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Sentiment Analysis and Sentence Classification in Long Book-Search Queries

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Abstract. Handling long queries can involve either reducing its size by retaining only useful sentences, or decomposing the long query into several short queries based on their content. A proper sentence classification improves the utility of these procedures. Can Sentiment Analysis has a role in sentence classification? This paper analysis the correlation between sentiment analysis and sentence classification in long book-search queries. Also, it studies the similarity in writing style between book reviews and sentences in book-search queries. To accomplish this study, a semi-supervised method for sentiment intensity prediction, and a language model based on book reviews are presented. In addition to graphical illustrations reflecting the feedback of this study, followed by interpretations and conclusions.

Keywords: sentiment intensity · language model · search queries · books · word embedding · seed-words · book reviews.

1 Introduction

The book search field is a subsection of data search domain, with a label of recommendation. Users would be seeking book suggestions and recommendations by a request of natural language text form, called user query. One of the main characteristic of queries in book search is their length. The user query is often long, descriptive, and even narrative. Users express their needs of a book, opinion toward certain books, describe content or event in a book, and even sometimes share personal information (e.g. *I am a teacher*).

Being able to differentiate types of sentences, in a query, can help in many tasks. Detecting non-useful sentences from the query(e.g. *Thanks for any and all help.*), can help in query reduction. And classifying sentences by the type of information within, can be used for adapted search. For example, sentences including good read experience, with a book title, can be oriented to a book similarity search, but sentences including a certain topic preferences should be focusing on a topic search. And also, sentences including personal information can be used for personalised search.

In this work, sentence classification is studied on two levels: the usefulness of the sentence towards the search, and the type of information provided by the useful sentence. And three types of information are highlighted on: book titles and author names (e.g. *I read "Peter the Great His Life and World" by Robert K. Massie.*), personal information (e.g. *I live in a very conservative area*), and narration of book content or story (e.g. *The story opens on Elyse overseeing the wedding preparation of her female cousin.*).

"Different types of sentences express sentiment in very different ways" [4], therefore, the correlation is studied between the sentiment in a sentence and its type. And for the task, sentiment intensity prediction is calculated using a semi-supervised method, explained in Section 4.

In addition, sentences in a query can share similar writing style and subject with book reviews. Below is a part of a long book search query:

*I just got engaged about a week and a half ago and I'm looking for recommendations on books about marriage. I've already read a couple of books on marriage that were interesting. **Marriage A History talks about how marriage went from being all about property and obedience to being about love and how the divorce rate reflects this. The Other Woman: Twenty-one Wives, Lovers, and Others Talk Openly About Sex, Deception, Love, and Betrayal not the most positive book to read but definitely interesting. Dupont Circle A Novel I came across at Kramerbooks in DC and picked it up. The book focuses on three different couples including one gay couple and the laws issues regarding gay marriage ...***

In the example query, the part in bold present a description of specific books content with books titles, e.g. "*Marriage A History*", and interpretations or personal point of view with expressions like "*not the most positive book ... but definitely interesting*". These sentences seem as book reviews sentences. Therefore, finding similarities between certain sentences in a query and books reviews can be an important feature for sentence classification. To calculate that similarity in a general form, a reviews' statistical language model is used to find for each sentence in the query its probability of being generated from that model (and therefore its similarity to that model's training dataset of reviews).

This work covers an analysis of sentence's type correlation with its sentiment intensity and its similarity to reviews, and the paper is presented as below :

- Presenting the user queries used for this work.
- Extracting sentiment intensity of each sentence in the queries.
- Creating a statistical language model based on reviews, and calculating the probability for each sentence to be generated from the model.
- Analyzing the relation between language model scores, sentiment intensity scores and the type of sentences.

2 Related Work

For the purpose of query classification, many machine learning techniques have been applied, including supervised [9], unsupervised [6] and semi-supervised learning [2]. In book search field, fewer studies covered query classification. Olgagnier et al. [10] worked on a supervised machine learning method (Support Vector Machine) for classifying queries into the following classes: **oriented** (a search on a certain subject with orienting terms), **non-oriented** (a search on a theme in general), **specific** (a search for a specific book with an unknown title), and **non-comparable** (when the search do not belong to any of the previous classes). Their work was based on 300 annotated query from INEX SBS 2014³. But the mentioned work, and many more, processed the query classification and not the classification of the sentences within the query. The length of book-search queries created new obstacles to defeat, and the most difficult obstacle is the variety of information in its long content, which require a classification at the sentence level.

Sentences in general, based on their type, reveal sentiment in different ways, therefore, Chen et al. [4] focused on using classified sentences to improve sentiment analysis with deep machine learning. In this work, the possibility of an opposite perspective is studied, which is the improvement of sentence classification using sentiment analysis.

In addition, this work is studying the improvement of sentence classification using language model technique. Language models (LM) have been successfully applied to text classification. In [1], models were created using training annotated datasets and then used to compute the likelihood of generating the test sentences. In this work, a model is created based on book reviews and used to compute the likelihood of generating query sentences, as a similarity measurement between book reviews style and book-search query sentences type.

3 User queries

The dataset of user queries, used in this work, is provided by CLEF - Social Book Search Lab - Suggestion Track⁴. The track provides realistic search requests (also known as user queries), collected from LibraryThing⁵.

Out of 680 user queries, from the 2014's dataset of Social Book Search Lab, 43 queries are randomly selected based on their length. These 43 queries have more than 55 words, stopwords excluded. Then, each query is segmented into sentences, which results a total of 528 sentences. These sentences are annotated based on usefulness towards the search, and on the information provided as: book titles and authors names, personal information, and narration of book content, an example is shown in the below XML extraction at Listing 1.

³ <https://inex.mmci.uni-saarland.de/data/documentcollection.html>

⁴ <http://social-book-search.humanities.uva.nl/#/suggestion>

⁵ <https://www.librarything.com/>

```

1 <sentences>
2   <sentence relevant="False" info="Null" >
3     Where is the time to go online and talk?
4   <\sentence>
5   <sentence relevant="True" info="General">
6     No sappy romance involved
7   <\sentence>
8   <sentence relevant="True" info="Personal.Info">
9     I am a sixth grade science teacher
10  <\sentence>
11  <sentence relevant="True" info="Book_Content">
12    Pierre becomes for a while a Mason
13  <\sentence>
14  <sentence relevant="True" info="Book_Title_Author">
15    I have one by Robert Fitzgerald Peter
16  <\sentence>
17 <\sentences>

```

Listing 1: An example of annotated sentences from user queries.

4 Sentiment Intensity

As part of this work, sentiment intensity is calculated for each sentence of the queries. The following method is inspired by a semi-supervised method for sentiment intensity prediction in tweets, and it was established on the concepts of adapted seed-words and words embedding [8]. To note that the seed-words are words with strong semantic orientation, chosen for their lack of sensitivity to the context. They are used as paradigms of positive and negative semantic orientation. And adapted seed-words are seed-words with the characteristic of being used in a certain context or subject. Also, word embedding is a method to represent words in high quality learning vectors, from large amounts of unstructured and unlabeled text data, to predict neighboring words.

In the work of Htait et al. [8], the extracted seed-words were adapted to micro-blogs. For example, the word *cool* is an adjective that refers to a moderately low temperature and has no strong sentiment orientation, but it is often used in micro-blogs as an expression of admiration or approval. Therefore, *cool* is considered a positive seed-word in micro-blogs. In this paper, book search is the targeted domain for sentiment intensity prediction, therefore, the extracted seed-words are adapted to book search domain, and more specifically, extracted from book reviews since the reviews has the richest vocabulary in the book search domain.

Using annotated book reviews, as positive and negative, by Blitzer et al.⁶ [3], the list of most common words in every annotation class is collected. Then, after

⁶ Book reviews from Multi-Domain Sentiment Dataset by <http://www.cs.jhu.edu/~mdredze/datasets/sentiment/index2.html>

removing the stop words, the first 70 most relevant to book domain words, with strong sentiment, are selected manually from each previously described list, as positive and negative seed-words. An example of adapted to book-search positive seed-words : *insightful*, *inspirational* and *masterpiece*. And an example of negative seed-words : *endless*, *waste* and *silly*

Word embedding, or distributed representations of words in a vector space, are capable of capturing lexical, semantic, syntactic, and contextual similarity between words. And to determine the similarity between two words, the measure of cosine distance is used between the vectors of these two words in the word embedding model. In this paper, a word embedding model is created based on more than 22 million Amazon’s book reviews [7], as training dataset, after applying a pre-processing to the corpora, to improve its usefulness (e.g. tokenization, replacing hyperlinks and emoticons, removing some characters and punctuation)

For the purpose of learning word embedding from the previously prepared corpora (which is raw text), Word2Vec is used with the training strategy Skip-Gram (in which the model is given a word and it attempts to predict its neighboring words). To train word embedding and create the models, Gensim⁷ framework for Python is used. And for the parameters, the models are trained with word representations of dimensionality 400, a context window of one and negative sampling for five iterations ($k = 5$). As a result, a model is created with a vocabulary size of more than 2.5 million words.

Then, and for each word in the sentence, the difference between average cosine similarity with positive seed-words and negative seed-words represent its sentiment intensity score, using the previously created model. For example, the word *confusing* has an average cosine similarity with positive seed-words equals to 0.203 and an average cosine similarity with negative seed-words equals to 0.322, what makes its sentiment intensity score equals to -0.119 (a negative score represent a negative feeling). And for the word *young* the sentiment intensity score equals to 0.012.

To predict the sentiment intensity of the entire sentence, first the adjectives, nouns and verbs are selected from the sentence using Stanford POS tagger [12], then the ones with high sentiment intensity are used by adding up their score to have a total score for the sentence.

To note that the created tool Adapted Sentiment Intensity Detector (ASID), used to calculate the sentiment intensity of words, is shared by this work’s researchers as an open source⁸.

5 Reviews language model

The book reviews are considered a reference in sentence’s characteristic detection, since a similarity in style is noticed between certain sentences of user queries and the reviews. To calculate this similarity in writing style, a statistical language

⁷ <https://radimrehurek.com/gensim/index.html>

⁸ IN HER I PUT LINK

modeling approach is used to compute the likelihood of generating a sentence of a query from a book reviews language model.

The statistical language modeling were originally introduced by Collins in [5], and it is the science of building models that estimate the prior probabilities of word strings [11]. The model can be presented as $\theta_R = P(w_i|R)$ with $i \in [1, |V|]$, where $P(w_i|R)$ is the probability of word w_i in the reviews corpora R , and $|V|$ is the size of the vocabulary. And this model is used to denote the probability of a word according to the distribution as $P(w_i|\theta_R)$ [13].

The probability of a sentence W to be generated from a book reviews language model θ_R is defined as the following conditional probability $P(W|\theta_D)$ [13], which is calculated as following:

$$P(W|\theta_D) = \prod_{i=1}^m P(w_i|\theta_R) \quad (1)$$

where W is a sentence, w_i is a word in the sentence W , and θ_R represents the book reviews model.

The tool SRILM⁹ [11] is used to create the model from book reviews dataset (as training data), and for computing the probability of sentences in queries to be generated from the model (as test data). The language model is created as a standard language model of trigram and Good-Turing discounting (or Katz) for smoothing, based on 22 million of Amazon’s book reviews [7], as training dataset.

The tool SRILM offers details in the diagnostic output like the number of words in the sentence, the sentence likelihood to model or the logarithm of likelihood by $\log P(W|\theta_R)$, and the perplexity which is the inverse probability of the sentence normalized by the number of words. In this paper, the length of sentences vary from one word to almost 100 words, therefore the score of perplexity seems more reliable for a comparison between sentences. To note that minimizing perplexity is the same as maximizing probability of likelihood, and a low perplexity indicates the probability distribution is good at predicting the sample.

6 Analysing scores

As previously explained in Section 3, a corpora of 528 sentences from user queries is created and annotated as the examples in Listing 1. Then, for each sentence the sentiment intensity score and the perplexity score are calculated following the methods previously explained in Sections 4 and 5. To present the scores, Violin plots are used for their ability to show the probability density of the data at different values. Also, they include a marker(white dot) for the median of the data and a box(black rectangle) indicating the interquartile range.

⁹ <http://www.speech.sri.com/projects/srilm/>

6.1 Sentiment intensity, perplexity and usefulness correlation

The graph in Figure 1 shows the distribution (or probability density) of **sentiment intensity** between two categories of sentences: on the right the sentences which are useful to the search and on the left the sentences which are not useful to the search. The shape on the left is horizontally stretched compared to the right one, and mostly dilated over the area of neutral sentiment intensity (sentiment score = 0), where also exist the median of the data. On the other hand, the shape on the right is vertically stretched, showing the diversity in sentiment intensity in the useful to search sentences, but concentrated mostly in the positive area, at sentiment score higher than zero but lower than 0.5.

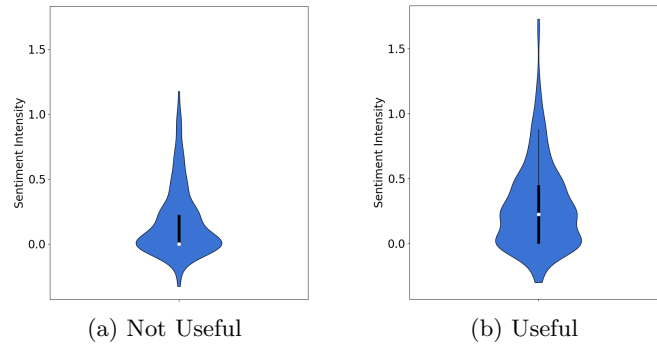


Fig. 1: The distribution of sentiment intensity between two categories of sentences: on the right the sentences which are useful to the search and on the left the sentences which are not useful to the search.

The graph in Figure 2 represent the distribution of **perplexity** between two categories of sentences: on the right the sentences which are useful to the search and on the left the sentences which are not useful to the search. Both shapes are vertically compressed and dilated over the area of low perplexity. But the graph on the right, of the useful sentences, shows the median of the data on a lower level of score of perplexity, than the left graph. Explained by the slightly horizontal dilation of the left graph above the median level.

6.2 Sentiment intensity, perplexity and information type correlation

The graphs in Figure 3 shows the distribution of sentiment between the informational sentences, consecutively from top to bottom:

- Book titles and authors names: on the right, the sentences with books titles or authors names, and on the left, the sentences without books titles and authors names. The graph on the right shows a high distribution of positive sentiment, but the left graph shows a high concentration on neural sentiment with a small distribution for positive and negative sentiment. Also, It

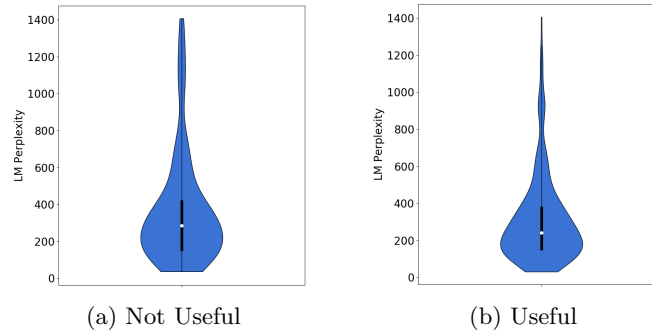


Fig. 2: The distribution of perplexity between two categories of sentences: on the right the sentences which are useful to the search and on the left the sentences which are not useful to the search.

is noticed the lack of negative sentiment in sentences with books titles or authors names.

- Personal information: on the right, the sentences containing personal information about the user, and on the left, the sentences without personal information. The graph on the right shows a high concentration on neutral sentiment, where also exist the median of the data, and then a smaller distribution in positive sentiment. On the left, the graph shows a lower concentration on neutral sentiment, but it is noticeable the existence of sentences with extremely high positivism.
- Narration of book content: on the right, the sentences containing book content or events, and on the left, the sentences without book content. Both graphs are vertically stretched but have different shapes. The graph on the right shows a higher distribution of negative sentiment as for sentences with book content, and the graph on the left shows higher positive values.

The graphs in Figure 4 shows the distribution of perplexity between the informational sentences, consecutively from top to bottom: Book titles and authors names, Personal information and Narration of book content. When comparing the first set of graphs, of book titles and authors names, the left graph has its median of data on a lower perplexity level than the right graph, with a higher concentration of data in a tighter interval of perplexity. For the second sets of graphs, of personal information, the right graph shows a lower interquartile range than the left graph. As for the third set of graphs, of book content, a slight difference can be detected between the two graphs, where the left graph is more stretched vertically.

6.3 Graphs interpretation

Observing the distribution of data in the graphs of the previous sections, many conclusions can be extracted:

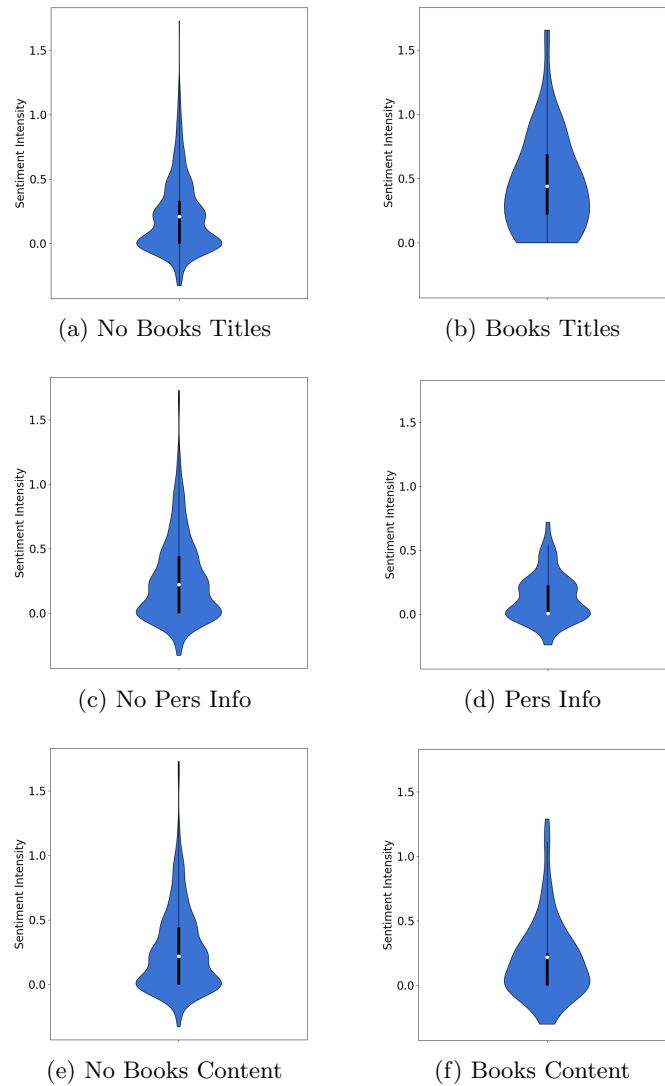


Fig. 3: The distribution of Sentiment between the informational categories of sentences: Books titles or authors names, Personal information and Narration of book content.

- In Figure 1, it is clear that useful sentences tend to have high level of emotions (positive or negative), but non-useful sentences are more probable to be neutral.
- The Figure 2 shows that sentences with high perplexity, which means they are not similar to book reviews sentences, have a higher probability of being not useful sentence than useful.

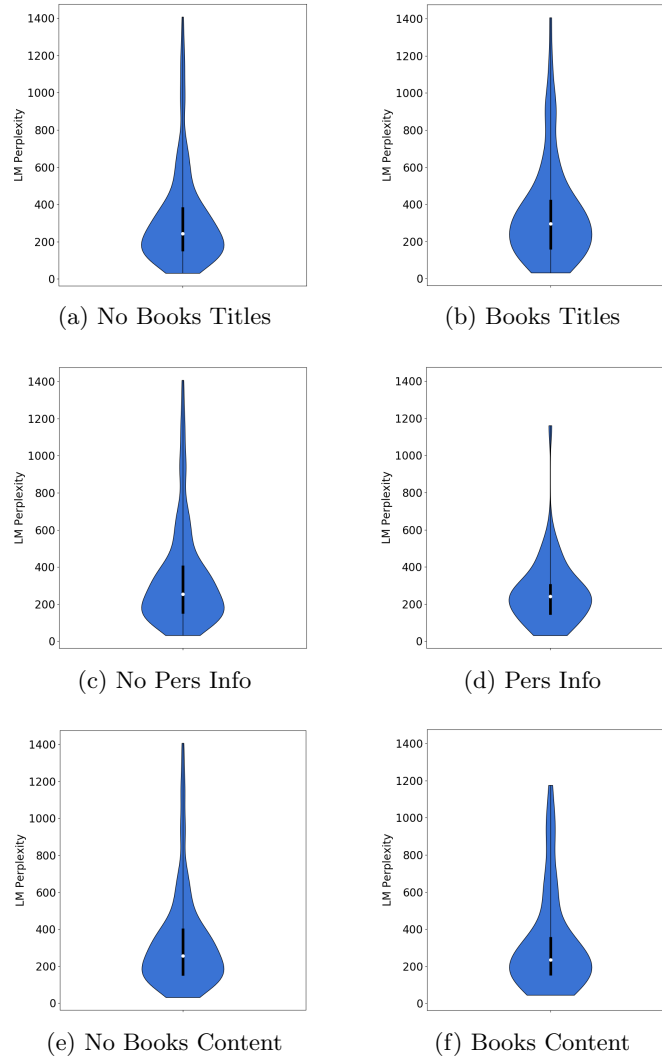


Fig. 4: The distribution of perplexity between the informational categories of sentences: Books titles or authors names, Personal information and Narration of book content.

- The Figure 3 gives an idea of sentiment correlation with sentences information: sentences with book titles or author names have a high level of positive emotions, but sentences with personal information tend to be neutral. And sentences with book content narration are distributed over the area of emotional moderate level, with a higher probability of positive than negative.
- The Figure 4 gives an idea of the correlation of reviews style similarity with sentences information: sentences with no book titles are more similar to

reviews than the ones with book titles. Also, sentences with personal information tend to be similar to reviews. And sentences with book content narration show a slight more similarity with reviews sentences style than the sentences with no book content narration.

7 Conclusion and Future work

This paper analysis the relation between sentiment intensity and reviews similarity toward sentences types in long book-search queries. First, by presenting the user queries and books collections, then extracting the sentiment intensity of each sentence of the queries (using Adapted Sentiment Intensity Detector (ASID)). Then, by creating a statistical language model based on reviews, and calculating the probability of each sentence being generated from that model. And finally by presenting, in graphs, the relation between sentiment intensity score, language model score, and the type of sentences.

The graphs show that sentiment intensity can be an important feature to classify the sentences based on their usefulness to the search. Since non-useful sentences are more probable to be neutral in sentiment, than useful sentences. Also, the graphs show that sentiment intensity can also be an important feature to classify the sentences based on the information within. It is clear in the graphs, that the sentences containing book titles are richer in sentiment and mostly positive compared to sentences not containing book titles. In addition, the graphs show that sentences with personal information tend to be neutral, in a higher probability than those with no personal information.

On the other hand, the graphs show that the similarity of sentences to reviews style can also be a feature to classify sentences by usefulness and by their information content, but in a slightly lower level of importance than sentiment analysis. Similarity between sentences and book reviews style is higher for useful sentences, for sentences with personal information and for sentences with narration of book content, but not for sentences containing book titles.

The previous analysis and conclusions gives a preview on the effect of sentiment analysis and similarity to reviews in sentence classification of long book-search queries. The next task would be to test these conclusions by using sentiment analysis and similarity to reviews, as new features, in a supervised machine learning classification of sentences in long book-search queries.

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