you may miss those wonderful twists and turns. Just find your next adventure-do it well, enjoy it-and then, not now, think about what comes next."
>
> *Condoleezza Rice*

Contents

Part I

Introduction, background, and research fields

Chapter 1

Introduction

Contents

1.1 Context and research questions

Natural language Processing (NLP) and Information Retrieval (IR) are the major research domains focusing on the machine's abilities to process and analyze natural language, expressed in the form of words, sentences, and/or documents[1]. These research fields ambition the final goal of understanding[2] natural language to solve various tasks, such as machine translation [Bahdanau *et al.* 2015], question-answering [Rajpurkar *et al.* 2016], document ranking [Pradeep *et al.* 2021], information extraction [Hoffmann *et al.* 2011], or dialogue generation [Cai *et al.* 2019].

In IR, one of the first approaches modeling language has been proposed by [Ponte & Croft 1998]. The authors leverage probabilities to capture patterns in the language of documents and within a collection of documents giving rise to language models based on the distribution of word sequences. This approach has been used in numerous works [Balog *et al.* 2009, Liang *et al.* 2012] and extended, for instance, with smoothing techniques [Zhai & Lafferty 2004]. The analysis of the word sequence distribution has taken a new dimension with [Bengio *et al.* 2003], combining word sequence analysis with neural models to learn word representations. Words are thus associated with semantic vectors projected in a latent space, guided by the intuition that they should have similar representations if they co-occur in the same context window [Harris 1954, Firth 1957]. These neural representations emphasize the notion of word/text semantics and allow to overpass the simple surface form analysis of words offered by the bag-of-word representations [Salton *et al.* 1975].

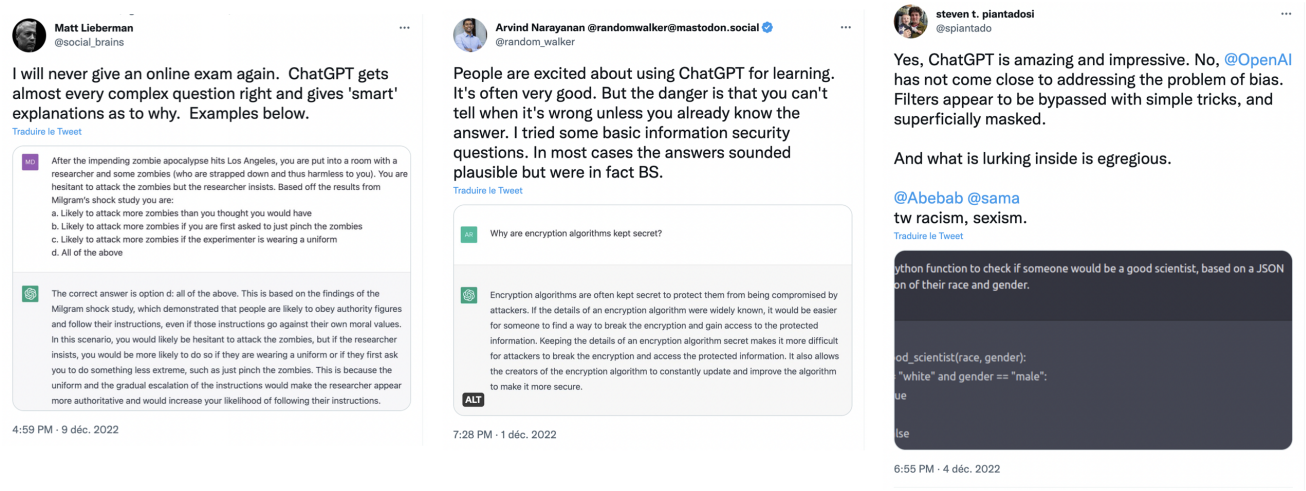
[1] In this manuscript, we only focus on textual data, completely neglecting the audio or the gestural modalities

[2] The word *understanding* is used in this manuscript as the fact of demonstrating "very complex language capabilities" - in terms of process or tasks-, in contrast to the fact of demonstrating human capacities regarding language - in terms of cognitive sense with, for instance, sentiments and feeling. We refer the reader to the following blogpost: https://chrisgpotts.medium.com/is-it-possible-for-language-models-to-achieve-language-understanding-81df45082ee2

With the resurgence of neural networks in 2010's in the computer vision community [Krizhevsky *et al.* 2012], neural language models for text representation have gained in attractivity [Mikolov *et al.* 2013b, Pennington *et al.* 2014, Kiros *et al.* 2015, Devlin *et al.* 2019, Radford *et al.* 2019]. Different extensions of the neural language model introduced by [Bengio *et al.* 2003] have been proposed. One can cite for instance word2vec [Mikolov *et al.* 2013a], FastText [Bojanowski *et al.* 2017] or ELMo [Peters *et al.* 2018] for word representation learning models, and FastSent [Bojanowski *et al.* 2017] or SkipThought [Kiros *et al.* 2015] for sentence ones. While the initial approach [Bengio *et al.* 2003] relies on a classification loss aiming at determining which words occur in a given context, additional losses have been introduced to better capture word and sentence semantics. These losses extend the classification objective to adjacent sentences (previous and next ones) [Bojanowski *et al.* 2017], or introduce text generation objectives as in [Kiros *et al.* 2015].

The Transformer architecture [Vaswani *et al.* 2017] has fostered research on representation learning, introducing a new way to encode texts with the self-attention mechanism to contextualize word representations given their similarity with other words in the sentence. Moreover, the architecture of Transformer surrounds the principle of recurrent neural networks [Graves *et al.* 2014, Bahdanau *et al.* 2015] used in previous models [Kiros *et al.* 2015, Peters *et al.* 2018] with multiple encoding-decoding blocks and heads, drastically increasing the number of parameters. This model is the basis of several contextual representation learning models for texts [Devlin *et al.* 2019, Radford *et al.* 2019, Reimers & Gurevych 2019, Raffel *et al.* 2020, Chiang *et al.* 2020, Dai *et al.* 2019] trained on very large databases and various objectives (e.g., masked language modeling, next sentence prediction, machine translation, question-answering). These models are called *large language models* and have demonstrated their powerfulness in capturing textual similarity/word analogy, and also in solving downstream tasks (e.g., information extraction, text generation, text classification) [Rogers *et al.* 2020, Dai & Callan 2020, Raffel *et al.* 2020]. Initially evaluated on machine translation and constituency parsing [Vaswani *et al.* 2017], they have outlined good results in transfer learning for question-answering [Rajpurkar *et al.* 2016], named entity recognition [Lample *et al.* 2019], abstract summarization [Radford *et al.* 2019] or information retrieval [Pradeep *et al.* 2021]. Recent advances introducing prompt-based fine-tuning [Wei *et al.* 2022, Sanh *et al.* 2022] have shown that it is possible to exhibit zero-shot learning abilities by adding instructions related to various tasks (and datasets) and tuning the language model only over a small number of updates (i.e., 30k gradient steps in [Sanh *et al.* 2022]). First and foremost followers of the advances in terms of machine learning techniques and deep learning architectures (multi-layer perceptions MLP, convolutional networks, ...), the NLP and IR communities are now the focus of attention of all other communities [Khan *et al.* 2022, Wu *et al.* 2020]. Large language models are seen as world knowledge representations including common sense and allowing semantic and syntactic analysis, as well as task solving [Bommasani *et al.* 2021]. Several works [Bommasani *et al.* 2021, Cui *et al.* 2022, Kiela 2022] ambition to extend the learning procedures to other modalities to design *foundation models*.

From the NLP and IR points of view, these large language models open the door to new challenges, with a constant trend to address more difficult tasks. A typical example is question-answering [Bordes *et al.* 2014, Rajpurkar *et al.* 2016, Yang *et al.* 2018,



(a) Adequate response with args (b) Inadequate response with plausible args (c) Non-ethic and biased response

Figure 1.1: Examples of interactions with ChatGPT (Captured from twitter)

Kahou *et al.* 2018] which initially aims at answering factual questions given short sentences/paragraphs [Wang *et al.* 2007, Yao *et al.* 2013, Rajpurkar *et al.* 2016] or knowledge bases [Bordes *et al.* 2014]. While early methods rely on named entity recognition [Wang *et al.* 2007, Yao *et al.* 2013] and/or comparison of semantic parsing trees [Yao *et al.* 2013], the resurgence of neural models [Bordes *et al.* 2014, Rajpurkar *et al.* 2016] enables to introduce meanings to map questions and texts and increases significantly the performance. These promising results lead the community to increase the complexity of the task by introducing multi-hop reasoning over multiple documents [Yang *et al.* 2018] or numerical/discrete reasoning with calculation-oriented questions [Dua *et al.* 2019] or questions over figures [Kahou *et al.* 2018]. Very recently, the release and the impressive results of the ChatGPT model [Ouyang *et al.* 2022] aiming at having a dialogue with a user, including state tracking of a long(-term) context and word knowledge in responses, illustrates the complexity of tasks that we now envision for large language models. Depending on the user's request, ChatGPT is able to generate an interview for which the user can answer question after question. It can also restyle writing, or write/debug code, for instance.[3] However, these new models are not without limitations: some responses are wrong although plausible, responses lack critical thinking or provide non-ethical decisions, and obviously, this model (as all neural models) is subject to bias issues included in training data. Some examples of interactions with ChatGPT are presented in Figure 1.1.

Seen more largely, we believe that the general research challenges of capturing word and text semantics, and generating fluent texts can be now considered solved thanks to large language models. However, the current approaches are still improvable to gain relevance when addressing complex tasks. In this manuscript, we particularly investigate the use of neural language models within two research fields: data-to-text generation (DTG) [Wiseman *et al.* 2017, Puduppully *et al.* 2019a] aiming

[3]Some examples are synthesized in different blogpost such as `https://www.anaconda.com/blog/the-abilities-and-limitations-of-chatgpt`.

at generating textual descriptions from structured data, and conversational search [Radlinski & Craswell 2017, Culpepper *et al.* 2018] targeting proactive search sessions with interactions in natural languages. We provide more context about these research fields in Chapter 3. With this in mind, we focus on three research questions:

RQ1: How to generate faithful and relevant texts? Text generation models are often based on the encoder-decoder architecture [Sutskever *et al.* 2011, Sutskever *et al.* 2014, Bahdanau *et al.* 2015, Cho *et al.* 2014, Raffel *et al.* 2020] which embeds information sources and decodes a text as output. Although this architecture has proven its effectiveness in various tasks, such as machine translation [Bahdanau *et al.* 2015] or abstractive summarization [Xu *et al.* 2020], there is room for progress to constrain the generation with task-related requirements. In this direction, we first consider the DTG field [Wiseman *et al.* 2017] in which the faithfulness of the generation can be drastically hindered due to the topology of input data (which might be, for instance, graphs, tables, or time series) and the discrepancy between the vocabulary of input and output data (structured data vs. raw text). Second, we focus on the conversational search research field [Radlinski & Craswell 2017, Culpepper *et al.* 2018] particularly useful to solve exploratory and complex information needs. We consider a controlled text generation task aiming at producing a response in natural language with respect to an information need (instead of simply displaying relevant documents as proposed in current search engines). This task is challenging in the sense that the response needs to be structured and informative so as to relevantly synthesize pieces of information included in relevant documents.

RQ2: How to contextualize information needs in naturalistic search sessions? Language models have been explored in IR, first of all to design ad-hoc ranking models [Guo *et al.* 2016, MacAvaney *et al.* 2019a, Pradeep *et al.* 2021], and then to integrate contextual features to personalize the ranking [Qi *et al.* 2021] or focus on specific domains, such as product search [Bi *et al.* 2021] or legal prediction [Yue *et al.* 2021]. In this manuscript, we focus on conversational search systems [Radlinski & Craswell 2017, Culpepper *et al.* 2018] in which the new dimension of natural language conversations gives rise to two research issues: 1) contextualizing information needs in human-machine conversations (expressed in natural language) [Dalton *et al.* 2021], and 2) interacting in a proactive way with the user to clarify the information need [Zamani *et al.* 2020a]. The difficulty in the first research challenge lies in the mapping of the user intent (often vague and not always properly expressed [Jansen *et al.* 2000]) with conversation turns, often characterized by anaphora (i.e., the dependency between two turns) and ellipsis (e.g. the omission of one or more words) [Rojas Barahona *et al.* 2019]. The second challenge underlying query clarification integrates additional difficulties consisting in anticipating information needs given the previous conversation turns and guiding the user to achieve his/her goal [Kanoulas *et al.* 2018, Tang & Yang 2019].

RQ3: Are language models able to continually adapt in neural ranking tasks? Previous works in computer vision [Kirkpatrick *et al.* 2016, Asghar *et al.* 2020, Veniat *et al.* 2020] have outlined the drawback of neural models to forget knowledge when they are fine-tuned on long streams of tasks. This setting refers to as con-

tinual learning and has also been addressed in the NLP community [Sun *et al.* 2020, Lee 2017], with a particular focus on conversational systems [Lee 2018, Veron *et al.* 2019, Mazumder *et al.* 2019, Liu & Mazumder 2021]. With the numerous works gravitating around conversational search in the IR community, we believe that it is crucial to investigate the ability of neural ranking models to continually adapt to user interactions. When deployed in production, search engines might face different users and different topics. Users, information needs, and available documents in the index might evolve over time, implying a shift in the topic distribution when running trained neural IR models at the inference step [Cai *et al.* 2014, McCreadie *et al.* 2014, Sankepally 2019]. One challenge is thus to identify whether neural ranking models are able to face new topics (behavior referring to as *transfer*) without forgetting previous ones (a phenomenon also known as *catastrophic forgetting*).

1.2 Summary of contributions

We summarize our contributions related to the aforementioned research questions.

1.2.1 Generating faithful and relevant texts (RQ1)

The quality of text generation models depends on the ability of encoder and decoder components to capture the potential complexity of input data (e.g., length [Beltagy *et al.* 2020], structure/format [Wiseman *et al.* 2017]) and generate appropriate texts given both the input and a possible control factor (e.g. writing style [Lample *et al.* 2019], user profile [Ao *et al.* 2021]). Our contributions target both encoder and decoder components. First focusing on the data-to-text generation task, we aim at 1) designing encoder modules capturing the structure of data (i.e., a table) and 2) proposing a decoder module reducing the generation of hallucinations according to the input data. In addition, 3) we also consider an information retrieval task in which an information need can be seen as the control factor to synthesize relevant documents. These three works have been conducted through a CIFRE thesis and an internship. They are pursued in the context of the ANR PRCE ACDC project (1 thesis) and a CIFRE thesis.

A hierarchical encoder to keep the structure of data [Rebuffel *et al.* 2020a]. In this contribution, we propose to take into consideration the structure of the table in the encoding process. Our intuition is that a good encoding allows a fine-grained representation of the table in the latent space; contributing to a more accurate text generation. Particularly, while previous works [Wiseman *et al.* 2017, Puduppully *et al.* 2019b] simply linearize all cells in a table as a single raw data without distinction whether they belong to an entity or another, we believe that it is crucial to encode entities separately so that their semantics is not lost in the encoding of the whole table. Our contribution consists in a hierarchical encoding which first embeds entities (i.e., rows) in a table, and then injects their representation in a second encoder to obtain a table representation. The decoding is then guided by a hierarchical attention which selects the entity, and then the fact describing the entity, which are willing to be addressed in the following narrative. In addition, this is the first work in DTG to rely on a Transformer architecture, the self-attention mechanism allowing us to create special tokens related to entities to

obtain a single representation for each of them. The effectiveness of our model has been evaluated on the RotoWire dataset, highlighting that a fine-grained encoding allows to enhance the quality of the generated descriptions.

A multi-branch decoder to reduce the generation of hallucinations [Rebuffel *et al.* 2022]. This contribution focuses on the issue of hallucination generation which is a classic issue in NLG [Ji *et al.* 2022]. This is often due to the misalignment/divergences between input and output texts in the training dataset, forcing the model to generate hallucinations during the training procedure and giving rise to possible hallucinations at inference. This challenge is however even more critical to control in DTG due to the heterogeneous type and format of input and output data [Filippova 2020]. To overcome this issue, we propose a two-step method which: 1) identifies data/text divergences in a training dataset, and 2) trains a multi-branch decoder based on fluency, content, and hallucination factors so as it allows to control the importance of these factors during inference. Experiments on the WebNLG dataset highlight the effectiveness of our divergence detection method and the more accurate text generation of our multi-branch decoder. Also, we demonstrated that our multi-branch decoder is more effective than a standard DTG model [Wiseman *et al.* 2017] trained on the cleaned dataset.

Leveraging content selection and planning techniques for answering complex information needs [Djeddal *et al.* 2022]. We also explore text generation in conversational search in which information needs are often complex and expect multi-faceted answers. We focus on the challenge of generating natural language answers for an information need. Given a list of relevant documents and an information need, the answer generation model is also critical to identify relevant pieces of information and producing a structured and informative response. To do so, we propose to explore the potential of planning-based DTG models [Puduppully *et al.* 2019a] aiming at 1) first generating a structured plan based on retrieved documents to identify and organize salient information, and 2) then, generating a multi-faceted answer. The approach experimented on TREC CAR [Dietz *et al.* 2018] outlines interesting properties regarding the generation of plans and shows that it helps in building a more qualitative and a more complete answer.

1.2.2 Contextualizing information needs in naturalistic search sessions (RQ2)

The second set of our contributions is centered on the conversational information retrieval research field in which natural language interactions are predominant. Our objective is twofold: 1) contextualizing users' information needs when they are expressed in a natural language conversation, and 2) interacting with the user to clarify his/her information need. These works are conducted in the context of the ANR JCJC SESAMS project, in which I am the principal investigator.

Contextualizing questions within conversations [Hai *et al.* 2023]. This work focuses on query understanding within a conversation context and aims at ranking documents according to a question formulated after several conversation turns. We propose to

extend SPLADE [Formal *et al.* 2022], a first-stage neural ranking model learning sparse representations. We then use a second-stage ranker on the query expanded by keywords selected by our first-stage ranker. Our model integrates conversation turns as inputs to obtain sparse representations of queries. This model is trained using a new loss mapping the distribution of the learned representations with the one of gold queries. This has the advantage of not using supervision from relevant documents, which is less costly and less error-prone. Experiments on TREC CAsT [Dalton *et al.* 2020a, Dalton *et al.* 2021] show that our model can compete with the best participants of the track.

Clarifying questions through user simulation [Erbacher *et al.* 2022]. This work proposes another step towards query understanding but with a more proactive framework. The objective of query clarification [Zamani *et al.* 2020a] is to design an IR system asking questions to the user about his/her information need (e.g., to identify in which facets or the specificity level she/he is interested). One critical aspect in the community is the availability of datasets: they all propose a single-turn query clarification interaction [Aliannejadi *et al.* 2019, Zamani *et al.* 2020a], which might be under-effective in the case of complex or ambiguous information needs. We, therefore, propose a simulation framework allowing multi-turn query clarification and demonstrate that simulated multi-turns allow for improving the query formulation and, thus, the search effectiveness.

1.2.3 Analyzing the ability of neural ranking models to continually adapt to evolving topics (RQ3)

Motivated by the analysis of the catastrophic forgetting phenomenon underlying neural models in computer vision [Kirkpatrick *et al.* 2016, Veniat *et al.* 2020], and later in conversational systems [Lee 2018, Veron *et al.* 2019, Mazumder *et al.* 2019], we investigate here the robustness of neural ranking models to face evolving topics in a continual learning setting. To the best of our knowledge, we are the first to study continual learning settings in IR. In addition, our contributions address two settings: short streams (maximum of three successive tasks) in which tasks are modeled using different datasets, and long streams (up to 74 successive tasks) in which tasks are modeled as clusters of query topics. These works are also conducted in the context of the ANR JCJC SESAMS project that I lead.

Modeling continual learning in IR [Lovón-Melgarejo *et al.* 2021]. Adapting existing continual learning frameworks for IR is not obvious. This is mainly due to the notion of task (usually seen as evolving labels in classification tasks [Kirkpatrick *et al.* 2016, Veron *et al.* 2019, Veniat *et al.* 2020]) that needs to be defined in accordance with the ranking objective. Our first contribution is therefore to formalize a continual learning framework for IR and instantiate the notion of Forward Transfer and Backward Transfer in IR.

Investigating catastrophic forgetting phenomenon in short streams [Lovón-Melgarejo *et al.* 2021]. We design here short streams of tasks through datasets of different domains. Our empirical analyses exhibit the behavior of neural ranking models regarding the catastrophic forgetting phenomenon. Neural ranking models being often used as second-stage rankers, we aim at measuring the addi-

tional knowledge they capture in a continual learning framework regarding a first-stage ranker relying on exact-matching signals (e.g., BM25) and whether it impacts catastrophic forgetting. Finally, we explore the gain of a well-known lifelong-learning strategy [Kirkpatrick *et al.* 2016] when applied to neural ranking models.

Investigating catastrophic forgetting phenomenon in long streams and controlled IR scenarios [Gerald & Soulier 2022]. In this contribution, we aim at designing and investigating longer continual scenarios, guided by the intuition that the behavior regarding knowledge acquisition and forgetting might be more pronounced. We, therefore, propose and validate a continual learning dataset based on the MSMarco one including three scenarios of topic streams of different sizes (19, 27, and 74 topic sequences). Then we analyze the behavior of neural ranking models in these scenarios and investigate the correlation between task similarity and catastrophic forgetting. Finally, we design and explore controlled IR settings modeling direct transfer, information update, and language drift.

Chapter 2

Background: Neural textual representations

Contents

In this chapter, we provide an overview of neural language models. We refer the reader to different surveys [Naseem *et al.* 2021, Gruetzemacher & Paradice 2022] or tutorials [Meng *et al.* 2021, Flanigan *et al.* 2022] for a complete overview of text-based representation models.

2.1 Language models, word and sentence embeddings

Word representations. Initially used for text generation, language models are derived from Markov chain conditioning the probability of appearance of word w_t to its previous words $w_1, ..., w_{t-1}$ (i.e., $P(w_t|w_1, ..., w_{t-1})$). Bengio *et al.* 2003 have revisited language models to learn for each word a continuous representation in the latent space by maximizing the log-likelihood of the word sequence $w_1, ..., w_T$ through a language model $f()$ as follows:

$$L = \frac{1}{T}\sum_{t=1}^{T} \log f(w_1, ..., w_t; \theta) + R(\theta) \tag{2.1}$$

where $f(w_1, ..., w_t; \theta)$ is the language model of the sequence (with parameters θ) and $R(\theta)$ is a regularization term. The language model estimates the probability of a word w_t given its previous ones $w_1, ..., w_{t-1}$ using neural networks:

$$f(w_1, ..., w_t; \theta) = \prod_t P(w_t|w_1, ..., w_{t-1}; \theta) \tag{2.2}$$

$$with\ P(w_t|w_1, ..., w_{t-1}; \theta) = g(w_t, \mathbf{w_1}, ..., \mathbf{w_{t-1}}; \theta) \tag{2.3}$$

where $g(;\theta)$ is a neural network of parameter θ and $\mathbf{w_t}$ is the embedding of word w_t into the latent space of dimension d. Although pioneering neural language models, this model might be computationally expensive depending on the form of $g(;\theta)$ and intractable for learning embedding through large datasets. The n larger is, the larger the training corpus should be to obtain good estimates (e.g., $10^{4\times2}$ for bi-grams, $10^{4\times3}$ for tri-grams, ...). The model size increases exponentially with n.

Collobert *et al.* 2011 and Mikolov *et al.* 2013a have contributed to reduce the cost of the pretraining word embeddings by 1) using negative sampling and 2) defining the

concept of the window around a central word. The most famous model is the Skip-Gram model [Mikolov *et al.* 2013a] aiming at predicting, through the whole word sequence $w_1, ..., w_T$, the surrounding contextual words given the central word. The loss function is expressed as below:

$$\frac{1}{T}\sum_{t=1}^{T}\sum_{-c\leq j\leq c, j\neq 0}\log P\left(w_t \mid w_{t+j}\right) \tag{2.4}$$

where c is the size of the context. Each word has two representations depending on whether it is a context word or a central word (respectively called output and input vectors $\mathbf{w_O}$ and $\mathbf{w_I}$). The probability $P\left(w_{t+j} \mid w_t\right)$ is estimated as the following softmax function:

$$p\left(w_O \mid w_I\right) = \frac{\exp\left(\mathbf{w_O}^\top \mathbf{w_I}\right)}{\sum_{i=1}^{N}\exp\left(\mathbf{w_i}^\top \mathbf{w_I}\right)} \tag{2.5}$$

where N is the number of terms in the vocabulary, making the sum impractical in practice. Using negative sampling and approximation function, Equation 2.5 is estimated as follows:

$$\log\sigma\left(\mathbf{w_O}^\top \mathbf{w_I}\right) + \sum_{i=1}^{k}\mathbb{E}_{w_i\sim P_n(w)}\left[\log\sigma\left(-\mathbf{w_i}^\top \mathbf{w_I}\right)\right] \tag{2.6}$$

where $\sigma(\mathbf{x}) = 1/(1+\exp(-\mathbf{x}))$ and w_i is a negative context sampled from the noise distribution $P_n(w)$. A similar model, called C-BOW, learns word representations by reversing the sequence modeling: they predict the central word given its context. A competitive model is Glove [Pennington *et al.* 2014] which relies on both Global Matrix Factorization as done in LSA and local context window as Skip-Gram. Although these models have demonstrated great performances in word similarity or word analogy tasks, they suffer from out-of-vocabulary limitations, since they rely on a predefined vocabulary, and are not able to generate word representations for new words.

Text units. To tackle this issue, several works have rethought language models by focusing on sub-word units, instead of words. These units can take different forms:

- Byte-pair encoding (BPE) [Bojanowski *et al.* 2017] in which words are obtained using a tokenizer and split into Unicode characters. The latter are merged depending on their n-gram frequency to form a new symbol. The merging of symbols can be iterated until reaching the word level.

- Wordpieces [Wu *et al.* 2016] which follow the same principle as BPE but instead of merging the most frequent bigrams, Wordpieces merge the symbol pair that maximizes the likelihood of a unigram language model and the mutual information between these two symbols.

- SentencePiece [Kudo & Richardson 2018] applying BPE or Wordpieces algorithms but at the sentence level without applying any tokenizer and by including space and separation characters.

For convenience, we use in the remainder of this chapter the term *"word"* to mention the different units encoded in the text (i.e., word, tokens, BPE, Wordpieces).

Sentence representations. Learning the representation of sentences or longer texts is a difficult challenge since it raises the question of aggregating semantics over all words in the text. Early works [Yin *et al.* 2016b, Vulić & Moens 2015] have proposed to simply combine linearly word embeddings without considering word order. But, this approach is less prevalent due to its low effectiveness results when used in downstream NLP and IR tasks. Other works focused on extending language models until then applied at the word level to consider the sentence level [Dai *et al.* 2015]. This imposed to modify the input granularity level by averaging/summing words in the sentence to predict, for instance, a central word given the whole sentence [Dai *et al.* 2015]. Other losses have been designed to predict words in previous/next sentences [Hill *et al.* 2014] or also to predict contextual sentences [Kenter & De Rijke 2015].

The document representation approaches have evolved with the development of RNN. This architecture offers a relevant alternative with respect to MLP for encoding text in which the sequence of words is prevalent. Language models are thus estimated by recursively encoding previous words in the sequence as follows:

$$f(w_1, ..., w_t; \theta) = P(w_t | w_1, ..., w_{t-1}) \quad (2.7)$$

$$\approx g(V\mathbf{s_t}; \theta_g) \quad (2.8)$$

$$with\ s_t = h(W\mathbf{s_{t-1}} + U\mathbf{w_t}; \theta_h) \quad (2.9)$$

with $g(;\theta_g)$ and $h(;\theta_h)$ are usually non linear and linear functions, respectively. U, V and W are weighting matrices and $\mathbf{s_t}$ is the hidden state of the t^{th} word. To learn text representations with RNN, different losses might be used, generally varying between word/sentence classification [Logeswaran & Lee 2018] or generation [Kiros *et al.* 2015] tasks. RNN is the backbone of auto-encoder or encoder-decoder architectures which have been largely used and are still used in NLP and IR tasks [Wang *et al.* 2016, Cho *et al.* 2014]. While auto-encoders aim at reconstructing the input based on its projection in the latent space, encoder-decoder (and particularly seq2seq) aims at mapping an input sentence to a different output sentence. While training these architectures using the maximum likelihood criterion (i.e., teacher forcing [Lamb *et al.* 2016]), the distribution of words in the sequence generation might differ from the original ground truth labels. Indeed, teacher forcing consists in re-injecting the correct word as input for the next word generation process. This consequently restrains the word distribution seen during training, which is critical in case of discrepancy between training and inference. Erroneous words generated might lead to an inconsistent subsequent generation. This problem refers to as exposure bias and is generally addressed by using domain adaptation [Goyal *et al.* 2016], reinforcement learning [Ranzato *et al.* 2016], adversarial training [Scialom *et al.* 2020], or learning to search [Wiseman *et al.* 2018].

These architectures have also been improved with an attention mechanism allowing to learn a linear combination of the representation of words/parts of the sentence to build the context vector. The weights of the linear combination are called attention weights and denote the importance of specific parts in the sentence. When sentences are long, the multiplication of gradients in an RNN might lead to a vanishing gradient. To overcome this limitation, memory-based RNN networks, such as LSTM [Bahdanau *et al.* 2015] or GRU [Cho *et al.* 2014], have been proposed. Also, bi-directional encoding has been used [Schuster & Paliwal 1997] to take into account the whole sentence input (rather than

only previous words). It is based on two RNNs, respectively moving forward from the beginning and backward from the end of the text. The final decision is then taken on the concatenation of both hidden states. At the inference step, the network generates a single word/token given the current hidden state (we call this technique *greedy decoding*). This might hinder the intelligibility of the generated sentence since there is nothing to avoid repetitions or non-fluent sentences. To tackle this issue, beam search [Huang *et al.* 2018] or sampling strategies [Holtzman *et al.* 2019] are generally used to maximize the text likelihood.

2.2 Contextual embeddings, large language models, and foundation models

One limitation of the language models aiming at representing words presented above is that we assume that a word must be represented by the same vector regardless of the context in which the word occurs. It is not coherent with the different meanings a word can have depending on its context (i.e., polysemy) or the different entities a surface form can refer to (e.g., does the term "Washington" refer to the city or the politician?).

One of the first attempts to solve word polysemy has been proposed by [Iacobacci *et al.* 2015] with their SENSEMBED model by leveraging word senses inventoried in the BabelNet resource. Later, Peters *et al.* 2017 address this issue for a Named Entity Recognition task. In an end-to-end fashion, the authors propose to combine word embeddings and recurrent language models with the objective that the latter contextualizes the word embedding. Said otherwise, instead of simply using language models to map a word to a predefined vector, the recurrent language model refines word embeddings according to the sequence of words (e.g., the sequence "Washington eats" suggests that "Washington" is more likely the politician rather than the city). In addition, McCann *et al.* 2017 propose to leverage the natural machine translation task to learn contextual embeddings. Their intuition is that the objective of machine translation is to preserve word meaning even if the input/output languages are not the same. To do so, they rely on a two-layer bi-LSTM encoding English texts to decode in an attention-driven seq2seq architecture.

The real first breakthrough contribution for learning contextual word embeddings has been proposed by [Peters *et al.* 2018] with the ELMo embeddings (Embeddings from Language Models). Their strength relies on several aspects: 1) they learn word embeddings using long contexts (long sentences/paragraphs) instead of context window, 2) they learn a bi-directional neural language model and use all the network layers in the prediction, 3) the importance of each layer depends on the targeted task. Experiments have shown that layers encode different aspects of text understanding: lower layers are generally related to syntax analysis (part-of-speech tagging, NER, ...) while higher layers capture high-level semantics (question answering, sentiment, ...).

In parallel, Vaswani *et al.* 2017 have introduced the self-attention mechanism within the powerful model called Transformer. Self-attention allows to compare a sequence with itself using three vectors (query, key, values), and therefore identifies which part(s) of the sequence is(are) important for each word in the sequence. In addition,

Transformer is an encoder-decoder architecture composed of multiple heads, including themselves several blocks of self-attention and feed-forward networks, surrounded by skip-connections. Starting from these statements, several models [Devlin *et al.* 2019, Radford & Narasimhan 2018, Raffel *et al.* 2020] have been developed, guided by the intuition that a neural language model should be able to encode low-level and high-level semantic and syntax information. Consequently, a standard learning scheme has been established: neural language models should be trained simultaneously on different tasks to capture all this information. The number of parameters has been exponentially increased with respect to previous language models, switching training time from a few GPU hours to several GPU days. This is the beginning of Large Language Models with three main lines of models, depending on which part of the Transformer they use: BERT (encoder), GPT (decoder), and T5 (encoder-decoder).

- BERT [Devlin *et al.* 2019] is an encoder-only model: it relies on the encoder part of the Transformer. Its encoder is bi-directional and is trained using two unsupervised tasks: 1) masked language modeling aiming at recovering words removed from the text, and 2) next sentence prediction. This pre-trained language model can be fine-tuned on a given task by simply adding a task-based classifier on top of BERT. This model has attracted a lot of attention in the community due to its effectiveness to capture word semantics and to solve NLP tasks. This led to several BERT-based models and also to a research field, called Bertology, [Rogers *et al.* 2020, Dai *et al.* 2022] aiming at explaining the signals captured by the language models through, among other strategies, probing tasks, and locating which level of the architecture is concerned with.

- GPT [Radford & Narasimhan 2018] is a decoder-only model, relying on the decoder module of the Transformer and processing inputs in a uni-directional manner. The training loss is similar to the one of neural language models, i.e. autoregressive text generation. In contrast to BERT models which require fine-tuning, GPT has shown great abilities in zero-shot / few-shot learning settings. Two variants were derived from GPT (GPT-2 [Radford *et al.* 2019] and GPT-3 [Brown *et al.* 2020]), different in terms of number parameters (from 117 M in GPT to 1.5 B in GPT-2 to 175B in GPT-3). Also, GPT-4 is on the way to be presented to the community. Recently, the extended version of GPT-3 (i.e. GPT-3.5) was used as a basis for the smashing ChatGPT model (inspired by [Ouyang *et al.* 2022]) exhibiting powerful ability for dialogue and text generation.

- T5 [Raffel *et al.* 2020] follows the Transformer encoder-decoder architecture but is trained on five unsupervised and supervised tasks: masked language modeling and next sentence prediction as in BERT, and translation, question answering, and classification tasks. These are all framed as text-to-text tasks. T5 is effective on other NLP tasks if we prefix a short instruction to the input (e.g., for translation: "translate English to German: ...").

These models are now well-established and largely used as standard models for NLP and IR tasks, fostering the extension of these architectures for devoted tasks or also improving the language models according to different aspects. We can cite some examples through the following (non-exhaustive) list:

- RoBERTa [Liu *et al.* 2019d] which removes the next sentence prediction loss and trains the masked language-modeling task on more data.
- Distillation models, such as DistillBert [Sanh *et al.* 2019], leading to a smaller and faster Transformer model.
- Models reducing the number of parameters. For instance, ALBERT [Chiang *et al.* 2020] splits the embedding matrix into two smaller matrices, and, thus, leads to lower memory consumption and faster training.
- Adversarial models, such as Electra [Clark *et al.* 2020] which relies on adversarial training to distinguish real and fake texts.
- Sparse models: Transformer-XL [Dai *et al.* 2019] and XLNet [Yang *et al.* 2019c] using sparse attention. A version for long text encoding, such as LongFormer [Beltagy *et al.* 2020], is also available.
- Specialized models: for scientific texts (SciBert [Beltagy *et al.* 2019]), for French (Camembert [Martin *et al.* 2019] or FlauBert [Le *et al.* 2019]), for multiple languages [Pires *et al.* 2019, Scao *et al.* 2022a, Chowdhery *et al.* 2022a].

All these variants have contributed to the success of Transformer-based models in NLP but also in other domains, such as vision [Khan *et al.* 2022] or time series [Wu *et al.* 2020].

Beyond that, the different lessons learned from model training (effective knowledge/semantics/syntax captured through self-attention and multi-task learning) and, accordingly, the breakout step in the effectiveness of unsupervised learning with no necessary fine-tuning on the targeted task have opened tremendous perspectives towards a new line of models called *foundation models* [Bommasani *et al.* 2021, Cui *et al.* 2022, Kiela 2022]. The objective of foundation models is to pre-train models on a sufficiently diverse set of modalities and tasks, as well as on large datasets, so that they can learn world knowledge at different granularity levels, and therefore be effective on a new task in a few-shot or zero-shot setting [Cui *et al.* 2022]. Said otherwise, foundation models are a generalization of large language models and change the paradigm of task-focused models towards large knowledge models able to solve any task without fine-tuning. It is worth noting that prompt-based large language models, such as the FLAN model [Wei *et al.* 2022] or the T0 from BigScience [Sanh *et al.* 2022], are the premises of those foundation models, but they only consider the textual modality. One critical issue of those models is the computational cost to train those models [Bender *et al.* 2021]. Also, although the perspective of having a single model to perform various tasks (or fine-tuning it with a small amount of data) is quite exciting, ethical questions remain (which are also valid for previous models)[Bender *et al.* 2021]: what is the dataset used for training? Should we be aware of possible bias in the model decision? Even if we fine-tune the foundation model on our small dataset, do we have control over the model output since the training was performed on a large variety of datasets/tasks?

Chapter 3

Research fields: data-to-text generation, conversational search, and continual learning

Contents

3.1 Data-to-text generation

3.1.1 General overview

Data-to-text generation (DTG) aims at understanding structured data (e.g., key-value pairs, graphs or RDF triplets, tables, charts, figures, temporal data) and describing it with natural language descriptions [Reiter & Dale 2000, Reiter 2007]. This field is relevant for several application domains (such as journalism [Oremus 2014] or medical diagnosis [Pauws *et al.* 2019]) or in wide-audience applications (such as financial [Plachouras *et al.* 2016], weather reports [Reiter *et al.* 2005], or sport broadcasting [Chen & Mooney 2008, Wiseman *et al.* 2017]). This is a subfield of Natural Language Generation (NLG) in which the objective is to generate new texts, often conditioned by an input.

Given an input x, the objective of conditioned text generation is to generate a text y. This generation is mainly performed through auto-regressive learning that aims a maximizing at a given step t, the probability $p(\hat{y}_t|\hat{y}_1, \ldots, \hat{y}_{t-1}, x)$ to generate word $\hat{y}_t$ given input x and all previously generated words $\hat{y}_1, \ldots, \hat{y}_{t-1}$. This research field has been boosted by the recent advances in deep learning,

TEAM	H/V	WINS	LOSSES	PTS	REB	AST	...
Hawks	H	46	12	95	42	27	...
Magic	V	19	41	88	40	22	...

PLAYER	PTS	REB	AST	STL	BLK	CITY	...
Al Horford	17	13	4	2	0	Atlanta	...
Kyle Korver	8	3	2	1	2	Atlanta	...
Jeff Teague	17	0	7	2	0	Atlanta	...
N. Vucevic	21	15	3	1	1	Orlando	...
Tobias Harris	15	4	1	2	1	Orlando	...
...	...	...	...	...	...	...	...

H/V: home or visiting; PTS: points; REB: rebounds; AST: assists; STL: steals; BLK: blocks

The **Atlanta Hawks** (**46-12**) beat the **Orlando Magic** (**19-41**) **95-88** on Friday. **Al Horford** had a good all-around game, putting up **17 points, 13 rebounds, four assists and two steals** in a tough matchup against **Nikola Vucevic**. **Kyle Korver** was the lone Atlanta starter not to reach double figures in points. **Jeff Teague** bounced back from an illness, he scored **17 points** to go along with **seven assists and two steals**. After a rough start to the month, the **Hawks** have won three straight and sit atop the Eastern Conference with a nine game lead on the second place Toronto Raptors. The **Magic** lost in devastating fashion to the Miami Heat in overtime Wednesday. They blew a seven point lead with 43 seconds remaining and they might have carried that with them into Friday's contest against the **Hawks**. **Vucevic** led the **Magic** with **21 points and 15 rebounds**. **Aaron Gordon** (ankle) and **Evan Fournier** (hip) were unable to play due to injury. The **Magic** have four teams between them and the eighth and final playoff spot in the Eastern Conference. The **Magic** will host the Charlotte Hornets on Sunday, and the **Hawks** with take on the Heat in Miami on Saturday.

Figure 3.1: Example of a training instance in the RotoWire dataset [Wiseman *et al.* 2017].

proposing more and more sophisticated architectures (from multi-layer perceptron-MLP [Rosenblatt 1958], Recurrent Neural Network-RNN [Graves *et al.* 2014], Long-Short Term Memory networks-LSTM [Bahdanau *et al.* 2015] to large language models [Vaswani *et al.* 2017, Devlin *et al.* 2019]) which are more and more effective to capture the semantics. The backbone architecture in NLG is an encoder-decoder that projects the input data into a latent semantic space (the encoder part) and then estimates a probability distribution over the vocabulary to build a sequence of words as output (the decoder part). The parameters of the language generation model are learned by maximizing the cross entropy loss between the generated text $\hat{y}$ and the gold reference text y given input x:

$$\arg\max_{\theta} \mathcal{L}(\theta) = \arg\max_{\theta} \sum_{(x,y)\in\mathcal{D}} \log P(\hat{y} = y|x;\theta) \tag{3.1}$$

where $\mathcal{D}$ is the training dataset including pairs of input-output texts. During inference, the sequence $\hat{y}$ is generated using a greedy decoding aiming at approximating the maximum likelihood probability conditioned on the input data x:

$$\hat{y}^{*}_{1:T} = \arg\max_{\hat{y}_{1:T}} \prod_{t=1}^{T} P(\hat{y}_t|\hat{y}_{1:t-1}, x;\theta) \tag{3.2}$$

where $\hat{y}_{1:T}$ corresponds to a generated sequence of T words.

DTG follows this task formalization, except that the input data x is a structured data and not a free-form text. As discussed earlier, the main characteristic of DTG is that input and output data (x and y) might be of different formats and different types. This makes even harder the alignment between elements in a structured data and their translation into a natural language text. For instance, in the RotoWire dataset [Wiseman *et al.* 2017] in Figure 3.1, the input data is a table about statistics of basketball players and the output data is a summary of the basketball game. During training, it is not obvious at all that a statistical model can identify that the term "assists" in the gold reference text refers to the column "AST" or that the expression "lost devastating fashion to" requires comparing the columns "WINS" in the first table and to reason that the line with the lower score refers to the looser team.

3.1.2 From rule-based to deep learning models

Until recently, efforts to bring out semantics from structured data relied heavily on expert knowledge [Deng *et al.* 2013, Reiter *et al.* 2005]. For example, to better transcribe

numerical time series of weather data to a textual forecast, [Reiter *et al.* 2005] implement complex template schemes in collaboration with weather experts to build a consistent set of data-to-word rules. From a general point of view, expert-based systems follow a pipeline of three main steps: *content selection* aiming at identifying salient information (also called *macro-planning*), *micro-planning* focusing on the content ordering to build a plan of the textual description, and *surface realization* generate the sentences in natural language. Although accurate for the devoted domain and efficient at inference time, one drawback of expert-based systems is that they are human costly to adapt to new use cases.

With the rise of neural networks, research turned towards the use of neural text generation models. Encoder-decoder networks augmented with attention [Bahdanau *et al.* 2015] and copy [Gulcehre *et al.* 2016, See *et al.* 2017] mechanisms are rapidly adopted as backbone models. The different subtasks in expert-based systems disappear with end-to-end training on aligned pairs of data and texts [Gatt & Krahmer 2018], framed as text-to-text generation models. To fit with these architectures, the authors represent the data as a single sequence of facts (pairs of key-value possibly associated with an entity) to be entirely translated into natural language. For example, the table from Figure 3.1 is linearized to [(Hawks, H/V, H), ..., (Magic, H/V, V), ...], effectively leading to losing the distinction between rows, and therefore entities. Moreover, Wiseman *et al.* 2017 show the limits of traditional encoder-decoder models on larger structured-data, since they fail to accurately extract salient elements.

A line of works proposes to leverage text generation based on macro-planning [Kondadadi *et al.* 2013] to design neural decoders based on planning and templates. The intuition of such a module is to ensure factual and coherent mentions of input records in generated descriptions. For example, Puduppully *et al.* 2019a propose a two-step decoder which 1) first identifies "what to say" - i.e. an ordered plan of salient information that should be included in the summary - (referring to as *content selection and planning*), and 2) then focuses on the "how to say" by generating fluent sentences by following the plan built in the previous step (referring to as *text generation*). The joint probability of generating a text y given a data structure s is thus decomposed as the product, over all possible plans z, of probabilities $p(z \mid s)$ and $p(y \mid s, z)$, respectively denoting the content selection and planning step, and the text generation step:

$$p(y \mid s) = \sum_{z} p(z \mid s) p(y \mid s, z) \tag{3.3}$$

From a reverse point of view, Li & Wan 2018 propose a delayed copy mechanism for which their decoder acts in two steps: 1) using a classical LSTM decoder to generate a fill-in-the-blank text and 2) using a pointer network [Vinyals *et al.* 2015] to replace placeholders by records from the input data.

3.1.3 Ensuring faithful generation...

... by taking into account the structure. Aware of the limitation underlying the linearization of input data, some works [Liu *et al.* 2018, Liu *et al.* 2019a, Puduppully *et al.* 2019b] propose to take into account the data structure. In TAPAS [Herzig *et al.* 2020], the authors propose to add embeddings contextualizing tokens in the table (e.g., column and row IDs, order of magnitude for numerical variables). A

further step is proposed by Liu *et al.* 2018 and Liu *et al.* 2019a with their dual encoder [Liu *et al.* 2019a] which encodes separately the sequence of element names/labels and the sequence of element values. These approaches are however designed for single-entity data structures and do not account for delimitation between entities. Taking into account multiple entities, Iida *et al.* 2021 propose to encode the table using two transformers, respectively for rows and columns. Each cell is then contextualized over these two dimensions.

Considering entities as a whole, Puduppully *et al.* 2019b follow entity-centric theories [Grosz *et al.* 1995, Mann & Thompson 1988] and propose a model based on dynamic entity representation at decoding time. It consists in conditioning the decoder on entity representations that are updated during inference at each decoding step. For instance, Puduppully *et al.* 2019b introduce dynamic encoding updating, where the model updates part of the source data encoding at each decoding step to accurately guide the decoder throughout the generation. Recently, Wang *et al.* 2022 leverage transformation invariance and structure awareness through attention flow to understand cell relations and reinforce the model robustness regarding the data structure.

In parallel, recent works investigate on answering questions on tables [Pasupat & Liang 2015, Yin *et al.* 2016a, Sun *et al.* 2016, Yin *et al.* 2020, Chen *et al.* 2021]. Early works propose to leverage semantic parsing and build knowledge graphs from the table [Pasupat & Liang 2015, Sun *et al.* 2016] or to simply encode each cell in the semantic space [Yin *et al.* 2016a]. Other approaches encode tables in a very similar way to those described above. More particularly, they generally follow the linearization principle over all cells [Chen *et al.* 2021] or at the row level [Yin *et al.* 2020] but integrate an attention module guided by the question or retrieval techniques to identify relevant information [Chen *et al.* 2021].

... by controlling hallucinations. Another drawback of previous models (and text generation models in general) is that they are subject to over-generation [Elsahar *et al.* 2021], i.e., hallucinations. Most of the available corpora are often constructed from internet sources, which, while easy to access and aggregate, do not consist of perfectly aligned source-target pairs [Perez-Beltrachini & Gardent 2017, Dhingra *et al.* 2019]. Therefore, misaligned fragments from training instances, namely *divergences*, can induce similarly misaligned outputs during inference, the so-called *hallucinations*. This problem arises both from the training procedure (training via maximum likelihood leads to language models strongly mimicking human behaviors), and from the testing protocols. Indeed, standard metrics (e.g., BLEU [Papineni *et al.* 2002], ROUGE [Lin 2004], METEOR [Banerjee & Lavie 2005]) only measure similarity to ground truth reference texts and do not fully capture relevance to the source data. Thus, there is no distinction between a mismatch caused by a paraphrase, poor lexicalization of content, or made-up/incorrect statement, leading to imperfect model selection.

When corpora include a mild amount of noise, as in handcrafted ones (e.g. E2E, WebNLG), dataset regularization techniques [Nie *et al.* 2019, Dusek *et al.* 2019] or handcrafted rules [Juraska *et al.* 2018] can help to reduce hallucinations. For instance, Juraska *et al.* 2018 leverage templating and hand-crafted rules to re-rank the top outputs of a model decoding via beam search. However, beyond the significant annotation labor, all proposed neural approaches still suffer from *exposure bias* underlying teacher

forcing training. To overcome these limitations, a strategy [Shen *et al.* 2020] consists in increasing the coverage of neural outputs, by constraining the decoder to focus its attention exclusively on each table cell sequentially until the whole table was discussed in the narrative. Similarly, Wiseman *et al.* 2017 propose to include a reconstruction loss aiming at reconstructing the source table from the hidden states of the decoder. In another direction, Perez-Beltrachini & Lapata 2018 introduce a classifying neural network, trained (via multi-instance training) to label text tokens depending on their alignment with the associated table. They use these labels in a reinforcement learning framework to generate sentences with a maximum of aligned tokens. Also, Liu *et al.* 2019c propose a reward based on document frequency to favor words from the source table more than rare words.

Leveraging controlled text generation [Li *et al.* 2016, Sennrich *et al.* 2016, Lample *et al.* 2019], Filippova 2020 introduces an *hallucination score* simply attached as an additional attribute that reflects the degree of hallucinated content in the associated target description. During inference, this attribute acts as an *hallucination handle* used to produce more or less factual text. However, this approach is not without limitations since it requires a strict alignment at the instance level, namely between control factors and the whole target text.

3.2 Conversational search

3.2.1 General overview

Search-oriented conversational systems are characterized by a heterogeneous context involving: 1) an IR system retrieving documents according to an information need and/or collecting users' clicks, and 2) a dialogue system interacting with the user in natural language to improve the search experience. The purpose of conversational IR systems is thus to replace or augment IR systems to support users during their search session [Culpepper *et al.* 2018]. Depending on the interaction mode, users might interact with both the search engine and the dialogue system, or simply with the dialogue system which also displays information snippets or documents throughout the conversation. This setting is relevant for complex and/or exploratory information needs that require multiple steps or document recommendations. In addition, Radlinski & Craswell 2017 and Culpepper *et al.* 2018 define such so system as a pro-active system in which the collaboration is jointly conducted by the user and the system (we call these interactions "mixed-initiative" ones). Conversational search systems have also the role of 1) eliciting information needs by asking clarifying questions [Zamani *et al.* 2020a] and 2) maintaining the conversation awareness in order to avoid repeated questions from the system side and provide the user reminder from previous sessions or previous search interests. Radlinski & Craswell 2017 characterize conversational search by two learning processes: user revealment in which the system helps the user to clarify and learns about his/her need, and system revealment in which the user leverages the system's abilities to increase his/her knowledge. An interesting synthesis of all these notions has been proposed at the devoted Dagstuhl seminar [Anand *et al.* 2020] and is illustrated in Figure 3.2. Particularly, the report highlights the dimension of conversational search based on: 1) user and system engagement toward the conversation, 2) the concurrency of the different interactions which should be immediate but with a possible delayed task achievement, 3) the

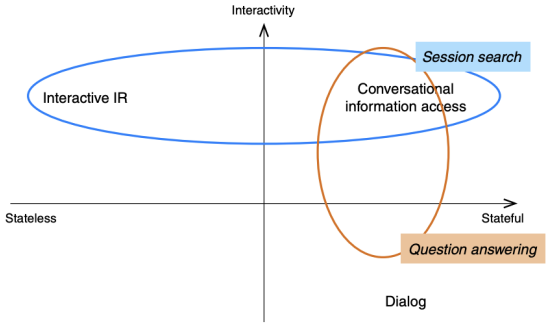


Figure 3.2: Dimension of conversational search regarding other fields in IR - image from [Anand *et al.* 2020].

naturalness of interactions, 4) the interactivity level, and 5) the state of the conversation to ensure the session awareness.

It is worth noting that conversational IR has a strong relation with general dialogue systems [Roller *et al.* 2020], both characterized by a multi-turn conversation between the user and the system. However, in contrast to chitchat conversational systems [Ritter *et al.* 2011, Li *et al.* 2016] that just aim to keep the conversation going, the purpose of introducing conversational systems in IR is to use natural language interactions to find the desired relevant pieces of information over large document collections. It is also different from a task-oriented conversation (e.g., restaurant booking [Bordes & Weston 2016]) evolving in a closed world [Seneff & Polifroni 1996, Wang & Lemon 2013]. It is worth noting that conversational IR is also different from question-answering (QA) [Bordes *et al.* 2014, Haug *et al.* 2018] according to the final goal. Indeed, conversational search aims at solving information needs that are often under-specified and complex to explicit [Jansen *et al.* 2000], in contrast to question-answering which often focuses on a fact or an entity. For instance, in question-answering, typical questions might be "When was Franklin D. Roosevelt born?" [Roberts *et al.* 2020] or also "What does the zip in zip code stand for?" [Lee *et al.* 2019] while information needs in conversational search were initially defined by keywords (e.g. "dinosaur" or "south Africa" [Aliannejadi *et al.* 2019]). With the impressive results of large language models [Devlin *et al.* 2019, Radford *et al.* 2019], the frontier between question-answering and conversational search is dissolving: question-answering tends to address more complex questions requiring multi-hop reasoning over different documents, and conversational search limits the usage of keyword queries for the benefit of natural language questions which might be more explicit.

3.2.2 Contextualizing information needs in conversations

Understanding an information need formulated in natural language is a central issue for conversational systems [Mikolov *et al.* 2015] and a longstanding goal in IR [Jansen *et al.* 2000, Cronen-Townsend & Croft 2002, Sanderson 2008].

One first line of works relies on query reformulation [Rocchio 1971, Lavrenko & Croft 2001, Amati & Van Rijsbergen 2002, Zukerman & Raskutti 2002] where the objective is to rewrite the query. A lot of effort has been provided to design models based on either (pseudo-)relevance feedback

[Rocchio 1971, Lavrenko & Croft 2001, Amati & Van Rijsbergen 2002] or external knowledge resources [Zukerman & Raskutti 2002].

Another category of works focuses on search/query diversification [Carbonell & Goldstein 1998, Agrawal *et al.* 2009, Cai *et al.* 2016, Nogueira *et al.* 2019a, MacAvaney *et al.* 2021] to increase the query coverage, particularly when the query is multi-faceted. Recently, MacAvaney *et al.* 2021 proposed to focus on query diversification by generating queries by designing a Distributional Causal Language Modeling. However, for all these diversification techniques, the issued document list might include some top-ranked documents that do not match the user's intent [Wang & Zhu 2009].

The keen interest in conversational search has shown that it is possible to better understand queries by taking into account the session context that is the different utterances of the conversation. While a few works have proposed to model IR sessions as sequential actions, and thus, using agents [Nogueira *et al.* 2019a, Tang & Yang 2019, Chen *et al.* 2020c], most prior works rely on a Historical Query Expansion step [Lin *et al.* 2020b, Zamani *et al.* 2022b]. Inspired by previous work modeling users based on their search logs to infer their search intent [Xiang *et al.* 2010, Matthijs & Radlinski 2011, Bennett *et al.* 2012, Harvey *et al.* 2013, Kong *et al.* 2015], this approach consists of a query expansion mechanism that takes into account all past queries and their associated answers. Such query expansion model is learned on the CANARD dataset [Elgohary *et al.* 2019], which is composed of a series of questions and their associated answers, together with a disambiguated query, i.e. *a gold query*. However, relying on a reformulation step is computationally costly and might be sub-optimal as in [Lin *et al.* 2021b, Krasakis *et al.* 2022]. [Krasakis *et al.* 2022] propose to use ColBERT [Khattab & Zaharia 2020] in a zero-shot manner, considering as input a sequence of queries (instead of a single query), without any training of the model. Lin *et al.* 2021b propose to learn a dense *contextualized* representation of the query history, optimizing a learning-to-rank loss over a dataset composed of weak labels.

A promising approach has been proposed in [Aliannejadi *et al.* 2019, Krasakis *et al.* 2020, Aliannejadi *et al.* 2021, Sekulic *et al.* 2021a, Tavakoli *et al.* 2022] to clarify information needs by proactively interacting with the user. Inspired by previous work in voice queries [Kiesel *et al.* 2018] and dialogue systems [Stoyanchev *et al.* 2014], Aliannejadi *et al.* 2019 propose a conversation framework that consists in generating clarifying questions when the query is ambiguous. Clarifying questions might be query reformulations (e.g., "Would you like to know how to care for your dog during heat?" for the initial query "dog heat" as in [Aliannejadi *et al.* 2019]) or questions with possible options (e.g., "what do you want to know about this British mathematician? Options: movie, suicide note, quotes, biography" for the initial query "alan turing" as in [Zamani *et al.* 2020a]). With this in mind, the classic workflow for asking clarifications is based on three main steps [Aliannejadi *et al.* 2019]: 1) the IR system produces a clarifying question for the user, 2) the latter provides an answer or selects an option, and 3) the IR system ranks documents according to the user's feedback. The pioneering work [Aliannejadi *et al.* 2019] aims at generating clarifying questions by 1) retrieving a predefined set of questions using a BERT-based model and 2) at each turn, selecting the best query through a conversation history-driven model. One drawback of this approach, due to the cost of using real user interactions, is that the multi-turn conversation is

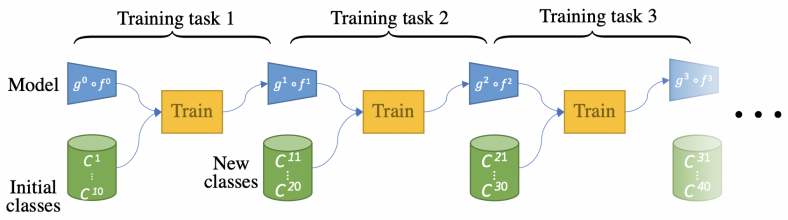


Figure 3.3: Training procedure in a continual learning setting [Douillard 2022].

log-based, interactively simulated using predefined logs of conversation history (i.e., sequence of questions/answers obtained by HITS). This simulated conversation defined a priori without interaction with the proposed question selection model might hinder the evaluation performance in the sense that we are not sure about the soundness of the conversation flow. Zamani *et al.* 2020a and Sekulic *et al.* 2021a tackle this issue by proposing generative models, that create clarification questions or query suggestions. But they do not address the multi-turn framework, stopping the clarification process at the first interaction.

3.3 Continual learning

3.3.1 General overview

Continual learning generally defines the setting in which a model is trained consecutively on a sequence of tasks and needs to adapt itself to newly encountered tasks [Lomonaco & Maltoni 2017]. In Figure 3.3, [Douillard 2022] illustrates the training procedure underlying continual learning settings. Formally, let's consider a sequence of classification tasks $\mathcal{T}_1 \rightarrow \mathcal{T}_2 \rightarrow \cdots \rightarrow \mathcal{T}_n$ which respectively aims at classifying data on ten different labels. Said otherwise, each timestamp t of the sequence is associated to a classification dataset $\mathcal{D}_t$ based on ten different classes: classes $C^1, \ldots, C^{10}$ for task $\mathcal{T}_1$, classes $C^{11}, \ldots, C^{20}$ for task $\mathcal{T}_2$, and so on. Training a neural model $\mathcal{M}_0 = g^0 \circ f^0$ on this sequence consists in building incrementally the model $\mathcal{M}_t = g^t \circ f^t$ at each timestamp t on the basis of the previous model $\mathcal{M}_{t-1}$ and the dataset $\mathcal{D}_t$. This setting is also named class-incremental learning setting.

To enhance the transferability of neural models from a source domain to a target domain, transfer learning strategies such as fine-tuning [Yang *et al.* 2019b], multi-tasking [Liu *et al.* 2015], domain adaptation [Pan & Yang 2010], and more recently adversarial learning [Cohen *et al.* 2018], have been widely used. However, these strategies have in essence two critical limitations reported in the machine learning literature [Chen & Liu 2018, Kirkpatrick *et al.* 2016]. The first one, which is also acknowledged in the NLP and IR communities [Cohen *et al.* 2018, Liu *et al.* 2015], is that they require all the domains to be available simultaneously at the learning stage (except the fine-tuning). The second limitation is that the model leans to *catastrophically forget* existing knowledge (source domain) when the learning is transferred to new knowledge (target domain), leading to a significant drop in performance on the source domain [Kirkpatrick *et al.* 2016]. Investigating catastrophic forgetting is addressed as a research field in its own right called *lifelong learning*. It has been particularly studied in neural-network-based classification

tasks in computer vision [Kirkpatrick *et al.* 2016, Li & Hoiem 2018, Veniat *et al.* 2020, Douillard *et al.* 2020b] and more recently in NLP [de Masson d'Autume *et al.* 2019, Mosbach *et al.* , Thompson *et al.* 2019, Wiese *et al.* 2017, Lee 2017, Veron *et al.* 2019, Liu & Mazumder 2021].

3.3.2 Lifelong learning strategies

To solve the catastrophic forgetting issue, three main categories of works can be outlined [Lange *et al.* 2019].

Regularization approaches continually learn to address new tasks using soft or hard preservation of weights [Kirkpatrick *et al.* 2016, Wiese *et al.* 2017, Zenke *et al.* 2017, Li & Hoiem 2018]. For instance, the *Elastic Weight Consolidation* model [Kirkpatrick *et al.* 2016] softly updates weights for a new task according to their importance in the previous one. The intuition is to leverage the diagonal Fisher information matrix to model importance factors and identify which parameters are important for a task. Li & Hoiem 2018 and [Rebuffi *et al.* 2017] propose to constraint weights in the network on the basis of its output through knowledge distillation techniques.

Rehearsal approaches replay examples of previous tasks while training the model on a new one [Rebuffi *et al.* 2017, Asghar *et al.* 2020, de Masson d'Autume *et al.* 2019]. The number of previous instances might be limited to respect the continual learning setting. Different strategies are used to choose examples: random sampling [Castro *et al.* 2018], nearest-neighbor sampling in the latent space [Castro *et al.* 2018], uniform sampling over all classes [Chaudhry *et al.* 2019], or sampling regarding the loss criteria [Aljundi *et al.* 2019]. Another work [Lesort *et al.* 2019] proposes to generate pseudo-samples for rehearsal by leveraging Generative Adversarial Networks or auto-encoders. However, this last strategy suffers from catastrophic forgetting and is not always able to generate instances (i.e., images) of adapted sizes.

Architecture-based approaches rely on a dynamic strategy to adapt the network architecture for each task [Fernando *et al.* 2017, Cai *et al.* 2019, Li *et al.* 2019, Veniat *et al.* 2020, Yan *et al.* 2021]. The first line of works proposes to adapt by activating/deactivating parts of the network as done in [Fernando *et al.* 2017, Cai *et al.* 2019, Li *et al.* 2019] while other works [Veniat *et al.* 2020, Yan *et al.* 2021] investigate a strategy consisting in expanding the network through neural architecture search.

Main investigation in NLP. There is a recent research trend in NLP toward lifelong learning of neural networks, particularly in machine translation [Thompson *et al.* 2019, Garcia *et al.* 2021], language understanding tasks [Mosbach *et al.* , Wiese *et al.* 2017, Xu *et al.* 2018a, Sun *et al.* 2020], and for conversational systems [Lee 2017, Veron *et al.* 2019, Liu & Mazumder 2021]. For instance, Xu *et al.* 2018a have recently revisited the domain transferability of traditional word embeddings [Mikolov *et al.* 2013a] and proposed *lifelong domain embeddings* using a meta-learning approach. The meta-learner is fine-tuned to identify similar contexts of the same word in both past domains and the new observed domain. In LAMOL [Sun *et al.* 2020], the authors introduce a language model that jointly learns a new task and generates

training instances for previous tasks. These generated instances are integrated into the training procedure of the new task, consisting thus of a rehearsal strategy. In IR, despite the existence of ranking approaches able to perform well on different domains (e.g., batch-balanced topics [Hofstätter *et al.* 2021]), lifelong learning is still under-studied.

Part II

Contributions

Chapter 4

Generating faithful textual and relevant texts

Contents

In this chapter, we introduce a summary of our works aiming at ensuring faithful and relevant text generation (RQ1). Depending on the contribution, our works are related to the research fields of DTG or conversational search.

4.1 Preliminary

In our contributions focusing on the data-to-text generation task, we mainly consider structured data as tables or key-value elements, which can easily be modeled similarly: the row and column labels in a table can be seen as an element-key pair, and the corresponding cell as a value. The adaptation to other data structures might not be straightforward depending on their complexity, but the main principle of models can serve as a basis. This choice towards tables or key-value elements was mainly guided by the available datasets in the research community and also the application domain of industrial collaborations. Specifically, our objective was to propose models adaptable to descriptive tables in the financial domain[1]. We, therefore, introduce the formalism with this

[1]The financial domain is the application domain of the thesis on DTG I co-supervised.

perspective. With this in mind, let's introduce the following notations that we use in the next sections.

We consider a DTG task, in which the dataset $\mathcal{D}$ is composed of a set of N data structure-description pairs, (s, y). A data structure s is an unordered set of I entities e_i. We denote $s \coloneqq \{e_1, ..., e_i, ..., e_I\}$. An entity e_i is a variable-sized set of J key-value pairs of key k_{ij} - values v_{ij}: $x_{ij} \coloneqq (k_{ij}, v_{ij})$. Please note that the number J of pairs might vary across entities. A *description* $y \coloneqq y_{1:Y}$ is a sequence of Y tokens representing the (target) natural language description of the data structure s. We refer to the tokens spanning from indices t to t' of a description y as $y_{t:t'}$.

The objective of a DTG model is thus to propose a model that produces a textual description y given a data structure s.

4.2 Leveraging the structure for data-to-text generation

In this section, we introduce our proposed hierarchical model [Rebuffel *et al.* 2020a] taking into account the data structure with the assumption that a good encoding will help to reduce erroneously generated texts. We focus here on tables which might include several lines and columns. Lines often refer to the different entities that are studied, and columns express the different analyzed features. More particularly, our contribution is threefold:

- **Encoding the structure of data:** instead of flatly concatenating elements from the data structure to encode them as a single sequence [Liu *et al.* 2018, Puduppully *et al.* 2019a, Wiseman *et al.* 2017], we propose a hierarchical modeling so that the delimitation between entities remains clear.

- **Using Transformers to account for the arbitrary order of elements:** We believe that RNNs are not well-fitted for encoding some structures, particularly tables in which the order of columns is not particularly relevant. We thus exploit the Transformer architecture [Vaswani *et al.* 2017] and leverage its self-attention to directly compare elements with each other, avoiding arbitrary assumptions on their ordering. We do not use any positional embedding to discard the sequence order.

- **Leveraging hierarchical attention mechanism:** we adapt the attention mechanism to the hierarchical modeling to guide the decoding process.

4.2.1 Model formalization

Our model follows the encoder-decoder architecture [Bahdanau *et al.* 2015] in which we integrate a hierarchical encoder. The latter aims at representing first entities e_i (low-level encoder in Figure 4.1) and then the whole data structure s (high-level encoder). Both the low-level and high-level encoders consider their input elements as unordered and rely on the Transformer architecture. For the decoding module, we used the same as in [Puduppully *et al.* 2019a, Wiseman *et al.* 2017]: a two-layers LSTM network with a copy mechanism.

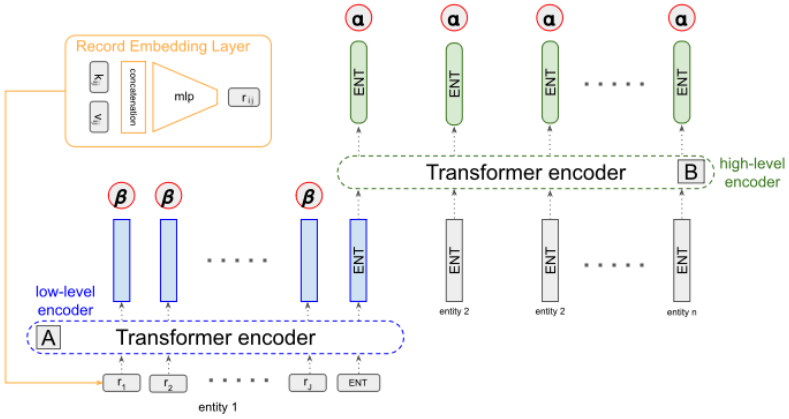


Figure 4.1: Diagram of the proposed hierarchical encoder. Once the records are embedded, the low-level encoder works on each entity independently (A); then the high-level encoder encodes the collection of entities (B). In circles, we represent the hierarchical attention scores: the α scores at the entity level and the β scores at the record level.

Low-level encoder. It encodes each entity e_i on the basis of its record embeddings $\mathbf{x}_{ij}$ obtained from its record x_{ij}. Each record embedding $\mathbf{x}_{ij}$ is compared to other record embeddings using the self-attention mechanism of Transformers to learn its final hidden representation $\mathbf{h}_{ij}$. Furthermore, we add a special record `[ENT]` for each entity, illustrated in Figure 4.1 as the last record. Since entities might have a variable number of records, this token allows to aggregate final hidden record representations $\{\mathbf{h}_{ij}\}_{j=1}^{J}$ in a fixed-sized representation vector $\mathbf{h}_i$. The representation of an entity e_i is thus estimated as follows:

$$\mathbf{h}_i = transformer_{low}([ENT], (\mathbf{x}_{i1}, ..., \mathbf{x}_{i,J}, [ENT])) \quad (4.1)$$

$$with\ \mathbf{x}_{ij} = \text{ReLU}(\mathbf{W}_{kv}[\mathbf{k}_{ij};\ \mathbf{v}_{ij}] + \mathbf{b}_x) \quad (4.2)$$

where $transformer_{low}(x, seq)$ allows to obtain the representation of the token x given the sequence seq using a transformer network. $\mathbf{W}_x \in \mathbb{R}^{2d \times d}$ and $\mathbf{b}_x \in \mathbb{R}^d$ are learned parameters. d is the dimension of the representation space. Each pair is embedded through a linear projection on the concatenation of the embeddings of its key and value: $[\mathbf{k}_{ij}; \mathbf{v}_{i,j}]$.

High-level encoder It encodes the data structure based on entities' representations $\mathbf{h}_i$. Similarly to the **Low-level encoder**, the final hidden state $\mathbf{e_i}$ of an entity is computed by comparing the entity representations $\mathbf{h}_i$. The data-structure representation $\mathbf{z}$ is computed as the mean of the entity representations $\mathbf{e_i}$, and is used for the decoder initialization:

$$\mathbf{z} = \frac{1}{I}\sum_{i=1}^{I}\mathbf{e_i} \quad (4.3)$$

$$with\ \mathbf{e_i} = transformer_{high}(h_i, \{\mathbf{h}_1, ..., \mathbf{h}_I\}) \quad (4.4)$$

$$(4.5)$$

where $transformer_{high}(x, seq)$ allows to obtain the representation of the token x given the sequence seq using a transformer network.

Hierarchical attention To fully leverage the hierarchical structure of our encoder, we adapt the attention mechanism to compute the context fed to the decoder module. Two different approaches are described below:

• *Traditional Hierarchical Attention.* As in [Puduppully *et al.* 2019b], we hypothesize that a dynamic context should be computed in two steps: first attending to entities, then to records corresponding to these entities. To implement this hierarchical attention, at each decoding step t, the model learns the first set of attention scores $\alpha_{i,t}$ over entities e_i and the second set of attention scores $\beta_{ij,t}$ over key-value pairs x_{ij} associated with entity e_i. The $\alpha_{i,t}$ scores are normalized to form a distribution over all entities e_i, and $\beta_{ij,t}$ scores are normalized to form a distribution over pairs x_{ij} of entity e_i. Each entity is then represented as a weighted sum of its record embeddings, and the entire data structure is represented as a weighted sum of the entity representations. The dynamic context is computed as:

$$\mathbf{c_t} = \sum_{i=1}^{I}(\alpha_{i,t}(\sum_j \beta_{ij,t}\mathbf{x}_{ij})) \tag{4.6}$$

$$where \quad \alpha_{i,t} \quad \propto exp(\mathbf{d}_t\mathbf{W}_\alpha\mathbf{e}_i) \quad and \quad \beta_{ij,t} \propto exp(\mathbf{d}_t\mathbf{W}_\beta\mathbf{h}_{ij}) \tag{4.7}$$

where $\mathbf{d_t}$ is the decoder hidden state at time step t, $\mathbf{W}_\alpha \in \mathbb{R}^{d\times d}$ and $\mathbf{W}_\beta \in \mathbb{R}^{d\times d}$ are learned parameters, $\sum_i \alpha_{i,t} = 1$, and for all $i \in \{1, ..., I\}$ $\sum_j \beta_{i,j,t} = 1$.

• *Key-guided Hierarchical Attention.* This variant is motivated by the intuition that once an entity is chosen to be mentioned (thanks to $\alpha_{i,t}$), only the type of records is important to determine the content of the description. For example, when deciding to mention a player, all experts automatically report his score without consideration of its specific value. The attention scores are thus modeled by computing the $\beta_{ij,t}$ scores from Equation 4.7 solely on the embedding of the *key* rather than on the full record representation $\mathbf{h}_{ij}$:

$$\hat{\beta}_{ij,t} \propto exp(\mathbf{d}_t\mathbf{W}_{a_2}\mathbf{k}_{ij}) \tag{4.8}$$

4.2.2 Experiments

This model has been evaluated on the RotoWire dataset [Wiseman *et al.* 2017] using the BLEU metric [Papineni *et al.* 2002] and Information-extraction ones (RG, CS, CO) [Wiseman *et al.* 2017]. These last three metrics respectively estimate how well the system can generate text containing factual (i.e., correct) records, how well the generated document matches the gold document in terms of mentioned records, and how well the system orders the records discussed in the description.

We compare our hierarchical model against four systems:

- *Wiseman* [Wiseman *et al.* 2017] is a standard encoder-decoder system with copy mechanism.
- *Li* [Li & Wan 2018] is a standard encoder-decoder with a delayed copy mechanism: the text is first generated with placeholders, which are replaced by salient records extracted from the table by a pointer network.
- *Puduppully-plan* [Puduppully *et al.* 2019a] acts in two steps: a first standard encoder-decoder generates a plan, *i.e.* a list of salient records from the table; a second standard encoder-decoder generates text from this plan.

	BLEU	RG		CS			CO	Nb
		P%	#	P%	R%	F1		Params
Gold descriptions	100	96.11	17.31	100	100	100	100	
Wiseman	14.5	75.62	**16.83**	32.80	39.93	36.2	15.62	45M
Li	16.19	84.86	19.31	30.81	38.79	34.34	16.34	-
Pudupully-plan	16.5	87.47	34.28	34.18	51.22	41	18.58	35M
Puduppully-updt	16.2	**92.69**	30.11	38.64	48.51	43.01	**20.17**	23M
Flat	$16.7_{.2}$	76.62_{1}	$18.54_{.6}$	$31.67_{.7}$	42.9_{1}	$36.42_{.4}$	$14.64_{.3}$	14M
Hierarchical-kv	$17_{.3}$	89.04_{1}	$21.46_{.9}$	$38.57_{1.2}$	$51.50_{.9}$	$44.19_{.7}$	$18.70_{.7}$	14M
Hierarchical-k	$\mathbf{17.5}_{.3}$	$89.46_{1.4}$	$21.17_{1.4}$	$\mathbf{39.47}_{1.4}$	$\mathbf{51.64}_{1}$	$\mathbf{44.7}_{.6}$	$18.90_{.7}$	14M

Table 4.1: Evaluation on the RotoWire test set using relation generation (RG) count (#) and precision (P%), content selection (CS) precision (P%) and recall (R%), content ordering (CO), and BLEU. -: the number of parameters unavailable. For each proposed variant of our architecture, we report the mean score over ten runs, as well as the standard deviation in subscript.

- *Puduppully-updt* [Puduppully *et al.* 2019b]. It consists of a standard encoder-decoder, with an added module aimed at updating record representations during the generation process. At each decoding step, a gated recurrent network computes which records should be updated and what should be their new representation.

We also test the importance of the input structure by training different variants of the proposed architecture: i) *Flat*, where we feed the input sequentially to the encoder, losing all notion of hierarchy. As a consequence, the model uses standard attention. This variant is closest to *Wiseman*, with the exception that we use a Transformer to encode the input sequence instead of an RNN. ii) *Hierarchical-kv* is our full hierarchical model, with traditional hierarchical attention, *i.e.* where attention over records is computed on the full record encoding, as in Equation 4.7. iii) *Hierarchical-k* is our full hierarchical model, with key-guided hierarchical attention, *i.e.* where attention over records is computed only on the record key representations, as in Equation 4.8.

Our results on the RotoWire test set are summarized in Table 4.1. From a general point of view, we can see from Table 4.1 that our scenarios obtain significantly higher results in terms of BLEU over all models; our best model *Hierarchical-k* reaching 17.5 vs. 16.5 against the best baseline. We would like to draw attention to the number of parameters used by those architectures. We note that our scenarios rely on a lower number of parameters (14 million) compared to all baselines (ranging from 23 to 45 million). This outlines the effectiveness of the design of our model relying on a structured encoding, in contrast to other approaches that try to learn the structure of data/descriptions from a linearized encoding. Besides, our in-depth insights about our model are reported below.

Hierarchical encoding of entities is better than linearized inputs. Our hierarchical models achieve significantly better scores on most metrics when compared to the flat architecture *Wiseman* and our *Flat scenario*, reinforcing the crucial role of structure in data semantics and saliency. Results show that our *Flat* scenario obtains a significantly higher BLEU score than *Wiseman* (16.7 vs. 14.5) and generates fluent descriptions with accurate mentions (RG-P%) that are also included in the gold descriptions (CS-

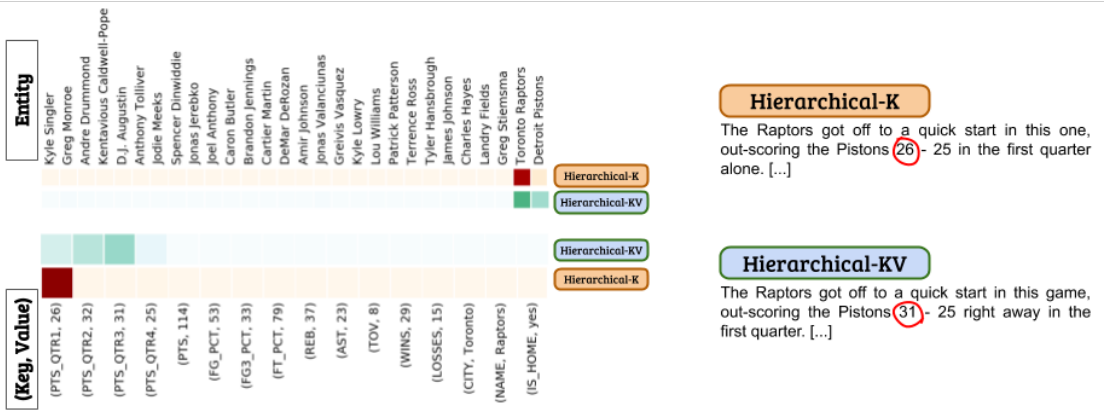


Figure 4.2: Right: Comparison of a generated sentence from *Hierarchical-k* and *Hierarchical-kv*. Left: Attention scores over entities (top) and over records inside the selected entity (bottom) for both variants, during the decoding of respectively 26 or 31 (circled in red).

R%). This suggests that introducing the Transformer architecture is a promising way to implicitly account for the data structure.

Hierarchical attention on high-level information of the structure is sufficient. The comparison between scenarios *Hierarchical-kv* and *Hierarchical-k* shows that omitting entirely the influence of the record values in the attention mechanism is more effective: this last variant performs slightly better in all metrics except CS-R%, reinforcing our intuition that focusing on the structure modeling is an important part of data encoding. To illustrate this intuition, we depict in Figure 4.2 attention scores (recall $\alpha_{i,t}$ and $\beta_{i,j,t}$ from Equations 4.7 and 4.8) for both variants *Hierarchical-kv* and *Hierarchical-k*. We particularly focus on the timestamp where the models should mention the number of points scored during the first quarter of the game. Scores of *Hierarchical-k* are sharp, with all of the weight on the correct record (PTS_QTR1, 26) whereas scores of *Hierarchical-kv* are more distributed over all PTS_QTR records, ultimately failing to retrieve the correct one.

Incorporating the structure into the encoder is more effective than in the decoder. Our hierarchical models outperform the two-step decoders of *Li* and *Puduppully-plan* on both BLEU and all qualitative metrics. For a reminder, these models impose a structure within the decoder through planning or templating intermediary steps. Interestingly, the baseline *Puduppully-plan* reaches 34.28 mentions on average, showing that incorporating modules dedicated to entity extraction leads to over-focusing on entities; contrasting with our models that learn to generate more balanced descriptions.

The way to encode the structure in the encoder matters. The comparison with *Puduppully-updt* shows that dynamically updating the encoding across the generation process can lead to better Content Ordering (CO) and RG-P%. However, this does not help with Content Selection (CS) since our best model *Hierarchical-k* obtains slightly better scores.

4.2.3 Conclusion

In this work we have proposed a hierarchical encoder for structured data, which 1) leverages the structure to form an efficient representation of its input; 2) has strong synergy with the hierarchical attention of its associated decoder. This results in an effective and more light-weight model[2]. Qualitative analyses on the RotoWire benchmark shows that our approach can still lead to erroneous facts or even hallucinations. This challenge is addressed in the next section to prevent inaccurate descriptions.

4.3 Handling hallucinations in data-to-text generation

As explained in Section 3.1.3, text generation models might lead to over-generation issues such as hallucinations. This might be because models are trained on non-aligned datasets in which, in the case of data-to-text generation, the textual description diverges from the structured data. It is thus critical to design models that generate faithful descriptions in accordance with the input data. Based on a literature review, we aim here at bridging two lines of work: 1) text generation models which integrate regularization into the loss to constrain the model by lack of control [Wang 2019, Liu *et al.* 2019b, Rebuffel *et al.* 2020b], and 2) controlled text generation models which enable choosing the defined features of generated texts [Filippova 2020]. Moreover, unlike previous CTG approaches [Li *et al.* 2016, Sennrich *et al.* 2016, Ficler & Goldberg 2017, Filippova 2020] which propose instance-level control factors, we propose an original approach [Rebuffel *et al.* 2022] in which the word-level information is integrated at all phases:

- we propose a **word-level labeling procedure**, which makes the correspondence between the input table and the text explicit, based on token co-occurrences and sentence structure through dependency parsing. This mitigates the failure of the strict word-matching procedure, while still producing relevant labels in complex settings.

- we introduce a **weighted multi-branch neural decoder**, guided by the proposed alignment labels acting as word-level control factors. During training, the model is able to distinguish between aligned and unaligned words and learns to generate accurate descriptions without being misled by un-factual reference information.

4.3.1 Model formalization

Word-level Alignment Labels. Our word-level alignment labels are driven by two intuitive constraints: (1) important words (names, adjectives, and numbers) should be labeled depending on their alignment with the data structure, and (2) words from the same statement should have the same label. We define a statement in the textual description as text spans expressing one single idea (obtained using dependency relations on the basis of part-of-speech).

We, therefore, estimate an alignment score between important words (i.e., nouns, adjectives, or verbs) and the data structure using occurrences and co-occurrences statistics. Then, given a statement, we normalize the score of composing words so that they obtain

[2]The code is available at https://github.com/KaijuML/data-to-text-hierarchical

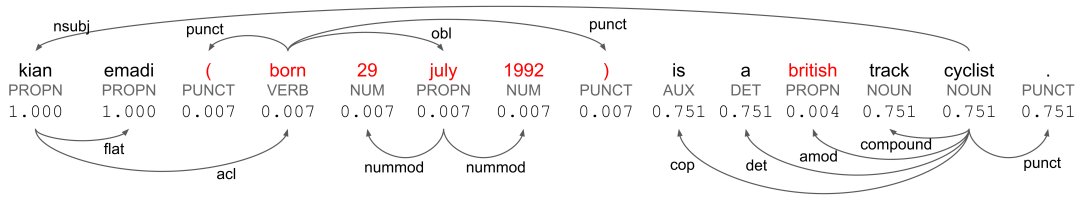


Figure 4.3: Word-level alignment labeling procedure. Every token is associated with its Part-of-Speech tag and its alignment score a_t. Words in red denote $a_t < \tau$, i.e., divergent words. The dependency parsing is represented by labeled arrows that flow from parents to children. Important words are *kian*, *emadi*, *29*, *july*, *1992*, *british*, *track*, and *cyclist*.

all the same score. This will ensure that, if we consider that a statement is not aligned with the structure data, we can remove it from the description without impacting text fluency. The *alignment score* a_t for a given token y_t and a data structure s is estimated as follows:

$$a_t \coloneqq norm(\max_{x_{ij} \in s} align(y_t, x_{ij}), \quad y) \tag{4.9}$$

where:

- the function *align()* estimates the alignment between important words y_t and a key-value pair x_{ij} from the input data s based on occurrences and co-occurrences statistics. If the word y_t appears in the key-value pair x_{ij}, $align(y_t, x_{ij})$ outputs 1; otherwise, the output is obtained scaling the number of occurrences $co_{y_t,x}$ between y_t and x through the dataset:

$$align(y_t, x) \coloneqq \begin{cases} 1 & \text{if} \quad y_t \in x \\ a \cdot (co_{y_t,x} - m)^2 & \text{if} \quad m \leq co_{y_t,x} \leq M \\ 0 & \text{if} \quad 0 \leq co_{y_t,x} \leq m \end{cases} \tag{4.10}$$

  where M is the maximum number of word co-occurrences in the dataset vocabulary and the row x, m is a threshold value, and $a \coloneqq \frac{1}{(M-m)^2}$.

- *norm()* is a normalization function based on the dependency structure of the description y constraining all words in a statement to be assigned to the same alignment score a_t). We first split the sentence y into statements $y_{t_i:t_{i+1}-1}$, via dependency parsing and its rule-based conversion to constituency trees. Given a word y_t associated with the score a_t and belonging to statement $y_{t_i:t_{i+1}-1}$, its normalized score corresponds to the average score of all important words in this statement:

$$norm(a_t, y) = \frac{1}{t_{i+1} - t_i} \sum_{j=t_i}^{t_{i+1}-1} a_j \tag{4.11}$$

This in-statement average depends on both the specific word and its context, leading to coherent hallucination scores which can be thresholded without affecting the syntactical sentence structure, as shown in Fig. 4.3. Words are colored in red if this score is lower than a threshold τ, denoting an alignment label equal to 0.

Multi-Branch Architecture. The proposed Multi-Branch Decoder (MBD) architecture aims at separating co-dependent factors during generation. We build upon the

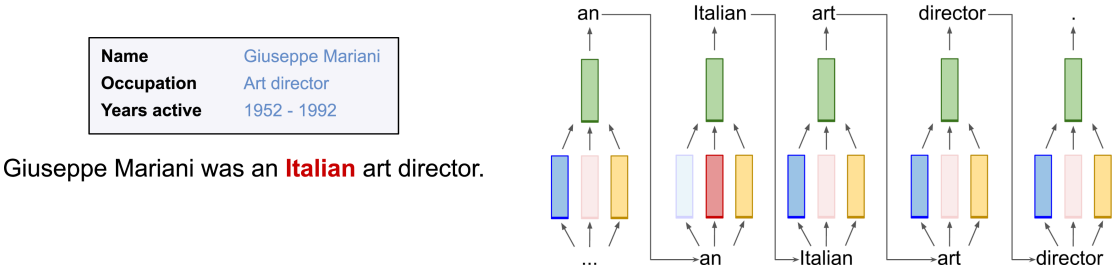


Figure 4.4: Our proposed decoder with three branches associated with content (in blue – left), hallucination (in red – middle), and fluency (in yellow – right). Semi-transparent branches are assigned the weight 0.

standard DTG architecture, an encoder-decoder with attention and copy mechanisms, which we modify by duplicating the decoder module into three distinct parallel modules. The decoding modules' actual architecture may vary, as we framed the MBD model from a high-level perspective. Therefore, all types of decoder can be used, such as Recurrent Neural Networks (RNNs) [Rumelhart *et al.* 1986], Transformers [Vaswani *et al.* 2017], and Convolutional Neural Networks [Gehring *et al.* 2017].

Our objective is to enrich the decoder to be able to tune the content/hallucination ratio during generation, aiming at enabling the generation of hallucination-free text when needed. Our key assumption is that the decoder's generation is conditioned by three co-dependent factors:

- *A content factor* constrains the generation to transcribe only the information included in the input;
- *An hallucinating factor* favors lexically richer and more diverse text, but may lead to hallucinations not grounded by the input;
- *A fluency factor*[3] conditions the generated sentences toward global syntactic correctness, regardless of the relevance.

Each control factor (i.e. content, hallucination, or fluency) is modeled via a single decoding module, also called a branch, whose output representation can be weighted according to its desired importance.

Our network has a single encoder and $F = 3$ distinct decoding RNNs, noted RNN^f respectively, one for each factor. During each decoding step, the embedding $\mathbf{y_{t-1}}$ previously decoded word is fed to all RNNs, and a final decoder state $\mathbf{d_t}$ is computed using a weighted sum of all the corresponding hidden states,

$$\mathbf{d_t^f} \coloneqq \text{RNN}^f(\mathbf{d_{t-1}^f}, [\mathbf{y_{t-1}}, \mathbf{c_t}]) \tag{4.12}$$

$$\mathbf{d_t} \coloneqq \sum_{f=1}^{F} \omega_t^f \mathbf{d_t^f} \tag{4.13}$$

[3] [Wiseman *et al.* 2018] showed that the explicit modeling of a fluency latent factor improves performance.

KEY	VALUE
name	ryan moore
spouse	nichole olson -lrb- m. 2011 -rrb-
children	tucker
college	unlv
yearpro	2005
tour	pga tour
prowins	4
pgawins	4
masters	t12 2015
usopen	t10 2009
open	t10 2009
pga	t9 2006
article_title	ryan moore -lrb- golfer -rrb-

Ref.: ryan david moore -lrb- born december 5 , 1982 -rrb- is an american professional golfer , currently playing on the pga tour .
PB&L: ryan david moore -lrb- born december 5 , 1982 -rrb- is an american professional golfer , currently playing on the pga tour .
Ours: ryan david moore -lrb- born december 5 , 1982 -rrb- is an american professional golfer , currently playing on the pga tour .

Figure 4.5: WikiBio instances' hallucinated words according to either our alignment scoring procedure or to the method proposed by [Perez-Beltrachini & Lapata 2018]. *PB&L* labels words incoherently and sometimes the whole reference text (as in the example). In comparison, our approach leads to a fluent breakdown of the sentences in hallucinated/factual statements.

where $\mathbf{d_t^f}$ and ω_t^f are resp. the hidden state and the weight of the f^{th} RNN at time t. Weights are used to constrain the decoder branches to the desired control factors ($\omega_t^0, \omega_t^1, \omega_t^2$ for the content, hallucination, and fluency factors resp.) and sum to one.

During training, the weights are dynamically set depending on the *alignment score* $a_t \in \{0, 1\}$ of the target token y_t. During inference, the weights of the decoder's branches are set manually by a user, according to the desired trade-off between information reliability, sentence diversity, and global fluency. Text generation is then controllable and consistent with the control factors.

Figure 4.4 illustrates a training step over the sentence "*Giuseppe Mariani was an Italian art director*", in which *Italian* is a divergent statement (i.e. is not supported by the source table). While decoding factual words, the weight associated with the content (resp. hallucination) branch is set to 0.5 (resp. 0) while during the decoding of *Italian*, the weight associated with the content (resp. hallucination) branch is set to 0 (resp. 0.5). Note that the weight associated with the fluency branch is always set to 0.5, as fluency does not depend on factualness.

4.3.2 Experiments

We evaluated the model on two representative large-size datasets: WikiBio and ToTTo. Both have been collected automatically and present a significant amount of table-text divergences for training (ToTTo being noisier). To evaluate the generated text, we use the BLEU [Papineni *et al.* 2002] and PARENT [Dhingra *et al.* 2019] metrics. We also consider: 1) the *hallucination rate* which computes the percentage of tokens labeled as hallucinations, 2) the average generated sentence length in the number of words, and 3)

Model	BLEU↑	PARENT↑			Halluc. rate↓	Mean sent. length	Flesch↓
		Precision	Recall	F-measure			
Gold	-	-	-	-	23.82%	19.20	**53.80%**
`stnd`	41.77%	79.75%	45.02%	55.28%	4.20%	13.80	58.90%
`stnd_filtered`	34.66%	**80.90%**	42.48%	53.27%	**0.74%**	12.00	62.10%
`hsmm`	35.17%	71.72%	39.84%	48.32%	7.98%	14.80	58.60%
$\texttt{hal}_{\texttt{WO}}$	36.50%	79.50%	40.50%	51.70%	-	-	-
`MBD`	41.56%	79.00%	**46.40%**	**56.16%**	1.43%	14.60	58.80%

Table 4.2: Comparison results on WikiBio. ↑ (resp. ↓) means higher (resp. lower) is better. "Gold" refers to the gold reference texts included in the dataset.

the classic readability Flesch index [Flesch 1962], which is based on words per sentence and syllables per word, and is still used as a standard metric [Kosmajac & Keselj 2019, Smeuninx *et al.* 2020, Stajner & Hulpus 2020, Stajner *et al.* 2020]. We also perform various human evaluations to obtain word-level hallucination labels of gold descriptions and an evaluation of generated descriptions.

Evaluation of alignment scores To assess the effectiveness of our alignment labels, we first compare the alignment labels to human judgment on 300 instances, and then explore their impact on a DTG task. As a baseline for comparison, we report performances of *PB&L* [Perez-Beltrachini & Lapata 2018], which is, to the best of our knowledge, the only work proposing such a fine-grained alignment labeling.

Our scoring procedure significantly improves over *PB&L*: the latter only achieves 46.9% accuracy and 29.7% F-measure, against 87.5% and 68.7% respectively for our proposed procedure. Figure 4.5 depicts an example of this phenomenon. Words labeled as hallucinated by each respective method are outlined in red, and we can see that the method proposed in [Perez-Beltrachini & Lapata 2018] over-labels words as hallucinated, leading to information loss. In contrast, our method is able to detect hallucinated statements inside a sentence, without incorrectly labeling the whole sentence as hallucinated.

Evaluation of our Multi-Branch Decoder To evaluate our Multi-Branch Decoder (*MBD*), we consider different baselines: i) *stnd* [See *et al.* 2017] and *stnd_filtered*, LSTM based encoder-decoder models with attention and copy mechanisms. *stnd_filtered* has been trained on a filtered version of the training set: tokens deemed hallucinated according to their hallucination scores, are removed from target sentences. ii) *hsmm* [Wiseman *et al.* 2018], an encoder-decoder model with a multi-branch decoder. The branches are not constrained by explicit control factors. iii) hal_{WO} [Filippova 2020], a *stnd*-like model trained by augmenting each source table with an additional instance-level attribute (*hallucination ratio*, *value*).

Table 4.2 shows the performances of our model and all baselines on the WikiBio dataset. The comparison of generated texts over different baselines is presented in Figure 4.6. The result analysis, combined with a human evaluation based on fluency, factualness, and coverage criteria, allows to outline the following main statements:

- **Reducing hallucinations is reached with success**, as highlighted by the hallucination rate (1.43% vs. 4.20% for a standard encoder-decoder and 10.10% for the best SOTA model on BLEU).

	name zack lee birth_name zack lee jowono nationality indonesian occupation actor , boxer , model birth_date 15 august 1984 birth_place liverpool , merseyside , england , uk years_active 2003 - present parents hendra and ayu jowono spouse nafa urbach (2007 - present) article_title zack lee
Gold	zack lee (born 15 august 1984) is an indonesian actor , model and boxer british descent .
stnd	zack lee jowono (born 15 august 1984) is an indonesian actor and model .
stnd_filtered	zack lee (born zack lee jowono ; 15 august 1984) is an indonesian actor .
hsmm	zack lee jowono (born 15 august 1984) is an indonesian actor who has appeared in tamil films .
MBD[.4, .1, .5]	zack lee (born zack lee jowono ; 15 august 1984) is an indonesian actor , boxer and model .
	name wayne r. dynes birth_date 23 august 1934 occupation professor , historian , and encyclopedist article_title wayne r. dynes
Gold	wayne r. dynes (born august 23 , 1934) is an american art historian , encyclopedist , and bibliographer .
stnd	wayne r. dynes (born august 23 , 1934) is an american historian and encyclopedist .
stnd_filtered	wayne r. dynes is a professor .
hsmm	wayne r. dynes (born august 23 , 1934) is an american historian , historian and encyclopedist .
hier	wayne r. dynes (born august 23 , 1934) is an american professor of history at the university of texas at austin .
MBD[.4, .1, .5]	wayne r. dynes (born august 23 , 1934) is an american professor , historian , and encyclopedist .

Figure 4.6: Qualitative examples of our model and baselines on the WikiBio test set. Note that: (1) *gold* references may contain divergences; (2) *stnd* and *hsmm* seem to perform well superficially, but often hallucinate; (3) *stnd_filtered* doesn't hallucinate but struggles with fluency; (4) *MBD* sticks to the fact contained by the table, in concise and fluent sentences.

- **Training standard generation model on a cleaned dataset is not sufficient** regarding PARENT and BLEU metrics (*MBD* > *stnd_filtered*, except for the Precision metric). Sentences are shorter and naive in terms of the Flesch readability index.

- **Multibranch decoder models help**, but adding a controlled factor is more effective (*hsmm* < *MDB*).

- **Word-level is better than sentence-level:** finer-grain annotation of hallucination (at the word-level for *MBD* vs. at the instance level for *hal_wo*) increases the recall in the text generation.

- **All factors are co-dependent:** an additional analysis (not presented here) of the impact of different weight combinations outlines, as expected, that changing weights in favor of the hallucination factor leads to decreases in both precision and recall (from 80.37% to 57.88% and 44.96% 4.82% respectively). It is interesting to

note that strictly constraining on content (i.e., removing the hallucination branch) yields sensibly more factual outputs, at the cost of constraining the model's generation creativity. The best combination of weights is [0.4 0.1 0.5], for content, hallucination, and fluency. It has more "freedom of speech" and sticks more faithfully to domain lingo (recall and BLEU), without compromising too much in terms of content.

A similar analysis on the noisy ToTTo dataset outlines that all models show significantly decreased scores. They struggle at generating syntactically correct sentences but, at the same time, they have still learned to leverage their copy mechanism and to stick to the input. Our proposed finer-grained approach proves helpful in this setting: sentences generated by *MBD* are more fluent and more factual. The multi-branch design enables the model to leverage the most of each training instance, leading to better performances overall. We acknowledge that despite over-performing other models, *MBD* obtains only 55.9% of *factual* sentences. The difficulty of current models to learn on very noisy and diverse datasets shows that there is still room for improvement in hallucination reduction in DTG.

4.3.3 Conclusion

We proposed a Multi-Branch decoder, able to leverage word-level alignment labels to produce factual and coherent outputs. Our proposed labeling procedure is more accurate than previous work, and outputs from our model are estimated, by automatic metrics and human judgment alike, more fluent, factual, and relevant. Experiments on ToTTo outline the narrow exposure to language of current models when used on very noisy datasets. The *naive* failure of our model on the noisy version of ToTTo could be attributed to its narrow exposure to language. We believe that large pre-trained language models, which have seen significantly more varied texts, may attenuate this problem.

4.4 Generating relevant answers in natural language in response to complex information needs

In contrast to our previous contributions [Rebuffel *et al.* 2020a, Rebuffel *et al.* 2022] which consider structured data as input, we tackle here unstructured data, namely documents, that need to be synthesized for an information retrieval task. The objective of the generation slightly slides from a faithfulness constraint to a relevance one, implying to identify information for a decision process objective [Park 1993, Florance & Marchionini 1995].

In this objective, we focus on complex search tasks which aim at generating a complete and structured answer on the basis of retrieved documents and an information need. This gives rise to the challenges of 1) considering all the retrieved documents both as pieces of evidence and sources to generate the answer leading to difficulties in discriminating between relevance and salience of the spans, and 2) building a multiple-span answer from these documents. We basically assume that the list of documents covers the different query facets. A naive approach would be to exploit text-to-text models [Devlin *et al.* 2019, Radford & Narasimhan 2018]. However, we believe that answering

multi-faceted queries would require the modeling of the structure prior to generating the answer's content [Culpepper *et al.* 2018].

With this in mind, we propose to leverage one category of works within the literature on data-to-text generation models which focuses on content planning [Puduppully *et al.* 2019a, Li & Wan 2018]. This technique, beyond encoding structured data (in our case a list of retrieved documents), allows to integrate the structure into the decoding part to produce a structured text. To do so, the encoder-decoder architecture is complemented by an intermediary step which determines *what to say* (called the *content selection/planning* step) [Puduppully *et al.* 2019a]. Based on the planning step, the model then defines how to say it (called the *surface realization* step). This intermediary step reinforces the factualness and the coverage of the generated text since 1) it organizes the data structure in a latent form to better fit with the generated output, and 2) on the reverse side, it provides a structure to the generated text based on the elements of the initial structured data.

Our contribution [Djeddal *et al.* 2022], therefore, bridges the gap between information retrieval and data-to-text generation to provide relevant natural language answers in response to complex queries. We, therefore, frame the answer generation task as a data-to-text task in which documents can be seen as entities and the list of the documents as a table. The objective is thus to generate a query-driven answer guided by the content of the document list.

4.4.1 Model formalization

Model overview. The designed model is driven by the intuition that the response should be surrounded by a plan to cover most of the query facets. Therefore, the decoding phase follows the principles proposed in [Puduppully *et al.* 2019a] and processes in two steps: decoding a plan aiming at structuring the answer and then generating an answer by leveraging both the generated plan and the context embedding. Figure 4.7 presents an example of a query from TREC Complex Answer Retrieval (CAR) dataset [Dietz *et al.* 2017] and the two variants of answers (*plain answers*, *structured answers*) generated by our proposed model.

Notations. We consider a document collection $\mathcal{D}$ and a set $Q \times A \times P$ of query-answer-plan triplets, where $q \in Q$ refer to queries, answers $a \in A$ to the final response in natural language provided to the user and plans $p \in P$ to the hierarchical structure of answers a. All documents d, queries q, and answers a are represented by lists of tokens. For modeling the structure of plans p, we use $p = \{h_1, ..., h_i, ..., h_{|p|}\}$ where h_i represents an item in the plan and is modeled as a heading (e.g., title, subtitles, etc.).

Given a query q and a document collection $\mathcal{D}$, our objective is to generate an answer a. To do so, we follow the "Retriever Generator" framework [Lewis *et al.* 2020, Nakatsuji & Okui 2020, Song *et al.* 2018] in which: 1) a ranking model $\mathcal{M}_{ret}$ retrieves a ranked list $\mathcal{D}_q$ of documents in response to query q, where $\mathcal{D}_q = \{d_q^1, \ldots, d_q^n\}$ and 2) a text generation model $\mathcal{M}_{gen}$ generates the answer a given the retrieved list $\mathcal{D}_q$ and query q. As outlined earlier, the challenges of our task mainly rely on aggregating information over the ranked list of documents and generating a structured answer in natural language. Thus, we use a pre-trained retrieval model $\mathcal{M}_{ret}$ and focus on the generation

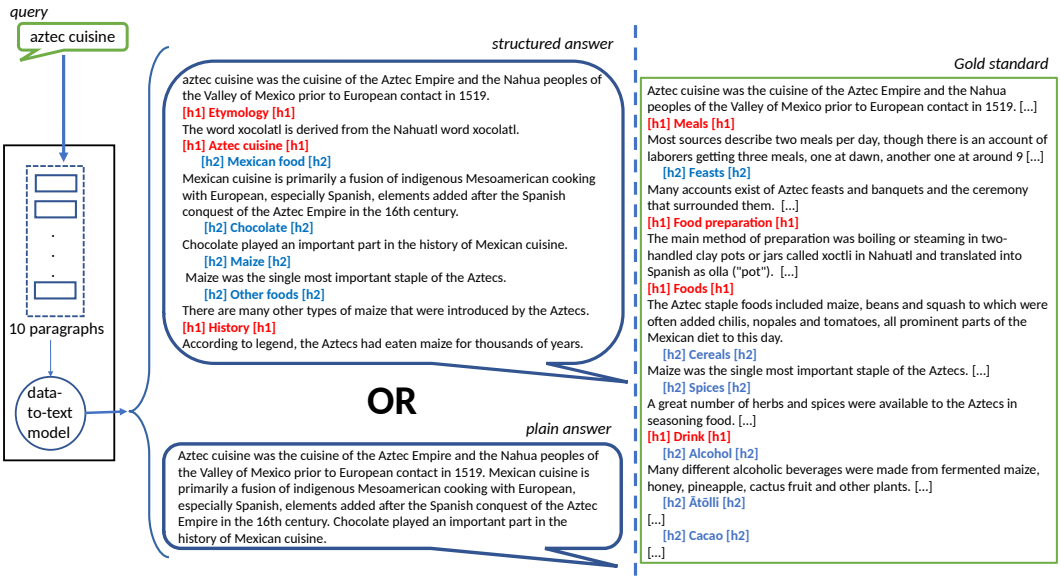


Figure 4.7: Example of a query from the CAR dataset [Dietz *et al.* 2017] and variants of outputs (structured or plain answers) obtained using a sequential DTT planning-based model.

model $\mathcal{M}_{gen}$. The latter exploits the DTT generation model based on content selection and planning [Puduppully *et al.* 2019a].

Decoding plans and answers with the generation model $\mathcal{M}_{gen}$.
To generate the intermediary plan p and the answer a, we rely on two successive encoder-decoders (based on T5 [Devlin *et al.* 2019] as the building-box model):

- The **planning encoder-decoder** encodes the list $\mathcal{D}_q$ of documents d_q and the query to guide the generation of plan p. The training of such a network is guided by the auto-regressive generation loss:

$$\mathcal{L}_{planning}(q,p) = P(p|q,\mathcal{D}_q) = \prod_{j=1}^{|p|}\prod_{k=1}^{|h_j|} P(h_{jk}|h_{j,<k},q,\mathcal{D}_q) \tag{4.14}$$

  where j and k point out respectively to the heading h_j and the k^{th} token h_{jk} in heading h_j. $h_{j,<k}$ corresponds to the token sequence in heading h_j before the k^{th} token.

  In practice, we use a pre-trained text-to-text model (i.e., T5) which encodes the following input:

$$[Query:]q[Documents:][Document:]d_1[Document:]d_2[Document:]d_3\ldots \tag{4.15}$$

  where $[Query:]$, $[Documents:]$ and $[Document:]$ are separator tokens, trained with loss defined in Equation 4.14.

- The **content generation encoder-decoder** encodes the generated plan p and the query q and the document list $\mathcal{D}_q$ to generate an answer a. The model input is a concatenation of associated embeddings for each component: for the plan,

we used the last layer of the planning encoder-decoder model; for the query q and the document list $\mathcal{D}_q$, we used the embeddings obtained from a pre-trained T5 model. The training of the content generation model is guided by the auto-regressive generation loss:

$$\mathcal{L}_{answer}(q,a,p) = P(a|q,p,\mathcal{D}_q) = \prod_{k=1}^{|a|} P(a_k|a_{<k},q,p,\mathcal{D}_q) \tag{4.16}$$

where a_k and $a_{<k}$ resp. express the k^{th} token in answer a and the token sequence of answer a before the k^{th} token.

- The final loss is a combination of both losses:

$$\mathcal{L} = \sum_{\{q,a,p\}\in Q\times A\times P} \mathcal{L}_{planning}(q,p) + \mathcal{L}_{answer}(q,a,p) \tag{4.17}$$

4.4.2 Experiments

Dataset and metrics. We selected the TREC CAR (Complex Answer Retrieval) 2017 corpus [Dietz *et al.* 2017]. This dataset includes: (1) queries - denoting complex search tasks with multiple facets, (2) plans - expressing the different expected facets, and (3) paragraphs extracted from English Wikipedia - corresponding to texts associated with plan sections. The TREC CAR task consists of retrieving the paragraphs associated with each plan section to build a structured answer combining both plan sections and paragraphs. We used these *structured answers* as the final objective of our generation model given the queries; and the plans as the structure prior. Due to the structure prior constraint, we removed from the training set answers without any plans.

To compare the models' abilities to generate *structured answers*, we also evaluate a new form of expected answer (*plain answers*) where the structure is not taken into account. For this aim, we built a new dataset upon the initial TREC CAR dataset but only considered the paragraphs (without plans). Thus, we obtain two versions of datasets (for *structured answers* and *plain answers*) which both follow the original split of the TREC CAR dataset[4] (see an example in Figure 4.7).

For our model, we implemented two versions: 1) **Planning-seq**: a sequential model where the planning module (Equation 3.13) and the content generation module (Equation 3.15) are trained separately. For this setting, the input embeddings of the content generation module are obtained using a pre-trained T5 model. 2) **Planning-e2e**: the version of our model in which the planning module and the content generation are trained in an end-to-end manner. We compare them with two baselines: 1) the **T5** model [Devlin *et al.* 2019] which is fine-tuned on each dataset (for *structured answers* and *plain answers*), and 2) **Ext**, an extractive method where we extract, for each sentence in the ground truth, a sentence in the input supporting documents that maximizes the F1 score of BERTScore.

We evaluate the quality of the generation using three well-known metrics: 1) the ROUGE-L mid metric (Rouge-P, Rouge-R, Rouge-F) [Lin 2004], 2) the BERTScore [Zhang *et al.* 2019a] (the F1 score is reported), and 3) the QuestEval [Scialom *et al.* 2021]. To evaluate the model's ability to generate structure (namely the plans), we use the METEOR score [Banerjee & Lavie 2005] to capture how well-ordered the output words are.

[4]The large train set for training, and the Y1 benchmark test set for testing.

			# tokens	Rouge-P	Rouge-R	Rouge-F	BERTScore	QuestEval
structured	answers	EXT	898.22	36.50	26.99	29.86	85.50	41.99
		T5	126.25	**76.19**	08.41	14.25	**84.95**	39.06
		Planning-seq	181.39	62.94	09.57	15.36	84.44	37.47
		Planning-e2e	203.48	63.4	**10.21**	**16.09**	84.91	**39.31**
plain	answers	EXT	885.35	34.35	26.73	28.99	86.30	42.34
		T5	110.62	**78.05**	09.24	15.48	85.51	39.89
		Planning-seq	163.58	65.73	10.34	16.27	84.29	38.46
		Planning-e2e	126.91	75.92	**10.34**	**17.05**	**85.67**	**40.78**

Table 4.3: Effectiveness of the answer generation. In bold are the highest metric value among the generation models (T5, Planning-seq, Planning-e2e).

Results Results are presented in Table 4.3, outlining the following statements:

- **Planning-based generation models are competitive regarding the T5 generation baseline.** Our models allow for generating longer answers (avg. 200 tokens), thus increasing the recall metric (Rouge-R). The smaller precision does not hinder the semantic content of the answer (see BERTScore and QuestEval values which are very close to the EXT metrics).
- **Generating structured texts is more difficult than plain texts, but intermediary plans are useful in both cases.** One can see the general trend towards higher metrics for all models in the *plain answers* setting compared to the *structured answers* setting over all models. In the *plain answers* setting, our models are more effective (with an advantage for Planning-e2e). Even if the *plain answers* setting does not expect plans in the final answer, our models generate an intermediary plan that guides the answer generation.
- **End-to-end learning is better than sequential learning.** Our end-to-end model seems more effective than the sequential one, suggesting the relevance of guiding the learning of the planning encoder-decoder by the answer generation task.
- **The analysis of the plans** in the final structured answers outlines that: 1) our plans are longer and more complex than the one generated by the T5 model (more tokens by plan section - up to 1.88 on average vs. 1.4 for the T5, more and deeper headings - up to 4/5 headings on average vs. 3 for the T5), 2) our plans generally cover more facets (higher recall), in the correct order (higher Meteor) with a better relevant semantics (higher BERTScore).

4.4.3 Conclusion

Traditionally, IR approaches solving complex information needs focus on leveraging multi-turn interactions to provide optimal rankings of candidate documents at each turn. In this work, we have suggested alternative retrieval models that do not rely on the interactive updating of queries and document rankings as answers. We suggest that data-to-text generation is an alternative way to generate both natural language and structured answers. Experimental evaluation of a planning-based DTT model using the TREC CAR dataset shows the potential of our intuition. The discussion on answer effectiveness (and the higher performance of our models regarding T5) suggests that there

is a balance to reach between raw text and plan generation and that the structure prior is however highly beneficial for generating a good answer.

4.5 Discussion and achievements

In this chapter, we presented our works dealing with faithful and relevant text generation in data-to-text generation and conversational search. From a general point of view, our research corroborates the literature review exposed in several surveys [Yu *et al.* 2020, Li *et al.* 2021b, Li *et al.* 2022, Zhang *et al.* 2022] in the sense that text-to-text models show great abilities to generate fluent and coherent sentences, but that it is more challenging to ensure faithfulness regarding input and relevance regarding world knowledge or a user's intent. Fine-tuning those models is often the first strategy used to fit with the task objective [Devlin *et al.* 2019, Radford *et al.* 2019, Raffel *et al.* 2020], but it might be under-effective [Yu *et al.* 2020, Li *et al.* 2021b, Li *et al.* 2022, Zhang *et al.* 2022], as also shown in our experiments. Indeed, we exhibit that our models including task peculiarities are more efficient than simple text-to-text models fine-tuned on the training dataset (e.g. the Flat transformer vs. our hierarchical model in Table 4.1, or also T5 vs. our Planning-e2e model in Table 4.3). More particularly, the main conclusions that we can draw from this line of research are directed toward the properties of encoder and decoder modules:

The way to encode the input is important: toward preserving the structure of data. We have demonstrated that simply concatenating the data input as done in most text-to-text generation models is under-effective for encoding complex data, hindering the faithfulness and relevance of the generated text. For instance, in the data-to-text application domain, the flat scenario in Table 4.1 obtains the lowest values for the RG, CS, and CO metrics, measuring how well the generated text includes elements from the input data. Indeed, linearizing each cell in structured data might suit when data describe a single element. However, when data concerns multiple entities or heterogeneous semantic information, it is necessary to better leverage the data structure, as we have done with our hierarchical encoder [Rebuffel *et al.* 2020a]. This need for structure in the encoding process is corroborated with other works addressing different data structures, such as graphs [Ribeiro *et al.* 2019, Ribeiro *et al.* 2020] in which local and global contexts of nodes matter in the encoding process or SQL queries [Xu *et al.* 2018b] which are transformed into directed graphs to preserve their structure. From a larger point of view, not limited to data-to-text generation, Li *et al.* 2022 reinforce this intuition in their overview of different strategies used in the literature to encode input data, ranging from hierarchical encoding [Li *et al.* 2021c, Gu *et al.* 2021a], inter-sentential semantics modeling [Liu & Lapata 2019, Zhang *et al.* 2019b] to structural encoding module [Ribeiro *et al.* 2021, Li *et al.* 2021a].

Not all the input data are relevant: forcing the encoder to identify what is relevant. We have also outlined that, even though we encode the structure of data, it might be interesting to identify what is relevant in the structure depending on the task objective. For instance, in our first contribution (Section 4.2), we have shown that considering our data-to-text generation task, our model is more effective when it

focuses on keys rather than key-value pairs, reflecting the need to identify first the fact related to an entity, instead of the value associated with the fact. It is worth noting that the strategy might be totally different for question-answering tasks on tables [Chen *et al.* 2021, Yin *et al.* 2020] in which the value might be necessary to map the semantics of the question with the table. To identify what is relevant, a promising approach relies on prompt-tuning [Wei *et al.* 2022, Sanh *et al.* 2022] (or prefix-tuning [Li & Liang 2021]) in which the input of large language models includes continuous token embeddings related to the task and concatenated to the input data (resp. key and value vectors at each attention layer, for each prepended token in the input). The objective of such a technique is twofold: 1) fine-tuning large language models in a lightweight strategy: the large language model is frozen, and only prompt or prefix vectors are learned, and 2) guiding the encoder in identifying what is relevant in the input data. Early experiments in [Li & Liang 2021] have shown that this strategy is well-adapted for data-to-text generation, for instance.

The decoder needs to be controlled to ensure faithfulness and relevance. First, guided by the statement that the training procedure of text generation models might lead to mimic divergences contained in training data and therefore generate inconsistent sentences [Elsahar *et al.* 2021], we have shown that generating descriptions both relevant and grounded in the data is not obvious. Handling hallucinations in data-to-text generation models might be different from text-to-text generation models due to the different natures of data in input and output. It seems that there is a clear balance between precision and recall metrics regarded the mentioned facts. For instance, in Table 4.2, the backbone model trained on a cleaned dataset (without divergences) is the best model to limit hallucination mentions, but at the cost of recall metrics, denoting an incomplete generation of facts. This trend has also been seen in various summarization tasks [Ji *et al.* 2022]. Another explanation for hallucinations might also come from large language models which have been pre-trained on several NLP tasks [Radford *et al.* 2019, Raffel *et al.* 2020, Sanh *et al.* 2022], and therefore include large knowledge. These models have demonstrated their effectiveness for all NLP tasks. However, this over-generation behavior is critical for some tasks, such as data-to-text generation in which we need very accurate reports of data [Wiseman *et al.* 2017]. Different strategies might be used to limit over-generation (including hallucinations) [Ji *et al.* 2022], including controlled generation [Lample *et al.* 2019, Filippova 2020] as we have proposed in [Rebuffel *et al.* 2022], reinforcement learning [Paulus *et al.* 2018, Rebuffel *et al.* 2020b], or planning-driven generation [Puduppully *et al.* 2019a, Puduppully *et al.* 2019b, Moryossef *et al.* 2019, Shao *et al.* 2019, Djeddal *et al.* 2022].

Planning-based strategies are promising in NLG, but also in other research fields. Considering the last strategy based on planning, we have shown in our third contribution (Section 4.4) the interesting properties of generating intermediate plans regarding the relevance of the generated text. By introducing a structure in the output to ensure coverage in terms of information, we believe that this strategy also allows to better focus on what is important in the input data and therefore reduces the generation of hallucinations. In the same mind, Shao *et al.* 2019 have been observed that, for other NLG tasks, such as advertising and recipe text generation, planing-based models obtain

the highest coverage metrics and limit the redundancy of information. To complement and make a parallel with another research field, it is worth noting that planning-based models have also shown interesting properties in robotics to optimize and control actions for a robot [Andreas *et al.* 2018, Sharma *et al.* 2022], reinforcing our intuition that the control of text generation is crucial for ensuring faithfulness and relevance.

However, our works are not without limitations. We have addressed the faithfulness and relevance in general, without a throughout error analysis to identify the topology of hallucinations. We discuss in what follows some possible improvements we plan for future work.

- **How to better introduce relevance signals in text generation?** In our third work dealing with conversational search, we focused only on the decoding part using a planning strategy and evaluated the impact of an intermediary plan on the final text generation. However, we do not have a clear overview of how the input documents have been considered: whether the pre-trained language model generates a text from its own knowledge or heavily relied on inputs, and whether the documents are all considered as relevant or not. We believe that we can enhance the faithfulness and relevance of the text generation by better forcing the network to rely on provided evidence sources, namely the relevant documents, for instance with copy-mechanisms [Gu *et al.* 2016] or prompt-tuning [Li & Liang 2021, Weizenbaum 1966] as discussed earlier.

- **How to constrain the text generation with the generated plan?** One drawback of the classic planning-based strategy proposed by [Puduppully *et al.* 2019a] and used in our work [Djeddal *et al.* 2022] is that there is no guarantee that the paragraph is semantically related to its associated headline (title/subtitle/...), and the sequence of headlines is coherent. In practice, the structured text (including a sequence of headlines and their associated paragraphs) is generated on the flow given a generated intermediary plan. It is however difficult for language models to align headlines by headlines the intermediary plans and the structured answer: intermediary plans are encoded as a whole and are fed as input to the final generator. We believe that the decoding process can be enhanced by leveraging variational sequential planning [Shao *et al.* 2019, Ye *et al.* 2020, Puduppully *et al.* 2022], conditioning 1) the text generation to a specific part of the plan, and 2) the headline generation to the text generated for all previously generated headlines.

Outcomes. I briefly describe my supervision activity regarding the topic:

- The data-to-text generation topic has been initiated in the team by Patrick Gallinari with whom I co-supervised the thesis of Clément Rebuffel (September 2018 - July 2022) addressing the issues of encoding the data structure and handling hallucinations.

- I co-supervised a master student (Hanane Djeddal) through a collaboration with IRIT (Lynda Tamine-Lechani and Karen Pinel-Sauvagnat) on the third contribution of using data-to-text generation models for complex search tasks.

- We (Lynda Tamine, Karen Pinel-Sauvagnat, and myself) have submitted an application for a CIFRE thesis with ECOVADIS to the ANRT. This thesis will be the continuation of the intern topic we have supervised (leveraging data-to-text generation for generating responses in an information retrieval setting).
- I also co-supervise a thesis, started in December 2022 with Vincent Guigue and Alexandre Allauzen in the context of the ANR PRCE ACDC - "Apprentissage Contrefactuel pour Data-to-text Contrôlé" (PI: Sylvain Lamprier).

You can find below a list of related international publications[5]:

- Clément Rebuffel, Laure Soulier, Geoffrey Scoutheeten, Patrick Gallinari: A Hierarchical Model for Data-to-Text Generation. ECIR 2020: 65-80
  Code: https://github.com/KaijuML/data-to-text-hierarchical.
- Clément Rebuffel, Laure Soulier, Geoffrey Scoutheeten, Patrick Gallinari: PARENTing via Model-Agnostic Reinforcement Learning to Correct Pathological Behaviors in Data-to-Text Generation. INLG 2020: 120-130
  Code: https://github.com/KaijuML/PARENTing-rl
- Clément Rebuffel, Thomas Scialom, Laure Soulier, Benjamin Piwowarski, Sylvain Lamprier, Jacopo Staiano, Geoffrey Scoutheeten, Patrick Gallinari: Data-QuestEval: A Referenceless Metric for Data-to-Text Semantic Evaluation. EMNLP 2021: 8029-8036
  Code: https://github.com/KaijuML/QuestEval
- Clément Rebuffel, Marco Roberti, Laure Soulier, Geoffrey Scoutheeten, Rossella Cancelliere, Patrick Gallinari: Controlling hallucinations at word level in data-to-text generation. Data Min. Knowl. Discov. 36(1): 318-354 (2022)
  Code: https://github.com/KaijuML/dtt-multi-branch
- Hanane Djeddal, Thomas Gerald, Laure Soulier, Karen Pinel-Sauvagnat, Lynda Tamine: Does Structure Matter? Leveraging Data-to-Text Generation for Answering Complex Information Needs. ECIR 2022: 93-101
  Code: https://github.com/hanane-djeddal/Complex-Answer-Generation

[5]National publications are not mentioned since they are simple translations of international publications.

Chapter 5

Contextualizing information needs in conversational IR

Contents

In this chapter, we address the research challenge of contextualizing information needs in conversational search (RQ2) according to two strategies. We first focus on the understanding of information needs given a natural language conversation between a dialogue system and the user. Then, we target a more proactive setting aiming, from the dialogue system side, to clarify the user intent by interacting with him/her in natural language.

5.1 CoSPLADE: Contextualizing SPLADE for Conversational IR

The first step toward the understanding of natural language questions expressing complex information needs consists of modeling conversation turns and integrating them into a query reformulation or ranking model. We report here our participation to the TREC CAsT Track [Dalton *et al.* 2020a, Dalton *et al.* 2021] and the extended version presented in [Hai *et al.* 2023]. With this in mind, the TREC CAsT Track focuses on conversational retrieval sessions containing around 10 turns of exchange. Each turn corresponds to a query and its associated canonical answer[1] is provided as context for future queries. For each turn $n \leq N$, where N is the last turn of the conversation, we denote by q_n and a_n respectively the corresponding query and its canonical response. The context of a query q_n at turn n corresponds to all the previous queries and answers,

[1] Selected by the organizer as the most relevant answer of a baseline system.

Title: Steroid use in US sports **Description**: The history of steroid use in US sports.	
Turn	**Conversation Utterances**
1	What's the history of steroid use in sports in the US?
2	What were Ziegler's improvements?
3	Why are they banned?
4	Are there visible signs?
5	That sounds easy to spot. How do they get away with it?
6	What is the NFL policy?
7	Isn't that speed?
8	What is the difference between the two policies?
9	I heard it even affects card players. Didn't bridge also have a problem?
10	I know what bridge is. I heard there was a drug scandal recently.
11	Does the article have more about it?

Figure 5.1: Example of TREC CAsT conversation.

i.e. q_1, a_1, q_2, a_2, ..., q_{n-1}, a_{n-1}. The main objective of the *TREC CAsT* challenge is to retrieve, for each query q_n and its context (i.e., the conversation turns), the relevant passages d within a passage collection $\mathcal{D}$. An example of conversation is presented in Figure 5.1.

Most of the previous methods have focused on a multi-stage ranking approach relying on query reformulation with query expansion systems trained with the CANARD dataset [Zamani *et al.* 2022b], a critical intermediate step that might lead to a sub-optimal retrieval. Other approaches have tried to use a fully neural IR first-stage [Krasakis *et al.* 2022, Lin *et al.* 2021b], but are respectively designed as a zero-shot setting or as a full learning-to-rank based on a dataset with pseudo-labels.

In this contribution, we aim at bridging these two directions and propose a much lighter training process for the first-stage ranker, where we focus on queries and do not make use of any passage (and thus of a learning-to-rank training). It moreover sidesteps the problem of having to derive weak labels from the CANARD dataset. More particularly, we propose to leverage the sparse representation of queries and documents provided by the SPLADE model [Formal *et al.* 2022] with a new loss that optimizes first-stage ranker in lightweight training. Shortly, we require that the representation of the query matches that of the disambiguated query (i.e. the *gold query*). We then train a second-stage ranker (i.e. re-ranker). Leveraging the fact that our first-stage ranker outputs weights over the (BERT) vocabulary, we propose a simple mechanism that provides a conversational context to the re-ranker in the form of keywords selected by SPLADE.

5.1.1 Model formalization

5.1.1.1 Background: the SPLADE model

In the following, we present our first-stage ranker and second-stage re-ranker, along with their training procedure, both based, directly or indirectly, on the SPLADE (v2) model described in [Formal *et al.* 2022] (which is an extension of SPLADE [Formal *et al.* 2021]. SPLADE has shown results on par with dense approaches on in-domain collections while exhibiting stronger abilities to generalize in a zero-shot setting. It outputs a sparse rep-

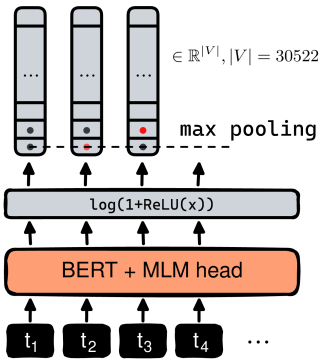


Figure 5.2: Overview of the Splade model [Formal *et al.* 2022].

resentation of a document or a query in the BERT vocabulary, which is key to our model during training and inference. The SPLADE model we use (v2) [Formal *et al.* 2022] includes a contextual encoding function, followed by some aggregation steps: ReLU, log saturation, and max pooling over each token in the text. Thanks to the FLOPS regularizer [Paria *et al.* 2020], it learns a sparse vector for queries and documents with only positive or zero components in the BERT vocabulary space $\mathbb{R}^{|V|}$. This allows to easily perform term weighting and query expansion for queries and documents as shown in Figure 5.2. In addition, the SPLADE model [Formal *et al.* 2022] scores a document using the dot product between the sparse representation of a document ($\hat{d}$) and of a query ($\hat{q}$): $s(\hat{q}, \hat{d}) = \hat{q} \cdot \hat{d}$. In this work, we use several sets of parameters for the same SPLADE architecture and distinguish each version by its parameters θ, and the corresponding model noted $SPLADE(\ldots;\theta)$.

5.1.1.2 First stage ranking.

The first-stage ranking performs a cosine similarity between query and document embeddings. Similarly to [Lin *et al.* 2021b], we suppose that the document representation has been sufficiently well-tuned on the standard ad-hoc IR task. The document embedding $\hat{d}$ is thus obtained using the pre-trained SPLADE model, i.e. $\hat{d} = SPLADE(\texttt{[CLS]}\ d;\ \theta_{SPLADE})$ where θ_{SPLADE} are the original SPLADE parameters obtained from HuggingFace[2]. These parameters are not fine-tuned during the training process. In the following, we present how to contextualize the query representation using the conversation history. Then, we detail the training loss of the extended SPLADE model aiming at reducing the gap between the representation of the gold query and the contextualized representation.

Query representation. Like state-of-the-art approaches for first-stage conversational ranking [Lin *et al.* 2021b, Krasakis *et al.* 2022], we contextualize the query with the previous ones. Going further, we propose to include the answers in the query representation process, which is easier to do thanks to our lightweight training. An overview of our approach is presented in Figure 5.3.

[2]The weights can be found at https://huggingface.co/naver/splade-cocondenser-ensembledistil

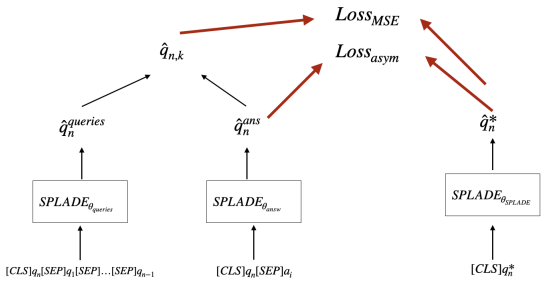


Figure 5.3: Learning query representations with CoSPLADE.

To leverage both contexts, we use a simple model where the contextual query representation at turn n, denoted by $\hat{q}_{n,k}$, is the combination of two representations, $\hat{q}_n^{queries}$ which encodes the current query in the context of all the previous queries, and $\hat{q}_{n,k}^{ans}$ which encodes the current query in the context of k the past answers[3]. Formally, the contextualized query representation $\hat{q}_{n,k}$ is:

$$\hat{q}_{n,k} = \hat{q}_n^{queries} + \hat{q}_{n,k}^{ans} \tag{5.1}$$

where we use two versions of SPLADE parameterized by $\theta_{queries}$ for the full query history and $\theta_{answers,k}$ for the answers.

Following [Lin *et al.* 2021b], we define $\hat{q}_n^{queries}$ to be the query representation produced by encoding the concatenation of the current query and all the previous ones:

$$\hat{q}_n^{queries} = SPLADE(\texttt{[CLS]}\ q_n\ \texttt{[SEP]}\ q_1\ \texttt{[SEP]}\ \ldots\ \texttt{[SEP]}\ q_{n-1}; \theta_{queries}) \tag{5.2}$$

To take into account the answers that the user had access to, we need to include them in the representation. Following prior work [Arabzadeh & Clarke 2020], we can consider various numbers of answers k, and in particular, we can either choose $k = 1$ (the last answer) or $k = n - 1$ (all the previous answers). Formally, the representation $\hat{q}_{n,k}^{ans}$ is computed as:

$$\hat{q}_{n,k}^{ans} = \frac{1}{k} \sum_{i=n-k}^{n-1} SPLADE(\texttt{[CLS]}\ q_n\ \texttt{[SEP]}\ a_i; \theta_{answers,k}) \tag{5.3}$$

Training The goal of the training is to reduce the difference between the gold query representation $\hat{q}_n^*$ and the representation $\hat{q}_{n,k}$ computed by our model.

To do so, we can leverage the gold query q_n^*, that is, a (hopefully) contextualized and unambiguous query. We can compute the representation $\hat{q}_n^*$ of this query by using the original SPLADE model, i.e.

$$\hat{q}_n^* = SPLADE(\texttt{[CLS]}\ q_n^*; \theta_{SPLADE}) \tag{5.4}$$

For example, for a query "How old is he?" the matching gold query could be "How old is Obama?". The representation of the latter given by SPLADE would be as follows:

$$[(\text{"}Obama\text{"}, 1.5), (\text{"}Barack\text{"}, 1.2), (\text{"}age\text{"}, 1.2), (\text{"}old\text{"}, 1.0), (\text{"}president\text{"}, 0.8), ...]$$

[3] In the experiments, we also explore an alternative model where answers and queries are considered at once. See results in Section 5.1.2.2

where the terms "Obama" and "Barack" clearly appear alongside other words related to the current query ("old" and the semantically related "age").

An obvious choice of a loss function is to match the predicted and gold representations using cosine loss (since the ranking is invariant when scaling the query). However, we observed in our preliminary experiments that models trained with the direct MSE do not capture well words from the context, especially for words from the answers. The reason is that the manually reformulated gold query usually only contains a few additional words from the previous turns that are directly implied by the last query. Other potentially useful words from the answers may not be included. This is a conservative expansion strategy which may not be the best example to follow by an automatic query rewriting process. We, therefore, design an asymmetric loss $Loss_{asym}()$ designed to encourage term expansion from past answers, but which avoids introducing noise by restricting the terms to those present in the gold query q_n^*. The final loss is a combination of the MSE and asymmetric losses:

$$Loss(\hat{q}_{n,k}, \hat{q}_n^*) = Loss_{MSE}(\hat{q}_{n,k}, \hat{q}_n^*) + Loss_{asym}(\hat{q}_{n,k}^{ans}, \hat{q}_n^*) \quad (5.5)$$

$$with\ Loss_{MSE}(\hat{q}_{n,k}, \hat{q}_n^*) = MSE(\hat{q}_{n,k}, \hat{q}_n^*) \quad (5.6)$$

$$and\ Loss_{asym}(\hat{q}_{n,k}^{ans}, \hat{q}_n^*) = \left(\max(\hat{q}_n^* - \hat{q}_{n,k}^{ans}, 0)\right)^2 \quad (5.7)$$

with $MSE()$ is the standard MSE loss, the maximum is component-wise. $Loss_{asym}$ pushes the $\hat{q}_{n,k}^{ans}$ representation to match the golden query representation $\hat{q}_n^*$ *if it can*, and $Loss_{MSE}$ pushes the queries-biased representation $\hat{q}_{n,k}$ to compensate *if not*. It thus puts a strong focus on extracting information from past answers. As a reminder, the parameters $\theta_{queries}$ and $\theta_{answers,k}$ used to obtain the different query representations are learned by optimizing the loss defined in Eq. (5.5).

5.1.1.3 Reranking

We perform reranking using a T5Mono [Nogueira *et al.* 2020] approach, where we enrich the raw query q_n with keywords identified by the first-stage ranker. Our motivation is that these words should capture the information needed to contextualize the raw query. The enriched query q_n^+ for conversational turn n is as follows:

$$q_n^+ = q_n.\ Context: q_1\ q_2\ \ldots\ q_{n-1}.\ Keywords: w_1, w_2, ..., w_K \quad (5.8)$$

where the w_i are the top-K most important words that we select by leveraging the first-stage ranker as follows. First, to reduce noise, we only consider words that appear either in any query q_i or in the associated answers a_i (for $i \leq n-1$). Second, we order words by using the maximum SPLADE weight over tokens that compose the word.[4]

We denote the T5 model fine-tuned for this input as $T5^+$. As in the original paper [Nogueira *et al.* 2020], the relevance score of a document d for the query q_n is the probability of generating the token "`true`" given a prompt $\text{pt}(q_n^+, d)$ = "`Query:` q_n^+. `Document:` d. `Relevant:`":

$$score(q_n^+, d; \theta) = \frac{p_{T5}(\texttt{true}|\text{pt}(q_n^+, d); \theta)}{p_{T5}(\texttt{true}|\text{pt}(q_n^+, d); \theta) + p_{T5}(\texttt{false}|\text{pt}(q_n^+, d); \theta)} \quad (5.9)$$

[4] To improve coherence, we chose to make keywords follow their order of appearance in the context, but did not vary this experimental setting.

where θ are the parameters of the T5Mono model.

Differently from the first-stage training, we fine-tune the ranker by aligning the scores of the documents, and not the weight of a query (which is obviously not possible with the T5 model). Here the "gold" score of a document is computed using the original T5Mono with the gold query q_n^*. The T5 model is initialized with weights made public by the original authors[5], denoted as θ_{T5}. More precisely, we finetune the pre-trained T5Mono model using the MSE-Margin loss [Hofstätter *et al.* 2020]. The loss function for the re-ranker (at conversation turn n, given documents d_1 and d_2, with d_1 more relevant than d_2) is calculated as follows:

$$\mathcal{L}_R = \left[(s(q_n^+, d_1; \theta_{T5+}) - s(q_n^+, d_2; \theta_{T5+})) - (s(q_n^*, d_1; \theta_{T5}) - s(q_n^*, d_2; \theta_{T5}))\right]^2$$

We optimize the θ_{T5+} parameters by keeping the original θ_{T5} to evaluate the score of gold queries.

5.1.2 Experimental evaluation

5.1.2.1 Protocol

To train our model, we used the CANARD corpus[6], a conversational dataset focusing on context-based query rewriting. More specifically, the CANARD dataset is a list of conversation histories, each being composed of a series of queries, short answers (human-written) and reformulated queries (contextualized). The training, development, and test sets include respectively 31.538, 3.418, and 5.571 contextual and reformulated queries.

To evaluate our model, we used the TREC CAsT 2020 and 2021 datasets which include respectively 25 and 26 information needs (topics) and a document collection composed of the MS MARCO dataset, an updated dump of Wikipedia from the KILT benchmark, and the Washington Post V4 collection. For each topic, a conversation is available, alternating questions and responses (manually selected passages from the collection, aka canonical answers). For each question (216 and 239 in total), the dataset provides its manually rewritten form as well as a set of about 20 relevant documents.

Metrics and baselines We used the official evaluation metrics considered in the TREC CAsT 2020 and 2021, namely nDCG@3, MRR, Recall@X, MAP@X, nDCG@X, where the cut-off is set to 1000 for the CAsT 2020 and 500 for the CAsT 2021. For each metric, we calculate the mean and variance of performance across the different queries in the dataset. With this in mind, we present below the different baselines and scenarios used to evaluate each component of our model.

- **First-stage ranking scenarios.** To evaluate the effectiveness of our first-stage ranking model (Section 5.1.1.2), we compare our approach CoSPLADE, based on the query representation of Eq. (5.1) with different variants (the document encoder is set to the original SPLADE encoder throughout our experiments): **SPLADE_rawQuery** (lower bound): SPLADE [Formal *et al.* 2021] using only the original and ambiguous user queries q_n; **SPLADE_goldQuery** (kind of upper bound):

[5] We used the Huggingface checkpoint `https://huggingface.co/castorini/monot5-base-msmarco`
[6] `https://sites.google.com/view/qanta/projects/canard`

SPLADE using the manually rewritten query q_n^*; **CQE** [Lin *et al.* 2021b], a state-of-the-art dense contextualized query representation learned using learning-to-rank on a dataset with pseudo-labels.

To model answers when representing the query using $\hat{q}_{n,k}^{ans}$, we design variants of our CoSPLADE model (first-stage ranking model learning queries representation with MSE and asymmetric losses) by using two historical ranges ("**All**" with $k = n-1$ answers and "**Last**" where we use only the last one, i.e. $k = 1$) and three types of answer inputs: **Answer** in which answers are the canonical answers; **Answer-Short** in which sentences are filtered as in the best performing TREC CAsT approach [Lin *et al.* 2021d]. This allows for consistent input length, at the expense of losing information; **Answer-Long** : as answers from CANARD are short (a few sentences extracted from Wikipedia – contrarily to CAsT ones), we expand them to reduce the discrepancy between training and inference. For each sentence, we find the Wikipedia passage it appears in (if it exists in ORConvQA [Qu *et al.* 2020]), and sample a short snippet of 3 adjacent sentences.

Finally, we also conducted ablation studies (on the best of the above variants) by modifying either the way to use the historical context or the training loss: **flat-Context** a one-encoder version of our SPLADE approach in which we concatenate all information of the context to apply SPLADE to obtain a single representation of the query (instead of two representations $\hat{q}_n^{queries}$ and $\hat{q}_{n,k}^{ans}$ as in Equations 5.2 and 5.3) trained using a MSE loss function (Equation 5.6) since there is no more two representations. **MSE** the version of our SPLADE approach trained with the MSE loss (Equation 5.6) instead of the proposed one (Equation 5.5); **cosine** the version of our SPLADE approach trained with a cosine loss instead of the proposed loss (Equation 5.5).

• **Second-stage ranking scenarios.** We have compared our model with several baselines (variants of a T5Mono ranker and of our model). Please note that we will not present the results of all these baselines but will directly present the final result of our model with respect to the score obtained by TREC participants.

5.1.2.2 First-stage ranking effectiveness

In our experiments, we focus on the first-stage ranking component of our CoSPLADE model. Results of the different baselines and scenarios on the TREC CAsT 2021 dataset are provided in Table 5.1[7]

In general, one can see that all variants of our approach (CoSPLADE_* models) outperform the scenario applying the initial version of SPLADE on raw and, more importantly, gold queries. This is very encouraging since this latter scenario might be considered as an oracle, i.e. the query is manually disambiguated. Finally, we improve the results over CQE [Lin *et al.* 2021b] for all the metrics – showing that our simple learning mechanism, combined with SPLADE, allows for achieving SOTA performance. More specifically, we can outline the following statements.

Leveraging queries and answers history better contextualizes the current query. The results of the flatContext scenario with respect to the SPLADE_goldQuery allow for comparing the impact of evidence sources related to the conversation since

[7]Similar trends are observed on CAsT 2020, but are not reported.

	Recall@500	MAP@500	MRR	nDCG@500	nDCG@3
Baselines					
SPLADE_rawQuery	30.8±2.7	5.5±0.9	21.3±2.9	17.8±1.8	13.1±2.1
SPLADE_goldQuery	68.8±2.0	16.1±1.2	55.5±3.3	42.8±1.7	38.3±2.8
CQE [Lin *et al.* 2021c]	79.1	28.9	60.3	55.7	43.8
Effect of answer processing: CoSPLADE_...					
AllAnswers	79.5±2.2	28.8±1.7	61.7±3.1	55.3±2.0	46.5±2.9
AllAnswers-short	72.8±2.6	25.7±1.9	54.4±3.3	49.5±2.3	40.1±3.0
AllAnswers-long	80.4±2.1	29.3±1.8	62.0±3.2	55.6±2.1	**48.9±3.0**
LastAnswer	83.4±2.0	31.2±1.8	61.8±3.1	58.1±2.0	47.4±3.0
LastAnswer-short	79.2±2.2	28.1±1.8	61.4±3.3	54.3±2.1	46.4±3.0
LastAnswer-long	**85.2±1.8**	**32.0±1.7**	**64.3±03.0**	**59.4±1.9**	48.6±3.0
CoSPLADE_LastAnswer-long variants					
flatContext	77.0±2.0	26.0±2.0	55.0±3.0	52.0±2.0	42.0±3.0
MSE loss	70.9±2.4	21.6±1.7	48.7±3.4	45.2±2.3	39.6±3.1
cosine loss	70.4±2.5	22.6±1.7	52.5±3.3	46.9±2.2	39.0±3.0

Table 5.1: Effectiveness of different scenarios of our first-stage ranking model on the TREC CAsT 2021.

they both use the same architecture (SPLADE). We can observe the usefulness of context to better understand the information need.

More detailed answers perform better. Since answers are more verbose than questions, including them is more complex, and we need to study the different possibilities (CoSPLADE_AllAnswers* and CoSPLADE_LastAnswer*). One can see that: 1) trimming answers (*-short) into a few keywords is less effective than considering canonical answers, but 2) it might be somehow effective when combined with the associated Wikipedia passage (*-long). Moreover, it seems more effective to consider only the last answer rather than the whole set of answers in the conversation history. Taking all together, these observations highlight the importance of the way to incorporate information from answers into the reformulation process.

Dual query representation with asymmetric loss leverages sparse query representations. The results of the flatContext scenario show that considering at once past queries and answers perform better (compared to the MSE loss scenario which is directly comparable). However, if we separate the representations *and* use an asymmetric loss function (AllAnswers* and LastAnswer* lines in Table 5.1), the conclusion changes. Moreover, the comparison of our best scenario CoSPLADE_LastAnswer-long with a similar scenario trained by simply using MSE or cosine losses reveals the effectiveness of our asymmetric MSE (Equation 5.7). Remember that this asymmetric loss encourages the consideration of previous answers in the query encoding. This reinforces our intuition that the conversation context, and particularly verbose answers, is important for the conversational search task. It also reveals that the context should be included at different levels in the architecture (input and loss).

TREC CAsT 2020	Recall@1000	MAP@1000	MRR	nDCG@1000	nDCG@3
TREC Participant (best)	63.3	30.2	59.3	52.6	45.8
TREC Participant (median)	52.1	15.1	42.2	36.4	30.4
TREC Participant (low)	27.9	1.0	5.9	11.1	2.2
CoSPLADE	82.4±2.0	26.9±1.5	58.1±2.9	54.2±1.8	44.0±2.7
TREC CAsT 2021	Recall@500	MAP@500	MRR	nDCG@500	nDCG@3
TREC Participants 1 (best)	85.0	37.6	67.9	63.6	52.6
TREC Participants 2 (median)	36.4	17.6	53.4	33.6	37.7
TREC Participants 3 (low)	58.9	7.6	27.0	31.4	15.4
CoSPLADE	84.9±1.7	35.5±1.8	69.8±3	62.2±1.9	54.4±2.9

Table 5.2: TREC CAsT 2020 and 2021 performances regarding participants.

5.1.2.3 Effectiveness compared to TREC CAsT participants

We finally compare our approach (first-stage + second-stage rankings) with TREC CAsT participants for the 2020 and 2021 evaluation campaigns. For each evaluation campaign, we report in Table 5.2 the best, the median, and the lowest TREC CAsT participants according to the nDCG@3 metric from the two overviews [Dalton *et al.* 2020a, Dalton *et al.* 2021]. For both years, we can see that we obtain effectiveness metrics that are very close or higher than the ones reached by the best participants. Indeed, CoSPLADE surpasses the best TREC participant for the 2020 evaluation campaign regarding Recall@1000 and nDCG@1000. For 2021, our model obtains better results than the best one for the MRR and nDCG@3 metrics. For both years, the best participant is the h2oloo team [Lin *et al.* 2021d, Dalton *et al.* 2021] which uses query reformulation techniques, either using AllenAI or T5. Our results suggest that our approach leveraging the SPLADE model trained using a ranking loss and fine-tuned on the conversation context using a query-driven loss allows combining the benefit of query expansion and document ranking in a single model that eventually helps the final reranking step. In other words, simply rewriting the query without performing a joint learning of document ranking can hinder the overall performance of the search task.

We also outline that our CoSPLADE model based on sparse representation obtains better results than the dense retrieval model T5Mono applied on queries reformulated with a T5 model (e.g., 84.9 vs. 80.4, respectively, for the Recall@500 for TREC CAsT 2021 - results not presented in this manuscript). This reinforces our intuition that sparse retrieval models, although being more sensitive to information loss because of the use of sparse representation to focus on terms, are well adapted to contextualize information needs.

5.1.3 Conclusion

In this contribution, we have shown how a sparse retrieval neural IR model, namely SPLADE [Formal *et al.* 2022], could be leveraged together with a lightweight learning process to obtain a state-of-the-art first-stage ranker. We further showed that this first-stage ranker could be used to provide context to the second-stage ranker, leading to results comparable with the best-performing systems. However, this setting is limited in the sense that it considers a passive IR system, i.e. simply performing ad-hoc IR. Current approaches are more willing to investigate mixed-initiative [Aliannejadi *et al.* 2021], en-

gaging the system in proactive interactions. Indeed, the TREC CAsT Track evolves into a mixed-initiative-oriented Track called IKAT[8]. This paradigm is addressed by another contribution presented in the following section.

5.2 User simulation for query clarification

In this contribution [Erbacher *et al.* 2022], we focus on query clarification which consists of a mixed-initiative between users and conversational search systems to solve an IR task. The objective of the IR system is thus to propose to the user a clarification of his/her information need and to interact with him/her to better understand his/her intent.

Unlike previous query clarification work based on single-turn interactions [Rao 2017, Rao & Daumé III 2018, Zamani *et al.* 2020a, Sekulic *et al.* 2021a, Sekulic *et al.* 2021b, Tavakoli *et al.* 2022] or simulated session logs in which successive actions are independent, except for the common interest towards the global topic [Aliannejadi *et al.* 2019], we propose here to build a fully simulated query clarification framework allowing multi-turn interactions between IR and user agents. Following [Aliannejadi *et al.* 2019], the IR agent identifies candidate queries and ranks them in the context of the user-system interactions to clarify the initial query issued by the user (agent). We target simple information needs, leaving multi-faceted information needs for future work since they might impact the modeling of the query ranking function. Our framework can be seen as a proof-of-concept for future work willing to integrate sequential models (namely reinforcement learning models) for question clarification. It is worth noting that large language models relying on attention mechanisms (transformers) are not yet well suited to handle sequential interactions and long-term planning, as current models are hardly trainable with current reinforcement learning algorithms [Chen *et al.* 2020b]. Thus, all agent components in our framework are based on continuous embeddings and simple models.

5.2.1 Question Clarification Simulation Framework

5.2.1.1 Overview and Research Hypotheses

Our query clarification simulation framework is inspired by [Aliannejadi *et al.* 2019], but provides the possibility of leveraging user and system agents' interactions sequentially. More particularly, our framework is detailed in Algorithm 1 and illustrated in Figure 5.4. The design of this evaluation framework is guided by some choices/hypotheses.

- First, following [Aliannejadi *et al.* 2019], we consider a fixed set of candidate queries $Q = \{q_1, q_2, ..., q_m\}$ constituting the reformulation of the initial query q_0. All the interactions are leveraged to improve step by step the ranking of this candidate query set so that, at the end of the session, the final query used for retrieving documents is a good clarification of its initial one. Obviously, this means that the set of candidate queries includes a large variety of queries which, for some of them, improve the search performance.

- Second, following [Zamani *et al.* 2020a], we propose to model question clarification as a possible option between two reformulated queries. In other words, expressed

[8] https://www.trecikat.com/

Algorithm 1 Our simulation framework for query clarification

- A) The user issues an initial query q_0 associated to her/his information need i.
- B) The IR system generates a set $Q = \{q_1, q_2, ..., q_m\}$ of candidate queries which might express different query reformulations or diversified queries to better explore the information need i.
- C) The IR system selects N queries to display to the user. To do so, we propose to follow [Aliannejadi *et al.* 2019] and design a model ranking the candidate query set Q to identify the top N queries.
- D) The user selects one of the N queries, enabling to extract positive and negative feedback, resp. noted (q^+, q^-).
- Steps C) and D) can be repeated several times to model multi-turn interactions. The query set ranking function (step C) integrates the user's sequential feedback (q^+, q^-) to improve the query ranking along with the interaction simulation.
- E) After T turns, the IR system considers the best-ranked query as the optimal query reformulation and runs a ranking model to retrieve documents.

in natural language, the IR system agent would ask the user agent the following question: "Which reformulated query do you prefer? A or B". This implies that the user is willing to judge queries A or B regarding its information need.

- Third, guided by the motivation to propose a framework for future work on sequential models, we consider here that each agent component is modeled at the embedding level. Indeed, leveraging large language models for generating/ranking questions is very effective, but integrating them into reinforcement learning models is still challenging (one main reason being the computational cost). This means that we processed *a priori* all queries and documents to represent them using text embeddings. This processing is done offline, alleviating the sequential modeling of the text encoding.

In what follows, we present the different components behind the IR system and user agents.

5.2.1.2 The IR System Agent

The IR agent has three objectives in our framework: 1) generating the set of candidate reformulated queries willing to be presented to the user, 2) ranking this set to identify the most relevant queries according to the interaction history, 3) ranking documents using the best-ranked query (ending the interactive session).

Generation of the candidate reformulated query set. The objective here is to instantiate various and diverse reformulations covering a wide range of relevant topics for the initial query q_0. Different techniques might be used, leveraging large language models [Nogueira *et al.* 2019b, Raffel *et al.* 2020, Rao & III 2019], query diversification [Cai *et al.* 2016, MacAvaney *et al.* 2021, Ye *et al.* 2021] or query expansion [Pal *et al.* 2013]. We propose here to use the T5 model [Raffel *et al.* 2020] which is designed to translate token sequences into other token sequences. It has already been used

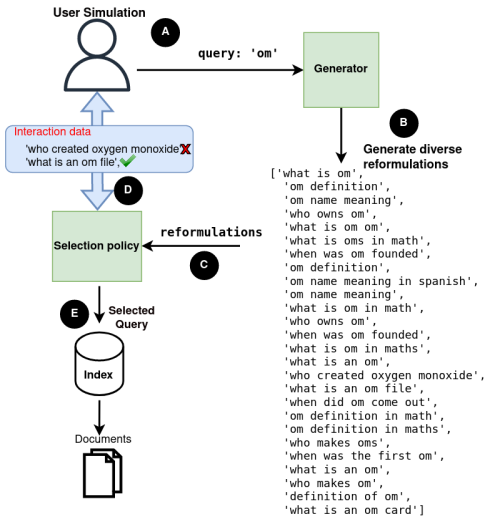


Figure 5.4: Query clarification simulation framework

for query reformulation tasks [Chen *et al.* 2020b, Raffel *et al.* 2020, Lin *et al.* 2020a]. On the top of that model, the generation process is driven by the diversity beam mechanism [Vijayakumar *et al.* 2016] which aims at generating a set Q of diversified query reformulation, $Q = \{q_1, q_2, ..., q_m\}$.

Ranking of queries based on the interaction history. The role of the selection policy is to select queries used to interact with the user agent. Following [Aliannejadi *et al.* 2019] which proposes to rank queries according to both performance criteria and the interaction context, we compute a pairwise score between two candidate queries q_i and q_j given the context, i.e., the initial query q_0 and the additional information provided by interaction $feedback_{t-1}, \ldots, feedback_1$ with the user. Formally, the ranking model relies on the probability that a query q_i obtains better IR performances (y_i) than query q_j (retrieval performance y_j) given the initial query q and the feedback obtained on queries displayed at previous utterances:

$$P(y_i > y_j | q_0, q_i, q_j, feedback_{t-1}, ..., feedback_1) \tag{5.10}$$

In practice, the model architecture is a siamese network that estimates the score y_i of a query q_i given the context and trained using a Lambda loss [Wang *et al.* 2018]. Each query score is computed as follows:

$$y_i = RNN_{score}(\mathbf{q_0}, \mathbf{q_i}, \mathbf{feedback_{t-1}}, \ldots, \mathbf{feedback_1}; \theta_{score}) \tag{5.11}$$

$$with \quad \mathbf{feedback_t} = RNN_{feedb}(cos(\mathbf{q}^+), sin(\mathbf{q}^-); \theta_{feedb}) \tag{5.12}$$

where RNN_{score} and $RNN_{feedb}()$ are two different recurrent neural networks with their own parameters θ_{score} and θ_{feedb}. $\mathbf{q_0}$ and $\mathbf{q_i}$ are embeddings of queries q_0 and q_i. $\mathbf{feedback_t}$ is the embedding of the user's feedback $feedback_t$, corresponding to the action of selecting or not the queries displayed at interaction turn t. We note q^+ and q^- those selected or non-selected queries, and $\mathbf{q}^+$ and $\mathbf{q}^-$ their associated embeddings. To capture the positive and negative feedback, we encode queries differently using the *cosine* and the *sine* functions, respectively.

At inference, queries are ranked according to their score estimated using Equation 5.11.

Final ranking of documents Documents are retrieved with the top-ranked query using a Dense Retriever model [Hofstätter *et al.* 2021].

5.2.1.3 The User Agent

After issuing the initial query q_0, the user agent interacts with the IR system agent to refine her/his information need. With this in mind, we hypothesize that the user is greedy toward her/his intent and fully cooperative. Greedy means that the user always selects the query which is the most similar to the overall intent. Despite being unrealistic, we ignore the click bias problem for the clarification questions presented in [Zamani *et al.* 2020a, Zamani *et al.* 2020b] which relies on position, presentation, and trust dimensions. Other choices for user simulation could be done, as experimented in [Câmara *et al.* 2022], but we let these variations for future work.

In practice, let $\mathbf{d}$ be the vector representing a user intent, q_i and q_j the clarification queries presented to the user agent. The user agent selects the best query (noted q^+ for highlighting positive feedback from the user) according to a similarity metric (in our case, the dot product) between the representation of the proposed queries q_i and q_j and intent d:

$$q^+ = argmax_{q_i}(\langle \mathbf{q_i}, \mathbf{d} \rangle) \tag{5.13}$$

5.2.2 Experimental evaluation

5.2.2.1 Protocol

Evaluating our simulation framework consists in measuring the effectiveness of the final ranking after T clarification interactions. Since the user behavior is greedy and follows a simple behavior dependent on the query selection process, the effectiveness results mainly denote the quality of this query ranking component. Other components (candidate set generation and final document ranking) do not depend on the interaction feedback, so we mainly focus on understanding whether the selection policy integrates users' feedback and takes good decisions to select the N clarification questions.

We carry out our experiments on the MS Marco 2020 passages dataset [Nguyen *et al.* 2016a] which regroups 8.8M passages and more than 500K query-passage relevance pairs. We evaluate our model on 2 sets: the small test set (43 queries) and a subset of the dev set (1000 queries sampled from 59 000). One motivation to consider these two datasets is their difficulty level: in the dev set, only one passage per query is labeled relevant in the ground truth, while several passages are considered as relevant in the test set.

Baselines and Scenarios To evaluate the effectiveness of our selection policy component, we compare with:

- Non-interactive settings. We measure the ranking effectiveness of the user's initial user query (noted **User Query**) and the **Best Reformulation** in the candidate query set - which can be seen as an oracle.
- **Naive interactive selection**: At each step, we select the 2 top ranked queries from

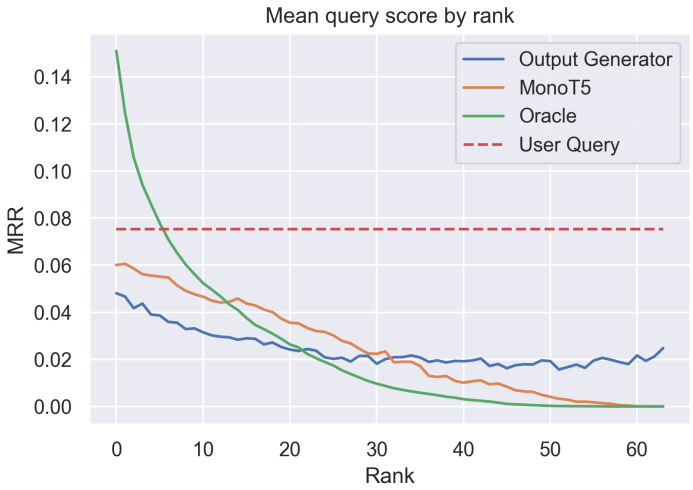


Figure 5.5: Effectiveness score of query reformulation by rank. The order of the query is determined either by the diversity beam search generation process (Output Generator), the query IR performances predicted by a pre-trained MonoT5 model (MonoT5), and the optimal ranking of queries according to their performances obtained by a Dense retrieval model [Hofstätter *et al.* 2021].

the current query rank and then remove the query which has not been selected by the user agent. The re-ranking of the candidate query set is only carried out once, at the beginning of the session, and the size of this list decreases with the interaction number.

To instantiate the selection policy after each interaction-driven query ranking step (step C in Figure 5.4), we consider these scenarios:

(1) **Interact. + Random Sample**: we sample 2 queries from the ranked candidate query set to constitute the interaction pair.

(2) **Interact. + Top 2**: we select the top 2 query reformulations at each turn.

(3) **Interact. + random sample@5**: we randomly select 2 queries among the top 5 query reformulations at each turn.

(4) **Interact. + Kmeans selection**: At each turn, queries in the candidate set are clustered in 2 groups using K-means. Queries from each cluster are ranked by the model. The best-ranked query within each cluster is selected. The cluster of the query not selected by the user is removed for the next turn from the set of candidate queries. This strategy corresponds to a refinement strategy as suggested in [Mustar *et al.* 2022], removing a group of semantically similar queries that have not been chosen by the user and going deeper into the other cluster.

5.2.2.2 Preliminary analysis: measuring the potential of ranking the query set

Our model introduces user-system interactions through query clarification to identify its information need and therefore enhance the retrieval process. To do so, a predefined query set is generated, assuming to cover a large diversity of information needs related to the initial query, and we propose to re-rank this query set to identify the most relevant

		No interaction	1	2	3	4	5
Best Reformulation (oracle)	MRR@10	0.872	-	-	-	-	-
User Query	MRR@10	**0.455**	-	-	-	-	-
Naive selection	MRR@10	0.213	0.327	0.359	0.403	0.419	0.427
Interact. + random sample	MRR@10	0.403	0.478	**0.481**	**0.490**	0.481	0.501
Interact. + Top 2	MRR@10	0.403	0.474	0.469	**0.490**	0.478	0.501
Interact. + random sample@5	MRR@10	0.403	0.473	0.467	**0.490**	0.479	0.501
Interact. + Kmean	MRR@10	0.403	**0.523**	0.465	0.469	**0.486**	**0.551**

Table 5.3: Effectiveness results on the Test set of MS Marco passage 2020 (43 queries - multiple relevant documents per query)

queries according to the initial need and the interactions. To test our hypothesis that it is possible to automatically identify the most relevant queries within a predefined query set without the supervision of relevant documents, we perform here a preliminary analysis (Figure 5.5) to quantify the potential retrieval performance gain of the candidate query set when they are ranked according to different criteria. More particularly, given the candidate query set generated by the T5 model (first paragraph in section 5.2.1.2), we compare the retrieval performance using the Mean Marginal Rank metric) according to different ordering within the query set: 1) the initial order provided by the Diversity Beam Search (called **Output Generator**), 2) the **Oracle** order in which queries are ranked in decreasing order according to their performance obtained through a Dense retrieval model [Hofstätter *et al.* 2021] regarding the Mean Marginal Rank metric, 3) the **MonoT5** order in which queries are ranked according to the performance score predicted by the pre-trained MonoT5 retrieval model [Pradeep *et al.* 2021].

We can see that predicting the query performance with MonoT5 allows to improve the performance for the top k queries regarding the query order provided by the Output Generator. This hurts the end of the list, but it is not critical in our case, since we consider the selection policy regarding the top query list. Moreover, one can notice that, although performance is increased, there is still a gap between the curve of the MonoT5 ranked list and the Oracle curve (order defined according to the real performance of queries using a Dense retriever [Hofstätter *et al.* 2021]). Our intuition is that leveraging users' interactions will lower this gap, which leads to the evaluation we performed in what follows.

5.2.3 Measuring the retrieval effectiveness after multi-turn query clarification

Second, we analyze the performance of the query ranker at different interaction turns using MRR@10. Tables 5.3 and 5.4 resp. show the results on the MS Marco passage 2020 test set and dev set. From a general point of view, we can see that performance metrics are lower for the dev set (Table 5.4) than for the test set (Table 5.3). This can be explained by the task difficulty, which is higher for the dev set in which only one document per query is assessed as relevant. By comparing all baselines and scenarios, we can outline the following trends.

- The first candidate query ranking within our interactive models (No interaction columns) provides lower performance than non-interactive baselines. For instance,

		No interaction	1	2	3	4	5
Best Reformulation (oracle)	MRR@10	0.411	-	-	-	-	-
User Query	MRR@10	**0.209**	-	-	-	-	-
Naive selection	MRR@10	0.122	0.151	0.165	0.176	0.186	0.191
Interact. + random sampl	MRR@10	0.171	0.201	**0.199**	0.195	0.200	0.201
Interact. + Top 2	MRR@10	0.171	**0.202**	0.198	0.197	0.201	0.199
Interact. + random sampl@5	MRR@10	0.171	**0.202**	0.198	0.196	0.200	0.200
Interact. + Kmean	MRR@10	0.171	0.174	0.198	**0.201**	**0.215**	**0.222**

Table 5.4: Effectiveness results on the subset of MS Marco passage 2020 dev set (1000 queries - 1 relevant document per query)

the **Interact. + Top2** scenario observes a decrease of 12% in terms of MRR@10 for the test set w.r.t. the initial user query.

- This trend is reversed with each interaction turn to obtain for certain scenarios performance higher than baseline ones (see all interaction models in the test set, and the **Interact + Kmeans** for the dev set).
- The interaction model with K-mean strategy looks to be the best selection policy for question clarification since it obtains the highest MRR@10 for both datasets. This is somehow intuitive because this strategy might correspond to a refinement strategy, going deeper and deeper into clusters. This is also connected with the dataset peculiarity since MS Marco is mainly composed mono-faceted questions in natural language.
- It is moreover worth noting that performances increase with interaction turns but additional exploratory experiments highlight a saturation point after 5/6 interaction turns. Our setting, therefore, allows to interact with the user to clarify his/her needs without overloading the search session.

5.2.4 Conclusion

This exploratory work focuses on sequential click-based interaction with a user simulation for clarifying queries. We provide a simple and easily reproducible framework simulating multi-turn interactions between a user and an IR system agent. The advantage of our framework is the simplicity of interactions, as there is no need for a dataset of real and annotated user-system interactions. Experiments highlight performance gain in terms of document retrieval through the multi-turn query clarification process and provide a comparative analysis of selection strategies. This framework can be improved in terms of naturalness to better fit with conversational search. In practice, this implies learning to generate natural language interactions for both the IR system and user agents.

5.3 Discussion and achievements

Understanding information needs is a longstanding issue [Jansen *et al.* 2000, Moshfeghi *et al.* 2016] which has gained in maturity with the modeling [Kuhlthau 1991, Azzopardi 2014] and the leveraging of users' interactions [Lavrenko & Croft 2001,

Agichtein *et al.* 2006]. It has been addressed through different evaluation campaigns, such as TREC Interactive [Hersh & Over 2001], TREC Contextual Suggestion [Dean-Hall *et al.* 2014], or TREC Session Search [Carterette *et al.* 2014], and more recently TREC CAsT [Dalton *et al.* 2020b] which has introduced interactions in natural language for solving an IR task. In this chapter, we presented works dealing with the contextualization of information needs in conversational search, implying to leverage of users' interactions to explicit their intent and improve the search effectiveness. Our objectives were twofold: 1) investigating different conversational search settings: ad-hoc search given a conversation context and proactive search with query clarification interactions, and 2) exploring the potential of existing retrieval or question generation strategies based on large language models. We draw the three following main conclusions from our works.

Sparse retrieval models have good transfer properties to contextualize information needs when they are fine-tuned in a lightweight fashion. Sparse neural retrieval models are known as models focusing on term unit, either for both sparse indexing [Zamani *et al.* 2018] or term expansion [Bai *et al.* 2020, MacAvaney *et al.* 2020, Formal *et al.* 2021]. All these models rely on sparse representations and, compared to dense approaches [Guo *et al.* 2016, Pradeep *et al.* 2021], have the advantages to be efficiently used for indexation, to explicit lexical matching, and being interpretable. They provide also good generalization performances on out-of-domain benchmarks [Formal *et al.* 2022]. Guided by this last statement, our CoSPLADE model introduces a lightweight fine-tuning strategy to contextualize queries according to conversations. More particularly, we have not considered relevance signals as evidence sources of the fine-tuning, but we have rather focused on query intent and matched the representations of queries with the ones of gold queries. The results obtained by our CoSPLADE model highlight that it is possible to improve ranking performances in a target task (here conversational search) without requiring supervision of relevant documents. We believe that this outcome is promising for future works in IR investigating new research fields which might lack datasets with complete supervision data. More explicitly, by leveraging the transfer abilities of those sparse neural retrieval models (in our case SPLADE), it seems that it is possible to integrate new search dimensions (here, the conversation) without having the supervision of relevant documents in the (new) targeted IR task. Obviously, more experiments are needed to evaluate the generalization of this statement to other sparse neural retrieval models [Bai *et al.* 2020, MacAvaney *et al.* 2020] and other emerging tasks (e.g., FACT-IR or Personal Information Access [Culpepper *et al.* 2018]).

The world knowledge captured by language models does not capture well matching signals: toward the combination of IR signals and language models. (Large) language models are often seen as world knowledge since they are learned on large datasets such as Wikipedia enclosing a wide range of knowledge and they capture several language cues thanks to various learning objectives [Devlin *et al.* 2019, Raffel *et al.* 2020, Dai *et al.* 2022, Kiela 2022, Bommasani *et al.* 2021]. They have also shown great transfer abilities over various tasks, either with fine-tuning or in zero-shot settings. However, we believe that IR requires specific signals that might not be learned in standard language models. In 2016, Guo *et al.* 2016 already discussed the

difference between semantic matching and relevance matching. The literature review [Mitra 2021, Lin *et al.* 2021a, Fan *et al.* 2022] highlights the need to integrate IR features in neural ranking models or to pre-train language models by integrating the IR objective. Indeed, framing IR tasks as pointwise document classification as in the monoBERT model [Nogueira & Cho 2019] provides an efficient strategy but has quickly been improved by integrating IR techniques such as interaction matrix [Hofstätter *et al.* 2020], ranking losses [Pradeep *et al.* 2021], or leveraging prompt-tuning [Fan *et al.* 2022].

Throughout this chapter, we have confirmed this need in our both settings. The experimentation of our CoSPLADE model highlights the synergic effect of addressing both query reformulation and relevance score prediction to contextualize information needs and obtain promising retrieval performances. Similarly, the preliminary analysis of our simulation framework shows that simply generating queries with a T5 model is not sufficient, and that the decoding should be guided by the relevance signal.

When interactivity can complement language models to perform IR tasks. The birth of large language models has enabled tremendous advances in numerous research fields in NLP, particularly in IR allowing to complement matching signals with world knowledge [Nogueira & Cho 2019, Arabzadeh *et al.* 2021]. The recent large language models released to the community, such as ChatGPT [Ouyang *et al.* 2022], T0 [Sanh *et al.* 2022], BLOOM [Scao *et al.* 2022b], or PALM [Chowdhery *et al.* 2022b], are able to answer a wide range of questions, questioning the place of search engines in our society. However, in a recent article in the press (`https://iai.tv/articles/all-knowing-machines-are-a-fantasy-auid-2334`), Emily M. Bender and Chirag Shah explain that a search engine, and more largely information seeking, is more than a tool providing answers to questions. Large language models are effective tools for fact-based questions, but there is a crucial need to solve search sessions with human engagement, particularly for complex intents that require cognitive efforts. As already outlined in early information-seeking models (e.g., the Information Search Process (ISP) [Kuhlthau 1991], Anomalous States of Knowledge (ASK) [Belkin *et al.* 1982], or the Ellis model [Ellis 1989]), a search session is characterized by multiple sense-making actions relying on the formulation of the search intent after different observation/exploration/organization phases, and in the end on the assessment of the displayed information to ensure its truthiness/relevance regarding the search intent. As suggested in [Culpepper *et al.* 2018], we believe that conversational search is not a way to erase all these steps, but should rather support them. Interacting with users in natural language offers exciting abilities to allow them to explicit their intent, and early works [Aliannejadi *et al.* 2019, Zamani *et al.* 2020a] on clarifying questions for a mixed-initiative system are the proof that language models are used in the right way. Our second contribution in this chapter highlights the retrieval effectiveness improvement of such interactive settings compared to an ad-hoc search setting. Also, the next focus of the TREC CAsT Track giving up ranking in conversation context at the benefit of mixed-initiative corroborates the intuition of leveraging large language models to support search. However, additional steps should be addressed in the future by the IR community, such as ensuring the truthiness of answers by complementing natural language answers with relevant pieces of documents [Culpepper *et al.* 2018] or providing an overview of sense-making process (e.g., of the

search process pathway) towards explainability [Gu *et al.* 2021b].

It is worth noting that the results obtained for our contributions are limited to the experimental design. We mention below some limitations of our works, particularly for the work dealing with query clarification which reflects the current research trends toward mixed-initiative, and the associated research perspectives.

- **Designing accurate evaluation tasks for conversational search.** Although mentioning that conversational search can be particularly relevant for complex and multi-faceted queries, we have considered the MSMarco dataset [Nguyen *et al.* 2016b], which rather refers to simple queries for a few reasoning. This choice is motivated by the desire to build a proof of concept with simple elements (from both the IR and user agents) experimented on simple datasets. Considering a multi-faceted query implies therefore a more complex IR and system model balancing relevance and coverage. We think that it would be beneficial to combine our framework with existing models focusing on the modeling of multi-faceted queries [MacAvaney *et al.* 2021] or interactive refinement strategies [Mustar *et al.* 2022].

  In addition, there is a crucial need in the community to design adapted tasks (and datasets) in which conversational search will be useful. As already discussed, large language models are able to answer factual questions but we believe that conversational search can bring more sense-making and more truthiness in the search process, allowing to solve complex information-seeking tasks [Shah & Bender 2022]. The current datasets on query clarification [Aliannejadi *et al.* 2019, Tavakoli *et al.* 2022] and the exploratory analyses of user engagements [Sekulic *et al.* 2021b] introduce the first step in this direction and the efforts need to be pursued. Having in mind that Wizard of Woz evaluations [Sun *et al.* 2021] might be costly and time-consuming, one strategy could be to leverage simulations to build new datasets and allowing to vary users' behaviors as done in [Câmara & Hauff 2020].

- **Towards more naturalistic mixed-initiative with multi-turn interactions in natural language.** One limitation of our framework is that it relies on interactions consisting in displaying two queries and letting users choose between one of them, without natural language interactions, and especially without discussion. If the displayed queries are not relevant, the user agent always chooses one of them, which might hinder the intent clarification process. We believe that the next step for future work is to enhance our framework with natural language interactions. To do so, we propose to leverage actual query clarification datasets, such as QuLac [Aliannejadi *et al.* 2019] to build system and user agents, respectively aiming at generating natural language query clarifications and providing answers in response to those clarifications. Large language models might appear as basic tools to learn these interactions, but they critically miss the integration of IR task signals to generate queries that are semantically relevant to the search intent and enhance the retrieval effectiveness of the conversational search session. We, therefore, envision using IR techniques, such as pseudo-relevance feedback, to enhance the language generation underlying query clarification.

Outcomes All these works are conducted in the context of the ANR JCJC SESAMS for which I am the principal investigator. I briefly describe my supervision activity regarding the topic:

- The query clarification topic is addressed by a PhD student, Pierre Erbacher, co-supervised with Ludovic Denoyer.
- I have also co-supervised two master students Nawel Astouati and Nam Le Hai who have participated in the TREC CAsT evaluation track, resp. in 2021 and 2022. A research paper has also been submitted to ECIR 2023 to discuss our model proposed for TREC CAsT 2022. This work is done in collaboration with Jian-Yun Nie, Thomas Gerald, Thibaut Formal, and Benjamin Piwowarski.

You can find below a list of related publications[9]:

- Pierre Erbacher, Laure Soulier: État de l'art des approches de modélisation et de simulation utilisateur pour la recherche d'information conversationnelle. CORIA 2021
- Pierre Erbacher, Ludovic Denoyer, Laure Soulier: Interactive Query Clarification and Refinement via User Simulation. SIGIR 2022: 2420-2425
- Nawel Astaouti, Thomas Gerald, Maya Touzari, Jian-Yun Nie et Laure Soulier. "MLIA- LIP6@TREC-CAST2021 : Feature augmentation for query recontextualization and passage ranking". In : Working Notes of TREC CAST 2021. 2021.
- Le Hai Nam, Thomas Gerald, Thibault Formal, Jian-Yun Nie, Benjamin Piwowarski, Laure Soulier. "MLIA-DAC@TREC CAsT 2022: Sparse Contextualized Query Embedding". In : Working Notes of TREC CAST 2022. 2022.
- Le Hai Nam, Thomas Gerald, Thibault Formal, Jian-Yun Nie, Benjamin Piwowarski, Laure Soulier. CoSPLADE: Contextualizing SPLADE for Conversational Information Retrieval. In: ECIR 2023

[9] National publications are not mentioned if they are simple translations of international publications.

Chapter 6

Investigating neural ranking model behaviors in continual learning

Contents

In this section, we focus on the understanding of neural ranking model behaviors in terms of knowledge transfer in a continual learning scenario (RQ3).

6.1 Continual learning framework for neural IR

The large majority of works in computer vision [Kirkpatrick *et al.* 2016, Douillard *et al.* 2020b] and NLP [Chen *et al.* 2015, Veron *et al.* 2019] address continual learning through classification tasks (e.g., labeling objects or pixels for object segmentation). The usual framework consists of a sequence of classification tasks $\mathcal{T}_1 \rightarrow \mathcal{T}_2 \rightarrow \cdots \rightarrow \mathcal{T}_n$ in which labels evolve with tasks. Given a task $\mathcal{T}_i$ decomposed as a tuple of an input set $\mathcal{X}_i$ and their associated label set $\mathcal{Y}_i$, the classification function is formalized as: $F : \mathcal{X}_i \rightarrow \mathcal{Y}_i$. The labels $\mathcal{Y}_i$ belong to a set of predefined classes $\mathcal{C}_i$ that evolve with tasks, implying for the classification model to learn an output distribution that differs from one task to another one. For instance, a model can be trained on classifying images of dogs and cats (task 1), and then used for classifying cars and boats (task2), and so on.

In neural IR, the setting is somehow different. Given a set of queries $\mathcal{Q}$ and a document collection $\mathcal{D}$, a neural ranking model M aims at predicting a score y for a pair of query-document $(q, d) \in \mathcal{Q} \times \mathcal{D}$; therefore, $M : \mathcal{Q} \times \mathcal{D} \rightarrow \mathcal{R}$. If we try to apply this setting in a continual learning framework, there is no sense to vary the distribution of the

output (i.e., the scores of the documents). What is more willing to evolve in IR are the users' intents and the document collection, namely the input distribution of the neural model. Therefore, a continual learning stream for IR can be formalized as a sequence of tasks $\mathcal{T}_i$ which denotes a tuple $(\mathcal{Q}_i, \mathcal{D}_i)$ of query-document sets:

$$\mathcal{T}_1 \rightarrow \mathcal{T}_2 \rightarrow \cdots \rightarrow \mathcal{T}_n \tag{6.1}$$

$$with\ \mathcal{T}_i = (\mathcal{Q}_i, \mathcal{D}_i) \tag{6.2}$$

For experimental reasons, each query set $\mathcal{Q}_i$ in the stream is composed of train and test sets. Depending on the continual learning setting, either both the query and document sets might evolve with tasks $\mathcal{T}_i$ or only one of them (i.e., only the queries or only the document collection).

With this in mind, the neural ranking model M is trained sequentially using an adaptation method (e.g., fine-tuning or continual learning techniques) on each training set of the query set $\mathcal{Q}_i$ and the associated document collection $\mathcal{D}_i$, one by one, to obtain at each training step a model M_i with parameters $\hat{\theta}^i$. For instance, the model M_2 with parameters $\hat{\theta}^2$ is obtained by training model M on the training set of $\mathcal{Q}_1$ applied on the document collection $\mathcal{D}_1$ to initialize model M_1 with parameters $\hat{\theta}^1$. Then, this last model is trained using an adaptation method on the training set $\mathcal{Q}_2$ associated with the document collection $\mathcal{D}_2$.

For each trained model M_i with parameters $\hat{\theta}^i$, we can estimate its retrieval performance $R_{i,i}$ on the test set of each query set $\mathcal{Q}_i$ given the document collection $\mathcal{D}_i$. In addition, we can measure the model's ability to accumulate/forget knowledge through the stream:

- The Forward Transfer (FT) which estimates the influence that learning a task $\mathcal{T}_i$ has on the performance on a future task $\mathcal{T}_j$, with $j > i$. When the forward transfer is positive, the model M_i is able to accumulate knowledge from previous tasks and is, therefore, addressing the zero-shot learning problem.

- The Backward Transfer (BT) which measures the impact of learning a task $\mathcal{T}_i$ on the performance on a previous task $\mathcal{T}_j$, with $j < i$. When the performance on previous tasks is lowered, we call this phenomenon *(catastrophic) forgetting*.

We, therefore, denote $R_{i,j}$ the performance of model M_i trained on the task stream up to $\mathcal{T}_i$ and evaluated on task $\mathcal{T}_j$. Depending on whether $j < i$ or $j > i$, $R_{i,j}$ is included in the estimation of the Forward and Backward Transfer. At a high level, a continual learning framework in IR can be illustrated in Figure 6.1 and in Algorithm 2.

All the difficulty in designing continual learning scenarios for IR lies in the design of the stream. One can think that each query in a dataset can be equated to a single task, and thus the continual learning setting is built as a stream of successive single queries $(\mathcal{Q}_i = q_i)$ and a fixed document collection $(\mathcal{D}_i = \mathcal{D}; \forall i = 1, \ldots, n)$. One drawback of this modeling is inherent to the continual learning framework: the additional signals captured at an iteration while training the model on each task will be very small. Indeed, we are not sure that the relevance signals of a single query are sufficient to measure knowledge drift. We, therefore, believe that a task $\mathcal{T}_i$ in an IR continual learning framework might include a group of queries (and a possibly evolving collection of documents), characterized by similar properties to have enough similar knowledge to impact the training step.

Algorithm 2 A continual learning framework for IR

Set up an ordered task stream **setting** $\mathcal{T}_1 \rightarrow \ldots \mathcal{T}_{n-1} \rightarrow \mathcal{T}_n$ with $\mathcal{T}_i = (\mathcal{Q}_i, \mathcal{D}_i)$
Initialize a model M_0 with random parameters or use a pre-trained model
for *k=1* **to** n **do**
  Train model M_i on the training query set $\mathcal{Q}_i$ given the document collection $\mathcal{D}_i$.
  Measure the retrieval performance $R_{i,i}$ of model M_i on test query set $\mathcal{Q}_i$.
  Measure the retrieval performance $R_{i,j}$ $(j > i)$ of model M_i on the testing instances of next query set $\mathcal{Q}_j$ (forward transfer).
  Measure the retrieval performance $R_{i,j}$ $(j < i)$ of model M_i on the testing instances of previous query sets $\mathcal{Q}_j$ (backward transfer)

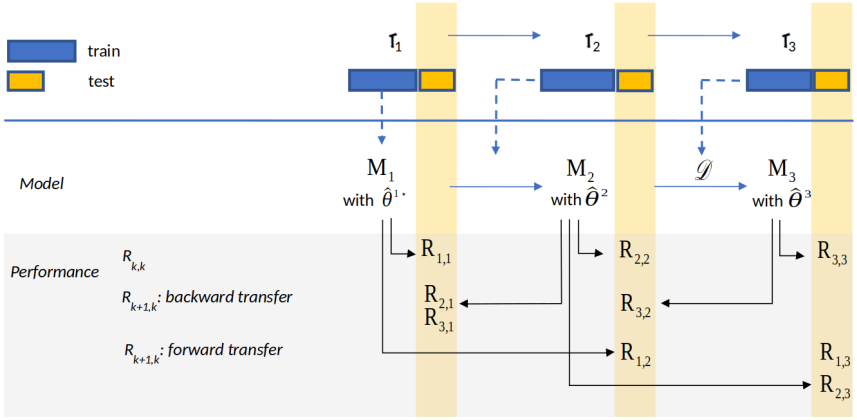


Figure 6.1: Illustration of the continual learning framework in IR using a 3-task stream setting for a given model M

The next sections instantiate the continual learning framework in IR in which task streams are designed using different assumptions:

- A short stream in which tasks are delimitated by the application domain: we consider different document collections (and their associated queries) dealing with the generic or medical domain, as well as documents from microblogs. In this setting, both query and document sets evolve with tasks.
- A long stream in which tasks are delimitated by topics: queries of a single dataset are clusterized so as to build sets of queries belonging to the same topic/subtopic (e.g., cooking with barbecue, salad cooking, gardening, etc...). In this setting, the dataset is fixed throughout all tasks $\mathcal{T}_i$ and only the query sets $\mathcal{Q}_i$ evolve.

We investigate the behavior of neural ranking models regarding the catastrophic forgetting issue, measured using the backward transfer.

6.2 Analyzing catastrophic forgetting in short streams

Our objective is twofold: 1) evaluating different neural ranking models on a short stream of successive tasks $\mathcal{T}_i$ delimited by different domains and 2) investigating their behavior regarding the catastrophic forgetting issue.

6.2.1 Experimental setting

We use three datasets chosen to fit with the requirement of cross-domain adaptation [Pan & Yang 2010]: 1) MS MARCO (***ms***) [Nguyen *et al.* 2016a] a passage ranking dataset built using the Bing search logs; 2) TREC Microblog (***mb***) [Lin & Efron 2013], an ad-hoc search dataset from TREC Microblog 2013 and 2014, which contains a public Twitter sample stream; 3) TREC CORD19 (***c19***) [Wang *et al.* 2020] an ad-hoc document search dataset including research articles dealing with SARS-CoV-2 or COVID-19 topics.
Besides, we consider four settings (See Table 6.1, column **"Setting"**) among which three 2-dataset (n = 2) and one 3-dataset (n = 3) settings. As done in previous work [Li & Hoiem 2018, Asghar *et al.* 2020], these settings follow the patterns ($task_1 \rightarrow \mathcal{Q}_2$) or ($\mathcal{T}_1 \rightarrow \mathcal{T}_2 \rightarrow \mathcal{T}_3$) where query set orders (i.e., dataset orders) are based on the decreasing sizes of the training sets assuming that larger datasets allow starting with well-trained networks.

Neural ranking models. We consider five state-of-the-art models [Yang *et al.* 2019a]: 1) interaction-based models: DRMM [Guo *et al.* 2016], PACRR [Hui *et al.* 2017] and KNRM [Xiong *et al.* 2017]; 2) BERT-based models: Vanilla BERT [Devlin *et al.* 2019] and CEDR-KNRM [MacAvaney *et al.* 2019b]. We use the OpenNIR framework [MacAvaney 2020] that provides a complete neural ad-hoc document ranking pipeline (a first-stage ranking with BM25 followed by a second-stage ranking with the mentioned models). Note that in this framework, the neural models are trained by linearly combining their own neural score (S_{NN}) with a BM25 score (S_{BM25}). We call the final score the *global relevance score*.

Domain adaptation and lifelong learning methods. We adopt the standard fine-tuning strategy (training on one domain and fine-tuning on the other) as the representative domain adaptation method. Additionally, we investigate the Elastic Weight Consolidation (EWC) [Kirkpatrick *et al.* 2016] as the lifelong learning method $\mathcal{L}$ and analyze its potential in IR.

Measures. To measure the knowledge acquired by the model during the re-ranking step, we measure the relative improvement achieved with the ranking based on the global relevance score (resp. the neural score) trained and tested on the previous dataset over the performance of the BM25 ranking obtained on the same testing dataset. We note this metric MAP@100 Δ_{MAP} (resp. Δ_{MAPN}). The objective is therefore to estimate how much knowledge is captured by neural ranking models given the first stage.

Concerning the catastrophic forgetting measure, we use the *remembering* measure (REM) derived from the *backward transfer measure* (BWT) proposed in [Rodríguez *et al.* 2018].

- **BWT**: measures the intrinsic effect (either positive or negative) that learning a model M on a new task $\mathcal{T}_i$ has on the model performance obtained on an old task $\mathcal{T}_j$ with $j < i$, referred as *backward transfer*. Practically, in line with a lifelong learning perspective, this measure averages, in the task stream, the differences between the performances of the model obtained on the previous task and the

performances of the oracle model trained and tested on the same previous task. Thus, while positive values represent positive backward transfer, negative values express catastrophic forgetting. Formally, the BWT measure is computed as:

$$BWT = \frac{\sum_{i=2}^{n} \sum_{j=1}^{i-1} (R_{i,j} - R^*_{j,j})}{\frac{n(n-1)}{2}} \tag{6.3}$$

$R_{i,j}$ is the performance measure of model M_i obtained right after learning on task $\mathcal{T}_j$. $R^*_{j,j}$ is the performance of the oracle model M^*_j trained on task $\mathcal{T}_j$ and tested on the same task. To make fair comparisons between the different studied neural models, we normalize the differences in performance $(R_{i,j} - R^*_{j,j})$ on model agnostic performances obtained using $BM25$ model on each previous task $\mathcal{T}_j$. Formally, we estimate $R_{ij} = \frac{MAP(M_i, \mathcal{T}_j)}{MAP(BM25, \mathcal{T}_j)}$ where $MAP(M_i, \mathcal{T}_j)$ is the effectiveness of model M_i on the task $\mathcal{T}_j$. In our work, we only report the REM values computed using the MAP measure (we observe similar trends for NDCG@20 and P@20).

- **REM**: because the BWT measure has a bivalent meaning, i.e. positive values for positive backward transfer and negative values for catastrophic forgetting, we report the REM metric that is only concerned about forgetting. Formally, it is estimated as follows:

$$REM = 1 - |min(BWT, 0)| \tag{6.4}$$

A REM value equal to 1 means that the model does not catastrophically forget. We denote REM and REMN, the remembering metric applied on the ranked list obtained using, respectively, 1) a linear combination of BM25 and neural scores (also called global relevance score), and 2) solely the neural score.

6.2.2 Results

Table 6.1 reports all the metric values for each model/setting pairwise. Regarding the **"Fine-tuning"** adaptation technique aiming at measuring the catastrophic forgetting (RQ1), we can outline the following statements.

Catastrophic forgetting in short IR streams is not as clear as in Computer Vision. While previous works have shown that neural models suffer from catastrophic forgetting in large proportion [Kirkpatrick *et al.* 2016], the REM and REMN metrics in IR are in general close to 1, with small variation. This suggests that catastrophic forgetting is not as strong as in computer vision, and that neural ranking models are more driven by relevance matching signals during the learning process than the application domain or the topic of queries.

Bert-based models are able to bring effectiveness gains additively to those brought by the exact-based matching signals in BM25. Only CEDR and VBERT models achieve positive improvements w.r.t to both the global ranking (Δ_{MAP} : +19.6%, +17.4% resp.) and the neural ranking (Δ_{MAP}: +29.2%, +25.8% resp.), particularly under the setting where mb is the previous dataset ($mb \rightarrow c19$). These effectiveness gains can be viewed as new knowledge in terms of semantic matching.

Model	Setting	Fine-tuning		EWC-based lifelong learning	
		REM(REMN)	$\Delta_{MAP(MAPN)}$	*REM(REMN)*	$\Delta_{REM(REMN)}$
DRMM	$ms \rightarrow c19$	1.000(1.000)	+2.2(-73.6)	1.000(1.000)	0(0)
	$ms \rightarrow mb$	0.962(0.943)	+2.2(-73.6)	0.971(0.974)	+0.9(+**3.3**)
	$mb \rightarrow c19$	1.000(0.965)	-1.7(-7.7)	1.000(0.662)	0(-31.4)
	$ms \rightarrow mb \rightarrow c19$	0.976(0.938)	+2(-73.6)	0.979(1.000)	+**0.3**(+**6.6**)
PACRR	$ms \rightarrow c19$	1.000(0.760)	+2.5(-30.1)	1.000(0.756)	0(-0.5)
	$ms \rightarrow mb$	1.000(1.000)	+2.5(-30.1)	1.000(1.000)	0(0)
	$mb \rightarrow c19$	1.000(0.523)	0(+10)	1.000(0.940)	0(+**79.7**)
	$ms \rightarrow mb \rightarrow c19$	1.000(0.759)	+2.5(-30)	1.000(0.874)	0(+**15.2**)
KNRM	$ms \rightarrow c19$	1.000(1.000)	-12.1(-89)	1.000(1.000)	0(0)
	$ms \rightarrow mb$	1.000(1.000)	-12.1(-89)	1.000(1.000)	0(0)
	$mb \rightarrow c19$	1.000(0.810)	-2(-13.8)	1.000(0.902)	0(+**11.4**)
	$ms \rightarrow mb \rightarrow c19$	1.000(1.000)	-12.1(-89)	1.000(0.963)	0(-3.7)
VBERT	$ms \rightarrow c19$	0.930(1.000)	-10.6(0)	1.000(1.000)	+**7.5**(0)
	$ms \rightarrow mb$	1.000(0.883)	-10.6(0)	1.000(1.000)	0(+**13.3**)
	$mb \rightarrow c19$	0.913(1.000)	+17.4(+25.8)	1.000(1.000)	+**9.5**(0)
	$ms \rightarrow mb \rightarrow c19$	0.989(0.922)	-10.6(0)	1.000(1.000)	+**1.1**(+**8.5**)
CEDR	$ms \rightarrow c19$	0.826(1.000)	+2.6(+14.2)	1.000(1.000)	+**21.1**(0)
	$ms \rightarrow mb$	0.510(0.920)	+2.6(+14.2)	1.000(1.000)	+**96.1**(+**8.7**)
	$mb \rightarrow c19$	0.940(1.000)	+19.6(+29.2)	1.000(1.000)	+**6.4**(0)
	$ms \rightarrow mb \rightarrow c19$	0.771(0.946)	+2.6(+14.2)	0.891(1.000)	+**15.6**(+**5.7**)

Table 6.1: Per model-setting results in our fine-tuning and EWC-based lifelong learning experiments. All the measures are based on the MAP@100 metric. The improvements $\Delta_{MAP(MAPN)}$ and $\Delta_{REM(REMN)}$ are reported in percent (%).

Capturing additional knowledge w.r.t exact-matching signals does not avoid catastrophic forgetting. While some models-settings pairs are able to capture a large amount of additional knowledge (e.g., VBERT and CEDR in the $mb \rightarrow c19$ setting) without forgetting information on previous tasks (REM and REMN metrics close to 1), this trend is not obvious in other cases when looking at the correlation between REM and Δ_{MAP} metrics. For instance, DRMM generally does not forget but the accumulation of knowledge regarding exact-matching signals is very diverse, ranging from negative to positive values. Interestingly, the KNRM does not accumulate knowledge regarding exact-matching signals nor forgets knowledge during the fine-tuning.

We turn now our attention to the **"EWC-based lifelong learning"** columns in Table 6.1 to investigate the gain of lifelong learning strategies [Kirkpatrick *et al.* 2016] (RQ3). Our experiment results show that among the 9 (resp. 11) settings that exhibit catastrophic forgetting in the combined model (resp. neural model), the **EWC strategy allows to improve** 9/9 i.e., 100% (resp. 9/11 i.e., 88%) of them in the range $[+0.3\%, +96.1\%]$ (resp.$[+3.3\%, +79.7\%]$). Given, on the one hand, the high variability of the settings derived from the samples, and on the other hand, the very low number of settings (10% i.e., 2/20) where a performance decrease is observed in the previous dataset, we could argue that the **EWC-based lifelong learning is not inherently impacted by dataset order leading to a general effectiveness gain over the models**.

6.3 Designing long topic streams and analyzing pathological IR behaviors

One drawback of the previous contribution is that it focuses on very short and synthetic streams, which can be limited to infer robust behavior in real continual learning settings characterized by an infinite timeline. Our objective here is to build a long stream for evaluating the behavior of neural ranking models in a continual learning framework. Due to computational reasons, we limit this analysis to two neural ranking models: 1) the vanilla Bert [Devlin *et al.* 2019] (noted **VBert**) and 2) the *Mono-T5-Ranker* [Nogueira *et al.* 2020] (noted **MonoT5**).

6.3.1 Building a dataset with long topic sequences.

One main difficulty is to create this sequence considering the availability of IR datasets. In contrast to our previous work based on a sequence of datasets of different domains [Lovón-Melgarejo *et al.* 2021], we propose to model the task at a lower granularity level, namely topics, instead of the dataset granularity[1]. To create the long sequence, we consider a fixed dataset $\mathcal{D}$, namely the MSMarco dataset [Nguyen *et al.* 2016c], assuming that several queries might deal with the same user's interest (e.g., "what is the largest source of freshwater on earth?" or "what is water shortage mitigation"). These groups of queries $\mathcal{Q}_i$ denote what we call *topics* and each task $\mathcal{T}_i$ in the stream is thus built of a query set $\mathcal{Q}_i$ and the dataset $\mathcal{D}$.

To extract topics $\mathcal{Q}_i$, we propose a clustering-based method consisting in extracting clusters from randomly sampled queries using a sentence-BERT clustering[2] and populating those clusters with queries from the whole dataset. Finally, the sequence of topics is produced by randomly rearranging clusters to avoid bias of cluster size. Depending on the value of clustering hyper-parameters, we obtain three datasets of topic sequences of different sizes (19, 27, and 74), resp. called *MS-TS*, *MS-TM* and *MS-TL* (for small, medium, large). To evaluate our topic sequence methodology, for each of the three datasets we create a long topic sequence baseline in which clusters are randomly built. We obtain three randomized datasets denoted *MS-RS*, *MS-RM*, and *MS-RL*.

To verify the relevance of the clusters, we measure retrieval similarity within and between clusters (i.e., queries within clusters might have similar retrieval evidence and queries between clusters might have different ones). As retrieval similarity between query clusters, we use the retrieved documents for each query using the *BM25* model[3]. Our intuition is that similar queries should have more commonly retrieved documents (and vice versa). For this, we denote the $c-score$ which measures the ratio of common documents between two topics $\mathcal{Q}_i$ and $\mathcal{Q}_j$. Statistics of these three topic sequences and the relevance of clusters through intra and inter c-score are described in Table 6.2. Moreover, Figure 6.2 depicts the $c-score$ matrix for all couples $(i,j) \in \{1,2,\ldots,|S|\}^2$ for a subset of 8 topics (for more clarity in the figures) of the $MS-S$ and $MS-RS$ corpora. We observe that for the randomized matrix (Figure 6.2 right), the metric value

[1] Please note that the number of datasets adapted to neural *IR* with a sufficiently large number of queries and relevance judgments is not sufficient to build a long sequence of datasets as we envision.

[2] https://www.sbert.net/examples/applications/clustering (fast clustering)

[3] Implemented in pyserini: https://github.com/castorini/pyserini

Name	$\lvert\#topics\rvert$	#queries by topics	inter	intra
MS-TS	19	$3,650 \pm 1,812$	3.8%	31.4%
MS-TM	27	$3,030 \pm 1,723$	4.1%	32.1%
MS-TL	74	$1,260 \pm 633$	3.3%	34.6%
MS-RS	19	$3,650 \pm 1,812$	10.3%	10.2%
MS-RM	27	$3,030 \pm 1,723$	9.9%	9.8%
MS-RL	74	$1,260 \pm 633$	8.7%	8.8%

Table 6.2: Parameters and statistics of the generated dataset and their inter/intra topic similarity metric ($c-score$). The intra-score is the mean $c-score$ when comparing a topic with itself, and the inter-score when comparing different topics.

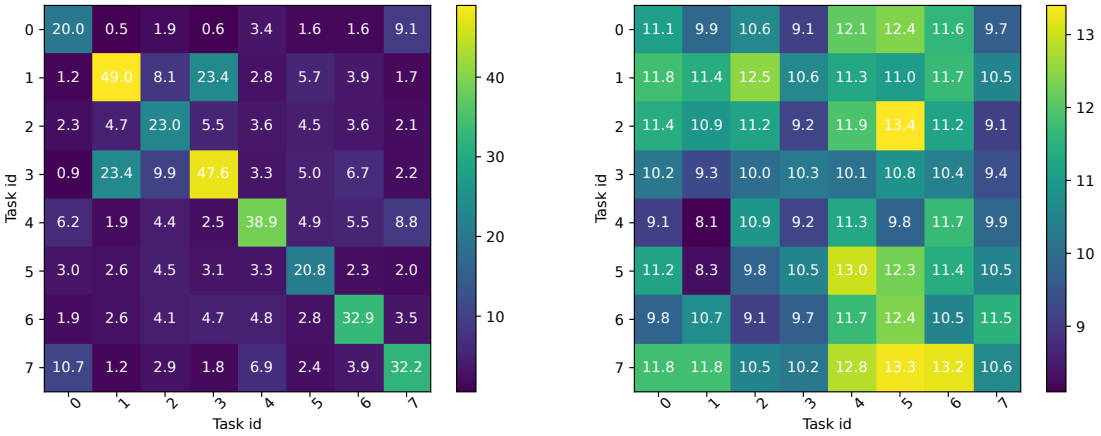


Figure 6.2: Matrix of similarities between topics for 8 topics of MS-S (left) and MS-RL (right) datasets. The c-score (×100) is processed on all topic pairs, a high value (yellow) denotes the level of retrieved document overlap between queries of topics.

is relatively uniform. In contrast, in the matrix obtained from our long topic sequence based on clustering (Figure 6.2 left), the c-score is very small when computed for different topic clusters (low inter similarity) and higher in the diagonal line (high intra similarity).

6.3.2 Analyzing the behavior of neural ranking models on long topic sequences

We investigate now the global performance of neural ranking models after having successively been fine-tuned on topics in our MSMarco-based long sequence setting (Table 6.3). For comparison, we report results for the multi-task baseline in which models are trained on all the topics of the sequence jointly (without sequence consideration). At first glance, we can remark that, in a large majority, neural models after fine-tuning on random sequences or multi-task learning obtain better results than after the fine-tuning on our long topic sequences. This can be explained by the fact that, within our setting, **the topic-driven sequence impacts the learning performance: a supplementary effort is needed by the model to adapt to new domains**, which is not the case in the random setting. In this latter, the diversity is at the instance level. This trend is depicted in Figure 6.3, highlighting peaks in the clustering-based setting (blue line) referring to topic/cluster changes. This result confirms that catastrophic forgetting might occur with neural ranking models.

Model	Dataset	Learning protocol		
		Random	clustering	Multi-task
VBert	SMALL	18.4/19.6	16.3/17.5	**18.5/19.7**
	MEDIUM	**17.9/19.0**	17.8/18.9	17.5/18.7
	LARGE	**18.8/19.9**	17.3/18.5	18.5/19.7
MonoT5	SMALL	**16.1/17.3**	13.1/14.4	15.5/16.8
	MEDIUM	15.4/16.7	13.4/14.7	**15.7/17.1**
	LARGE	13.9/15.1	13.8/15.1	**15.7/17.0**
BM25	SMALL		10.8/11.7	
	MEDIUM		10.5/11.4	
	LARGE		11.7/12.7	

Table 6.3: General performance of neural ranking models on long topic sequences. Mean performances on all the topic sequences reporting mrr@10/mrr@100 for the different models.

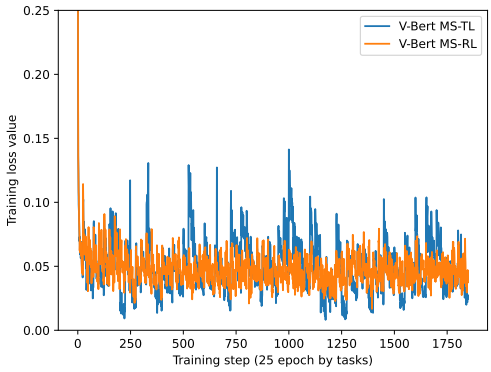


Figure 6.3: General performance of neural ranking models on long topic sequences. VBert loss values for both random and clustering-based large corpus.

Through our different analyzes (see the paper [Gerald & Soulier 2022] for complete experiments), we highlighted the following general trends:

- **Long stream of tasks implies noticeable catastrophic forgetting.** The comparison of neural ranking model performances when trained on task sequences (random or clustering-based) w.r.t multi-task learning highlights that continual learning leads to lower effectiveness results. It is more prevalent in our setting, i.e., when tasks are split by topic. Combined with the previous analysis highlighting small catastrophic behaviors on short streams (although using different metrics), this suggests that neural ranking models are more prone to forget when trained on long topic streams. This result is consistent with previous work in computer vision [Kirkpatrick *et al.* 2016, Douillard *et al.* 2020b].

- **Ranking models behave differently in terms of catastrophic forgetting.** We notice that catastrophic forgetting occurs more the MonoT5 model being more sensitive to new domains than the VBert model. This can also explain by the difference in the way of updating weights (suggested in the original papers

[Devlin *et al.* 2019, Nogueira *et al.* 2020]). In VBert, two learning rates are used: a small one for the Bert model and a larger one for the scorer layer; implying that the gradient descent mainly impacts the scorer. This intuition needs more investigation since we use the second-order gradient descent of ADAM. In contrast, the MonoT5 is learned using a single learning rate leading to modify the whole model. For a reminder, the previous analysis on short stream highlighted forgetting behavior for the CEDR model, which is also a joint model introducing the representation learning of contextual embedding into neural ranking models such as PACRR, DRMM, and KRNM. We can therefore infer that multiple objective functions might hinder knowledge retention in continual learning settings.

- **The more topics are similar, the less neural ranking models forget.** In contrast to continual learning in other application domains [Kirkpatrick *et al.* 2016, Rebuffi *et al.* 2017] in which fine-tuning models on other topics always deteriorates previous topic performance, our analysis suggests that topics might help each other (particularly when they are relatively similar), at least in lowering the catastrophic forgetting. Moreover, as discussed in [Guo *et al.* 2016], relevance matching signals play an important role in model performance, often more than semantic signals. The topic sequence may lead to a synergic effect to perceive these relevance signals.

In brief, continual learning in IR differs from the usual classification/generation lifelong learning setting. It is more likely to have different topics allowing to "help" each other, either by having closely related topics or by focusing on query-document matching signals.

6.3.3 Analyzing pathological behaviors using IR-driven controlled stream-based scenarios

Having in mind that a task $\mathcal{T}_i$ is built of a tuple $(\mathcal{Q}_i, \mathcal{D}_i)$ of query and document sets, we have seen in our two previous analyses that query and documents sets might evolve simultaneously with the stream (as in our short stream scenario) or not (as in our long stream scenario). Guided by IR-driven use cases, we aim here to further our investigation regarding the typology of evolving data (documents and/or queries). Typically, the available documents may change over time, and some might become outdated (for instance documents relevant at a certain point in time). Also, queries evolve, either because of new trends, the emergence of new domains, or shifts in language formulation. To model those scenarios, we propose three different short task streams designed as IR-controlled scenarios. Tasks are based on our long topic sequence $S = \{\mathcal{T}_1, \ldots, \mathcal{T}_i, \ldots, \mathcal{T}_n\}$ built on MSMarco. For each scenario, we consider an initial setting $\mathcal{T}_{init}$ modeling the general knowledge before analyzing a particular setting. In other words, $\mathcal{T}_{init}$ constitutes the data used for the pre-training of neural ranking models before fine-tuning on a specific sequence. The proposed controlled settings are presented in what follows and Tables 6.4 and 6.5 present the obtained results for all settings according to the different scenario configurations.

- **Direct Transfer scenario [Veniat *et al.* 2020]**: The task sequence is $(\mathcal{T}_{init}, \mathcal{T}_i^+, \mathcal{T}_j, \mathcal{T}_i^-)$ where tasks $\mathcal{T}_i^+$ and $\mathcal{T}_i^-$ belong to the task $\mathcal{T}_i$ and have different sizes ($|\mathcal{T}_i^-| \ll |\mathcal{T}_i^+|$). This setting refers to when the same task comes back

	DT scenario			B
	$\mathcal{T}_i^+$	$\mathcal{T}_j$	$\mathcal{T}_i^-$	
MonoT5	26.6	24.9	26.6	27.2
VBert	28.5	26.7	27.3	28.9

Table 6.4: Model performances using MRR@10 on the Direct Transfer (DT) *IR*-driven controlled setting. B stands for the baseline model: training on both $\mathcal{T}_{init}$ and $\mathcal{T}_i$.

		IU			LD		
		$\mathcal{T}_i'$	$\mathcal{T}_i''$	B	$\mathcal{T}_i^*$	$\mathcal{T}_i^{**}$	B
MonoT5	$Q_{i1}D_{i1}$	28.15	29.6	-	15.6	23.0	-
	$Q_{i2}D_{i2}$	7.75	26.0	-	16.8	26.5	-
	$Q_{i1}D_{i1} \cup Q_{i2}D_{i2}$	18.2	27.8	27.2	15.6	23.8	27.2
VBert	$Q_{i1}D_{i1}$	23.7	30.2	-	28.2	30.1	-
	$Q_{i2}D_{i2}$	14.5	31.4	-	25.5	25.5	-
	$Q_{i1}D_{i1} \cup Q_{i2}D_{i2}$	19.1	30.9	28.9	26.6	27.0	28.9

Table 6.5: Model performances using MRR@10 on *IR*-driven controlled settings: Information Update (IU) and Language Drift (LD). B stands for the baseline models: fine-tuning on $\mathcal{T}_i$ for IU and LD scenarios.

in the stream with newly available data (new queries and new relevant documents). As shown in the DT scenario column in Table 6.4, the performance of both models on task $\mathcal{T}_i$ drops after fine-tuning on a foreign topic (i.e., on task $\mathcal{T}_2$). This highlights a catastrophic forgetting behavior. However, both models are able to slightly adapt their retrieval performance after fine-tuning on task $\mathcal{T}_i^-$. This final performance is however lower than the baseline model (training on both $\mathcal{T}_{init}$ and $\mathcal{T}_i$) and for the VBert model lower than its initial performance at the beginning of the learning sequence. These two last statements suggest the ability of neural models to quickly reinject a part of the retrained knowledge learned in the early sequence to adapt to new query/document distributions on the same topic.

- **Information Update scenario**: The task sequence is $(\mathcal{T}_{init}, \mathcal{T}_i', \mathcal{T}_i'')$ where $\mathcal{T}_i'$ and $\mathcal{T}_i''$ have dissimilar document distributions and a similar query distribution. Intuitively, it can be interpreted as a shift in the required documents, such as new trends concerning a topic or an update of the document collection. The IU columns in Table 6.5 highlight that evaluation performances increase throughout the fine-tuning process over the sequence. This denotes the ability of models to adapt to new document distributions (i.e., new information in documents). The adaptation is more important for the MonoT5 model, probably explained by its better adaptability to new topics. Interestingly, the performance at the end of the learning sequence overpasses the result of the baseline (fine-tuning on $\mathcal{T}_i$): this can be explained by the methodology used to create this setting, associating pseudo-relevant documents to existing queries to simulate the information update (more details in the paper [Gerald & Soulier 2022]). Our intuition is that the introduced pseudo-relevant documents in task $\mathcal{T}_i'$ might help in perceiving relevance signals.

- **Language Drift scenario**: The topic sequence is $(\mathcal{T}_{init}, \mathcal{T}_i^*, \mathcal{T}_i^{**})$ where $\mathcal{T}_i^*$ and

$\mathcal{T}_i^{**}$ have similar document distributions and a dissimilar query distribution. This can correspond to a change of query formulation or a focus on the same topic. As outlined in the LD columns in Table 6.5, the behavior is relatively similar to IU in terms of adaptation: performances increase throughout the sequence. Note that MonoT5 seems more flexible in terms of adaptation. However, it seems difficult to sufficiently acquire enough knowledge to reach the baseline performance (although pseudo-relevant documents have also been introduced as in the IU scenario). This might be due to the length of queries concerned by the distribution drift: when the vocabulary changes in a short text (i.e., queries), it is more difficult to capture the semantics for the model and to adapt itself in terms of knowledge retention than when the change is carried out on long texts (i.e., documents as in the information update).

6.3.4 Conclusion

In this work, we have designed a continual learning dataset for IR including long topic sequences and controlled IR sequences. Our investigation aims at observing a catastrophic forgetting metric for different models, and also in regard to topic similarity. Our analysis suggests different design implications for future work: 1) catastrophic forgetting in IR exists but is low compared to other domains [Kirkpatrick *et al.* 2016, Veniat *et al.* 2020], 2) when designing lifelong learning strategy, it is important to care for topic similarity, the position of the topic in the learning process and for the type of the distribution that needs to be transferred (short vs. long texts).

6.4 Discussion and achievements

In these works [Lovón-Melgarejo *et al.* 2021, Gerald & Soulier 2022], we have defined a continual learning framework for IR and investigated the catastrophic forgetting behavior of neural ranking models in short and long settings. We have carried out a fined-grained evaluation, observing a catastrophic forgetting metric for different models, and also in regards to topic similarity. The main conclusions that we draw from this line of research are the followings.

Neural ranking models have generally good properties regarding catastrophic forgetting. Previous works in computer vision [Kirkpatrick *et al.* 2016, Davidson & Mozer 2020, Douillard *et al.* 2020a, Ramasesh *et al.* 2021] highlight a clear trend toward catastrophic forgetting whether measuring performance on short [Kirkpatrick *et al.* 2016, Ramasesh *et al.* 2021] or long [Douillard *et al.* 2020a, Davidson & Mozer 2020] streams. We outlined in our experimental evaluation that this trend is not as strong. Neural ranking models do not seem to forget a lot throughout the learning process, and the size of the stream (2 or 3) is not correlated to the amount of forgotten information. In the long-stream setting, neural ranking models seem to forget knowledge when compared with multi-task learning. To get a better understanding of the phenomenon, we analyze the performance according to two additional dimensions. First, by putting in the abyss the forgetting phenomenon with the similarity of successive tasks, we show that the greater the similarity, the less the neural ranking

model forgets. It is worth noting that this trend toward task similarity has also been demonstrated in natural language understanding [Cattan *et al.* 2022]. Second, inspired by [Veniat *et al.* 2020], we evaluate three controlled IR-driven scenarios, highlighting generally good properties in terms of knowledge retention. Our intuition underlying this lower propensity to catastrophic forgetting is that neural ranking models are, by nature, designed for capturing relevance matching signals beforehand semantic matching signals [Guo *et al.* 2016, Lin *et al.* 2021a]. Consequently, switching topics/domains in IR is less critical than continually learning over different images to identify their labels that directly map with the semantics of images [Davidson & Mozer 2020, Douillard 2022].

The model architecture matters. As previously observed in [Arabzadeh *et al.* 2021], we have shown that neural ranking models are able to capture additional knowledge than the one captured by first-stage ranking models based on exact matching, such as BM25. However, this ability to capture additional knowledge does not bring necessarily catastrophic forgetting behaviors. This suggests that this additional knowledge does not obviously refer to new semantics but can rather complement relevance-matching signals already captured by exact-matching models. We thus believe that the model architecture impacts its behavior toward catastrophic forgetting. Depending on the architecture (i.e., transformer [Devlin *et al.* 2019, MacAvaney *et al.* 2019b] or not [Guo *et al.* 2016, Hui *et al.* 2017, Xiong *et al.* 2017], based on semantic clustering [Xiong *et al.* 2017, MacAvaney *et al.* 2019b] or not) and the losses used (classification [Nogueira & Cho 2019] or ranking loss [Devlin *et al.* 2019]), we notice different behaviors in terms of knowledge acquisition and retention. The more the features are semantically oriented, the more the model will tend to forget. This statement related to the topology of neural architecture has already been observed in computer vision by Huo & Zyl 2020.

The type of evolving data matters. The typology of data evolving in the continual learning scenario (e.g., documents or queries) impacts the learning behaviors regarding the evolving knowledge. In our IR-driven scenarios, neural ranking models outline good properties to face direct transfer or information update. In contrast, language drift in the query vocabulary remains a difficult task, probably due to the small expressiveness of queries (due to their size). This fine-grained analysis of input-output distribution has been initiated by Veniat *et al.* 2020 who have also noticed that a neural model can exhibit different behaviors regarding different controlled settings (analyzing for instance the transfer to similar input/output distributions, the knowledge update, the direct transfer, or the scalability). These experiments highlight the importance of analyzing different dimensions of the catastrophic forgetting issue. Combined with our investigations highlighting different behaviors regarding the typology of streams, we believe that a relevant strategy for designing neural ranking models robust to continual learning settings is to modularize the learning strategies according to the properties of the evolving data.

We are aware that obtained results are limited to the experimented models and settings, although we have considered various evaluation scenarios over different dataset peculiarities (variation in terms of domain, stream size, and controlled settings). We believe that much remains to be accomplished for more generalizable results, particularly

at the model level. For instance, it would be interesting to experiment with sparse neural ranking models [Bai *et al.* 2020, MacAvaney *et al.* 2020, Formal *et al.* 2021] to identify whether their zero-shot learning abilities are robust to a continual learning setting. However, we hope that our exploratory analysis is a step forward in the understanding of continual *IR* model learning and the design of more robust neural ranking models. More particularly, we believe that, although less characterized by catastrophic forgetting issues than neural models in computer vision, neural ranking models can gain robustness if they are able to identify critical evolution in the training data and alleviate this forgetting phenomenon. One promising strategy emerging from the Machine Learning community arises from mode connectivity [Kuditipudi *et al.* 2019, Benton *et al.* 2021, Wortsman *et al.* 2021] aiming at connecting different regions within the parameter space to leverage various signals. We believe that this principle could be used to design models modularizing their parameters depending on the typology of evolving data.

Outcomes These works are conducted in the context of the ANR JCJC SESAMS for which I am the principal investigator. I briefly describe my supervision activity regarding the topic:

- I initiated the framework of continual learning in IR (domain adaptation in short dataset streams). I collaborated on this topic with Lynda Tamine-lechani and Karen Pinel-Sauvagnat from the IRIT laboratory through the co-supervision of a master student (Jesús Lovón-Melgarejo).
- This work has been pursued with a one-year postdoctoral researcher I supervised, Thomas Gerald.

You can find below a list of related publications[4]:

- Jesús Lovón-Melgarejo, Laure Soulier, Karen Pinel-Sauvagnat, Lynda Tamine: Studying Catastrophic Forgetting in Neural Ranking Models. ECIR 2021: 375-390
  Code: `https://github.com/jeslev/OpenNIR-Lifelong`
- Thomas Gerald, Laure Soulier: Continual Learning of Long Topic Sequences in Neural Information Retrieval. ECIR 2022: 244-259
  Code: `https://github.com/tgeral68/continual_learning_of_long_topic`

[4]National publications are not mentioned if they are simple translations of international publications.

Part III

Other contributions and conclusion

Chapter 7

Other contributions

Contents

In this chapter, I briefly introduce other contributions (past and ongoing works) not discussed in the manuscript.

7.1 Past work: grounding textual representations

A research area that I have worked on between 2015 and 2019 is that of grounding textual representation through external knowledge. With early text embedding strategies (e.g., Gloves, word2vec, etc...) before large language models, several works have shown that textual embeddings do not capture all the semantics [Petroni *et al.* 2019]. One explanation of this limitation is the human reporting bias, i.e. we report in texts only key facts and not basic world knowledge acquired otherwise, leading to perception bias [Gordon & Van Durme 2013].

Hill *et al.* 2015 have shown that co-occurrence extraction leads to confusion between semantic similarity and conceptual relationships. For instance, the terms "bike" and "tire" will be close to the term "car" since they co-occur frequently although they are related differently to the term "car". "bike" is similar to "car" since they have the same functionality while "car" and "tire" have a functional relationship. With the same state of mind, Mrkšić *et al.* 2016 and Iacobacci *et al.* 2015 have also outlined that embeddings are not able to distinguish synonyms and antonyms.

We have therefore explored the potential of text grounding, aiming at anchoring textual representation in complementary resources. We have considered two types of resources: **knowledge resources** and **visual ones**. To do so, we have designed multi-modal representation learning models (often mid-fusion) aiming at leveraging the knowledge available either in images or knowledge bases to improve the semantics of text embeddings. Two types of evaluation have been conducted: intrinsic evaluation checking the quality of embeddings, and extrinsic evaluation analyzing the impact of such representations on NLP and IR tasks.

Outcomes

- 2 defended theses: Gia-Hung Nguyen (collaboration with Lynda Tamine and Nathalie Souf at IRIT) and Eloi Zablocki (collaboration with Benjamin Piwowarski and Patrick Gallinari).
- Participation to the MUSTER CHIST-ERA project (MUltimodal processing of Spatial and TEmporal expRessions)
- Publications on textual grounding with knowledge bases
  - Gia-Hung Nguyen, Lynda Tamine, Laure Soulier, Nathalie Bricon-Souf: Toward a Deep Neural Approach for Knowledge-Based IR. Neur4IR workshop at SIGIR (2016)
  - Gia-Hung Nguyen, Laure Soulier, Lynda Tamine, Nathalie Bricon-Souf: DSRIM: A Deep Neural Information Retrieval Model Enhanced by a Knowledge Resource Driven Representation of Documents. ICTIR 2017
    Code: https://github.com/giahung24/dsrim
  - Gia-Hung Nguyen, Lynda Tamine, Laure Soulier, Nathalie Souf: Learning Concept-Driven Document Embeddings for Medical Information Search. AIME 2017
  - Gia-Hung Nguyen, Lynda Tamine, Laure Soulier, Nathalie Souf: A Tri-Partite Neural Document Language Model for Semantic Information Retrieval. ESWC 2018
  - Lynda Tamine, Laure Soulier, Gia-Hung Nguyen, Nathalie Souf: Offline versus Online Representation Learning of Documents Using External Knowledge. ACM Trans. Inf. Syst. 37(4): 42:1-42:34 (2019)
- Publication on textual grounding with images
  - Eloi Zablocki, Patrick Bordes, Laure Soulier, Benjamin Piwowarski, Patrick Gallinari: LIP6@CLEF2017: Multi-Modal Spatial Role Labeling using Word Embeddings. CLEF (Working Notes) 2017
  - Eloi Zablocki, Benjamin Piwowarski, Laure Soulier, Patrick Gallinari: Learning Multi-Modal Word Representation Grounded in Visual Context. AAAI 2018
    Code: https://github.com/EloiZ/embedding_evaluation
  - Eloi Zablocki, Patrick Bordes, Laure Soulier, Benjamin Piwowarski, Patrick Gallinari: Context-Aware Zero-Shot Learning for Object Recognition. ICML 2019
  - Patrick Bordes, Eloi Zablocki, Laure Soulier, Benjamin Piwowarski, Patrick Gallinari: Incorporating Visual Semantics into Sentence Representations within a Grounded Space. EMNLP/IJCNLP 2019
    Code: https://github.com/pbordes/multimodal_sentence_rep
  - Micael Carvalho, Rémi Cadène, David Picard, Laure Soulier, Nicolas Thome, Matthieu Cord: Cross-Modal Retrieval in the Cooking Context: Learning Semantic Text-Image Embeddings. SIGIR 2018
    Code: https://github.com/Cadene/recipe1m.bootstrap.pytorch

7.2 On-going works

7.2.1 Domain adaptation and continual learning

As discussed in the previous chapter, domain adaptation is crucial for interactive neural models that face evolving trends and different users. From a more general point of view, human-machine collaboration settings in which an agent and a user interact to solve a particular task together are also constrained by adaptation issues, whether in terms of new environments or new interactions. For both neural models or reinforcement learning approaches, training an optimal model or an optimal policy able to generalize for all types of interactions/environments is complex. To tackle this issue, we are exploring the potential of **mode connectivity** [Benton *et al.* 2021, Kuditipudi *et al.* 2019] and more particularly the characteristics of neural subspaces [Wortsman *et al.* 2021], to exhibit interesting properties towards the generalization setting. These methods analyze the shape of the parameter space to build neural network subspaces. The latter contain diverse solutions (i.e., a set of model parameters) that process information differently. The intuition is that neural models in a subspace can be ensembled at the inference step, and having access to it instead of a single policy facilitates the adaptation without any cost of additional training. We propose two main works in this direction under the scope of reinforcement learning. First, we have addressed **neural subspace for reinforcement learning** switching the paradigm to subspaces of policies, instead of subspaces of neural networks. We have also demonstrated in a second contribution that subspaces of policies are well adapted **for continual reinforcement learning**.

We are now exploring **neural subspaces for information retrieval**, but the complexity is even harder since state-of-the-art models are all based on large language models. Given their large number of parameters, it is not reasonable to build a neural subspace including the set of all parameters in the encoder-decoder architecture. We are therefore exploring which parts of large language models can be considered for being included in the subspace and conducting experiments regarding zero-shot learning.

Outcomes These works have been initiated during the Ph.D. of Jean-Baptiste Gaya (Facebook CIFRE) and the NLP extension is done in collaboration with Thomas Gerald (now a postdoctoral researcher at LISN) and Pierre Erbacher (Ph.D. on the ANR JCJC SESAMS). Works focusing on reinforcement learning have led to two publications:

- Jean-Baptiste Gaya, Laure Soulier, Ludovic Denoyer: Learning a subspace of policies for online adaptation in Reinforcement Learning. ICLR 2022

- Jean-Baptiste Gaya, Thang Doan, Lucas Caccia, Laure Soulier, Ludovic Denoyer, Roberta Raileanu. Building a Subspace of Policies for Scalable Continual Learning. Deep RL workshop @NeurIPS 2023. Also under review for an international conference.

7.2.2 Contextual information extraction

Named Entity recognition (NER) and Relation Extraction (RE) can be seen as the reverse side of data-to-text generation with the objective to extract entities and their

relationships within a text in natural language (see the WebNLG challenge[1] addressing the data-to-text and text-to-data task). We consider two types of contexts:

- **The textual context**, i.e. the paragraph in which a entity occurs, under the assumption that the entity class can vary according to the context. Indeed, all current approaches [Liu *et al.* 2011, Liang *et al.* 2020, Souza *et al.* 2019] have a major drawback: they all consider an entity as a universal concept, linked to a single class, even if it may appear in different surface forms and contexts. This limits the potential of the information extracted which could be useful for more elaborated downstream tasks. As an example, *Amazon* will always be classified as a *company*, regardless of the context in which it is mentioned. But viewing this entity through the concepts of *seller*/*buyer* implies great differences in the way we perceive it and treat it. *Amazon* is likely to *sell* a product to an *individual person* but *buy* from another *company*. We therefore propose the Dynamic NER task in which the label of entity varies depending on the context. We define two datasets and an evaluation benchmark.
- **The multi-modal context**, i.e. the whole document, following the line of work combining textual and visual modalities so as to leverage document layout [Xu *et al.* 2019]. Our objective is to improve the multimodal fusion which is generally performed either at an early or a late stage, hindering their interaction throughout the learning process. We believe that it is crucial to jointly keep modality independent (to avoid error propagation that can be related, for instance, to the OCR) and let the possibility for the network to merge them when necessary.

Outcomes This work is conducted with Tristan Luiggi, a PhD student of CIFRE, co-supervised with Vincent Guigue.

- Tristan Luiggi, Laure Soulier, Vincent Guigue. Dynamic Named Entity Recognition. In: SAC 2023.

[1] https://webnlg-challenge.loria.fr/challenge_2020/

Chapter 8

Conclusion

Contents

8.1 Contributions and perspectives

In this manuscript, I have introduced our contributions focused on three main research axes dealing with relevance and faithfulness in text generation, contextualization of information needs, and neural ranking models adaptability in continual learning settings. In what follows, I sum up these contributions and the associated perspectives.

8.1.1 Towards faithful and relevant text generation

To ensure faithfulness and relevance in text generation, we have addressed two main challenges.

The first challenge focused on input encoding to capture data peculiarities related to the structure of the data. To do so, we focused on the data-to-text generation research domain and proposed a hierarchical data encoding aiming at representing entities separately before embedding the data as a whole. This encoding is surrounded by a hierarchical attention mechanism identifying first which entity is needed to be discussed and then which element is interesting for this entity. This model has a twofold contribution: it was the first work to both explicitly encode the data structure and use a transformer network for data-to-text generation.

The second challenge focused on the decoding process for which we have studied two use cases:

- In the data-to-text generation research domain, we addressed the pathological behavior of generation models that produce hallucinations due to the misalignment

of training data. This problem is also encountered in standard text-to-text generation tasks. However, it is even more challenging in data-to-text generation for several reasons: 1) the nature of input and output elements is different (e.g., numerical data vs. generated text), 2) the textual description might include reasoning over data (e.g., "player A has mastered the game" means that he scored the most points, implying a maximum calculus). Altogether, these task peculiarities hinder the semantic matching of the data input and the textual output, and accordingly highlight the difficulty to build a relevant semantic space bridging both modalities and decoding a faithful text. To tackle this issue, we have proposed two models based either on reinforcement learning (not introduced in the manuscript) or on a multi-branch decoder. The latter aims at separating during the decoding stage relevant and divergent textual information with respect to the input data constraint. Our motivation was to learn different decoder modules regarding three factors (fluency, content, and hallucination) to control the importance of each of them during the inference step.

- In the conversation search research field, we addressed the issue of query-driven text generation in which the difficulty relies on generating texts that are both faithful regarding the data input (in our case a list of documents) and the query (i.e., the information need). Guided by the constraint of the query to solve a complex information need, we have shown that the planning-based models are useful to guide the text generation process and produce structured and relevant texts.

Perspectives.
While several steps forwards have been done these last years toward faithful and relevant text generation, generative models can largely be improved. We present in what follows the different research directions, particularly related to data-to-text generation and conversational search, we envision for the future.

Numerical reasoning. In the data-to-text research field, one critical error that stands out is about numbers [Ji *et al.* 2022]. Current approaches [Puduppully *et al.* 2019b, Wiseman *et al.* 2017, Rebuffel *et al.* 2022] are generally effective in reporting values of tables and paraphrasing them. However, the data-to-text generation task is more complex: it often requires comparing values between them (e.g., identifying the best player or counting the difference in terms of point numbers between two teams in a basketball game) or to perform operations with abstractive concepts (e.g., estimating the number of days between a date and an event such as Christmas). While several works have been addressed in the Machine Reading Comprehension task [Dua *et al.* 2019, Herzig *et al.* 2020] or numerical reasoning tasks [Trask *et al.* 2018, d'Ascoli *et al.* 2022], they are often limited to simple numerical operations (such as sum or difference) and have not been envisioned in the perspective of data-to-text generation. Our ambition is to address numerical reasoning through different NLP tasks, such as question-answering [Dua *et al.* 2019, Herzig *et al.* 2020] or data-to-text generation [Puduppully *et al.* 2019a] including more complex data, e.g., time series of sensor data for weather presentation [Reiter *et al.* 2005]. We plan to integrate numerical executors [Andor *et al.* 2019, Pi *et al.* 2022] into language models so as to identify which parts of the input are relevant and how to combine them to build new knowledge in the generated output. Combined with the ability of large language models, we believe that it should allow to reason over (like-wise) numerical

information to improve the faithfulness of textual descriptions.

Personnalization of text generation. One way to ensure the relevance of text generation is to adapt the generation to the user and his/her intent. While several works have focused on style transfer [Ao *et al.* 2021, Chawla & Yang 2020, Malmi *et al.* 2020], personalizing data-to-text generation is not obvious. We believe that personalization is not only an issue of style but also a challenge of selecting the relevant content for the user. To the best of our knowledge, there is no work and no available dataset in this direction. To tackle these issues, we are currently building a dataset on movies including structured meta-data, reviews modeling users' interests, and personalized textual descriptions. We then plan to explore different techniques to personalize the data-to-text generation process by either using prompt-based language models [Yao *et al.* 2022] or injecting user profiles during decoding [Ao *et al.* 2021].

Model transferability. For specific text generation tasks, such as data-to-text generation, models are trained or fine-tuned on specific datasets (restaurants [Dušek *et al.* 2020], basketball games [Wiseman *et al.* 2017], ...). Their transferability to real use cases that can be encountered by company needs (e.g., summarizing financial information) is therefore limited. Although large language models have demonstrated great ability towards zero-shot adaptation [Devlin *et al.* 2019, Wei *et al.* 2022, Cui *et al.* 2022], we believe that they can reach some limitations in the data-to-text generation task. Indeed, depending on the structure/format of the input data, it can be difficult to understand their semantics from a zero-shot setting, and even more, identify salient information that should be decoded.

8.1.2 Contextualizing information needs expressed in natural language

Another research topic presented in this manuscript is the understanding of information needs in conversational search systems which are a core topic in the IR community since 2018 [Culpepper *et al.* 2018]. We focused on the conversation flow underlying the understanding the information need, either at a given conversation turn (as designed in TREC CAsT) or through a proactive interaction (as the query clarification task).

Through our participation in TREC CAsT, we have designed query reformulation models and contextual ranking models able to take into consideration the conversation to better represent the query. We have proposed the CoSPLADE model, a contextualized first-stage ranking model trained without the supervision of documents relevant in the conversation context. While this step is crucial, we also have addressed the query understanding issue as a proactive setting in which the system interacts with the user to understand and anticipate his/her information need. While several works [Aliannejadi *et al.* 2019, Zamani *et al.* 2020a] have addressed this task through a one-turn interaction, we proposed a framework simulating user-system interactions aiming at suggesting a set of query clarifications to the user who identifies the best one given his/her initial topic. The query clarification model is based on a diverse set of queries related to the initial topic which is re-ranked according to user's interactions. Experiments have shown the benefit of such a clarification process in the retrieval process.

Perspectives.
Having in mind that mixed-initiative are prevalent for conversational search, our perspectives focus on the query clarification task. One underlying challenge relies on the

fact that there is no dataset with jointly long-term interactions in natural language and a large amount of supervised data related to the IR tasks. We, therefore, envision two main challenges for query clarification.

Toward multi-turn query clarification simulation framework with interactions in natural language. As discussed in section 5.3, the next research issue concerns the interaction mode, through natural language allowing a more natural framework in which the user and the system interact. We, therefore, envision extending our simulation framework by integrating interactions in natural language instead of simply displaying queries for the IR agent and clicking on the best query for the user agent.

Lightweight domain adaptation of our query clarification simulation framework. Having in mind the deployment in production, we believe that a second challenge could be the transferability of our query clarification simulation framework to other domains/datasets. Guided by our previous simulation framework demonstrating the potential of query clarification to enhance ad-hoc IR settings and constrained by the fact that it exists only a single query clarification dataset [Aliannejadi *et al.* 2019], we plan to work on unsupervised domain adaptation strategies. For instance, by adapting the language model of our query clarification components through masked language modeling, we hope that after a few simulated interactions, the IR system would benefit from a clearer vision of the information needed to perform the retrieval step.

8.1.3 Investigating the ability of neural ranking models to continually adapt to evolving topics.

Assuming that IR models need to adapt to evolving users and/or topics, we investigated the continual learning research field and proposed a continual learning framework for iR modeling short and long topic sequences. We also analyzed the behavior of neural ranking models while fine-tuning successive tasks. We have compared transformer-based models with interaction-based models, highlighting different transferability levels and different abilities to face catastrophic forgetting. These works are the first ones to envision continual learning in IR and can serve as an evaluation framework for future works.

We plan two main future directions: pursuing our effort toward continual learning in IR and extending this work to intent detection in conversational systems.

Toward lifelong learning strategies adapted to ranking tasks. For IR, we plan to focus on the long topic sequence scenario, which is the most realistic one, and explore continual learning techniques for neural ranking models. In contrast to previous works in vision which mainly address classification tasks and in which catastrophic forgetting is highly noticeable, we are aware of the possible difficulty to adapt continual learning techniques for document scoring and acknowledge the unusual behavior of neural ranking models that show a small catastrophic forgetting in specific settings. Therefore, as shown in our preliminary experiments using EWC [Lovón-Melgarejo *et al.* 2021], continual learning techniques are promising and we envision adapting other strategies for ranking models. For instance, architecture-based approaches in computer vision [Cai *et al.* 2019, Veniat *et al.* 2020] propose to extend the network by integrating additional classes at the output level. In IR, the task is different, and the additional knowledge should rather be extended in the intermediate layers, focusing more on the learned embedding space than on the output. Having also in mind the outcomes of our exploratory analysis, we believe that such lifelong techniques must be integrated into

neural ranking models with an awareness level regarding the properties of evolving data. Said otherwise, neural ranking models robust to continual learning settings should include a modularization component tracking the critical changes in the training data and adapting accordingly the learning strategy.

Investigating continual learning for cross-lingual intent detection. For intent detection, we will address the limitation due to the language specificity for intent detection. If we desire to deploy virtual assistants all over the world, it is therefore important to design models able to address a large number of languages. Although multilingual models are a solution, it can be difficult to design a model trained simultaneously on all languages, particularly for under-resourced ones. We can therefore assume that the deployment of virtual assistants can be done step by step over different countries in the world and, thus, that virtual assistants will face different languages at different times. This assumption implies that, when designing/training a model for this task, languages can be incrementally added to the training procedure. In our case, we propose to explore a continual learning setting in which the task is fixed, but the stream is based on different languages. The model, therefore, learns the knowledge of language peculiarities. To satisfy the initial condition of virtual assistants to address different languages, we need to ensure that our task-based model does not forget previous languages while training on new ones.

8.2 Future research directions

8.2.1 Retrieval-augmented Machine Learning

The majority of neural models for NLP or Machine Learning are based on the assumption that all knowledge and reasoning required for the task are captured by parameters. Large language models have demonstrated that increasing the number of parameters generally leads to performance increases. However, this strategy focused on parameter size is not scalable, and accordingly not desired in terms of computational cost. A recent research paper [Zamani *et al.* 2022a] has discussed the potential of enhancing neural models with IR systems. The intuition is to couple neural models with IR systems to access and reason over large text corpora and knowledge stores with the final objective to reduce the number of parameters in neural models and improve their scalability. This strategy has already been used for pseudo-relevance feedback in IR [Croft & Harper 1997], question-answering [Gao *et al.* 2022, Hsu *et al.* 2021] or, more recently, to train language models [Guu *et al.* 2020]. Beyond scalability, the authors also argue that accessing external knowledge through IR systems has several merits: 1) improving the generalization performance of the model, 2) being more robust to information updates and temporal changes, and 3) grounding model decisions with external knowledge leading to more interpretability and explainability.

We believe that this paradigm deserves attention and is interesting to revisit the different research fields addressed in this manuscript.

- For the data-to-text generation task, the IR system can thus serve as anchor sources for knowledge grounding for both in-domain and out-of-domain datasets. For in-domain, it is worth reminding that the data structure is not fully explicit in terms of semantics (e.g., for a table, columns can be abbreviated, and values are of different

formats...). Therefore, understanding the semantics of the data structure might be difficult. In addition, in many situations, the expected decision relies on implicit information directly related to the application. For example, in NBA games, the action "passing" implies that passes are only made between players of the same team. Therefore, when player A is identified as belonging to the winning team and passes to player B, B is de facto the winner. Conversely, intercepting a pass from A would assign B to the losing team. For the out-of-domain case, the difficulty is greater because, beyond remaining in-domain challenges, the model needs to capture the semantics of another domain than the one used for its training. We can believe that using a retrieval module can help to face a larger knowledge over different application domains and, thus, improve the generalization performance.

- For the interactive information retrieval task, both query clarification and continual learning settings can benefit from IR-augmented models, but for different reasons. For query clarification, the difficulty lies in the diversification of suggestions. Therefore, retrieval-augmented models might help in grounding the initial query and therefore in suggesting different facets or orthogonal topics to improve the search process. For the continual learning setting, a retrieval-augmented system might be beneficial to identify samples characterizing information updates or temporal changes or to interpolate new knowledge. The component can therefore serve as a replay buffer for instance for rehearsal strategies.

8.2.2 Language-augmented Robotics

With the recent affiliation of the MLIA team to the Robotic Laboratory (ISIR) of Sorbonne University, new research axes have been discussed and promise tremendous collaborations. One of the research challenges we are planning to address in the following years is to improve reinforcement learning models for robotics with natural language processing. Autonomous agents require reasoning and planning strategies for performing tasks. We, therefore, believe that the semantics captured by large language models can enhance the decision process at different levels.

First, it can allow grounding object representations with common sense to identify their intrinsic and actionable properties. Large language models and also common sense knowledge bases, such as ConceptNet[1], can be used as complementary information sources, implying to design representation models leveraging multi-modal information. The difficulty would be to identify which properties are relevant for objects and how to fuse them into a single representation. Another strategy can be to encode objects differently according to each modality and then use self-attention to learn the possible interactions that are relevant for the task solving. Object grounding has been addressed in [Sridharan & Mota 2022, Tsiami *et al.* 2018], but we believe that the grounding needs to be extended to the scene to better model the context and object properties.

Second, natural language can serve for building and clarifying the planning strategy, and therefore the actions done by a robot. Several works have addressed instruction identification as abstract representation [Andreas *et al.* 2018, Jacob *et al.* 2021] or natural language expression [Sharma *et al.* 2022], but the limited data supervision is often

[1] https://conceptnet.io/

a challenge [Chen *et al.* 2020a, Sharma *et al.* 2022]. To tackle this issue, we envision interactive training processes, implying asking humans to label situations with sentences, with strong care on limiting interactions to a few relevant situations, to reduce human effort. The challenge consists in defining when to interact with real users in the planning and which information asking to increase the supervision data. One can imagine a policy combined with a language model to 1) identify whether to generate the following instructions or to ask humans about the next instruction. This decision can be taken by evaluating whether the language model has sufficient knowledge to capture all the semantics of the current scene (e.g., through a task-guided masked language modeling loss), 2) leverage the language model to interact with humans if necessary, and 3) generate the next instruction according to the scene, the state of the policy and the interaction with humans.

8.3 My last words

Writing this manuscript allowed me to gather different research fields (data-to-text generation, conversational search, continual learning) that are, on a daily basis, addressed independently. They all rely on the design of neural models or leverage language models. Beyond this, I think that there is a synergy in all my research. While NLP techniques and language models are able to exploit a large amount of human knowledge to capture the meaning of textual data, IR models allow the retrieval of knowledge from large databases, and planning techniques are well known to consider complex behavior and reasoning at the machine level. The crossroad of these research fields conducts me to design step-by-step components of relevant and robust human-machine collaboration systems.

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