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ANTIDOTE: ArgumeNtaTion-Driven explainable artificial intelligence fOr digiTal mEdicine

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Abstract.

The need for transparent AI systems in sensitive domains like medicine has become key. In this paper we present ANTIDOTE, a software suite proposing different tools for argumentation-driven explainable Artificial Intelligence for digital medicine. Our system offers the following functionalities: multilingual argumentative analysis for the medical domain, explanation extraction and generation of clinical diagnoses, multilingual large language models for the medical domain, and the first multilingual benchmark for medical question-answering. Experimental results demonstrate the efficacy of ANTIDOTE across different tasks, highlighting its potential as an asset in medical research and practice and fostering transparency, which is crucial for informed decision-making in healthcare.

1 Introduction

Argument Mining (AM) is a research topic of increasing interest within Artificial Intelligence (AI). AM has been applied to different domains, such as persuasive essays [28], scientific articles [30], web debating platforms [13], and political speeches [21], aiming to automatically extract and analyze argumentative content in natural language. AM has also been employed in the medical domain [38, 12, 17], looking to support the decision-making process, like diagnosis. Different models and datasets have been proposed to aid in this process [18, 20, 16]. Recently, Large Language Models (LLM) have favored the predominance of black box methods for classification, leaving the issue of explainability and transparency of the decision-making process open [1, 8]. This is a key challenge, in particular for systems that support decision-making in sensible scenarios like medicine, where it is important to deliver explanations that are understandable and significant to the user [27, 9].

In this work, we present a publicly available online demo system¹, with an accompanying demo video², and open source code³ to aid students, professionals, and researchers in the medical field in exploring and evaluating medical data. It provides access to different tools resulting from the ANTIDOTE project⁴: (i) *argument mining for the medical domain* includes the demo of ACTA [22], access to

a mBERT [7] model fine-tuned for multilingual argument component detection [37], and access to a dual-tower multiscale convolution neural network model for argument structure learning [29]; (ii) *explanation extraction and generation* includes the SYMEXP demo, and access to a fine-tuned mDeBERTa [14] model and the dataset for the extraction of correct explanations in the medical domain [2, 11]; (iii) *Medical mT5* includes the first multilingual text-to-text LLM for the medical domain [10] plus all the resources generated to train and evaluate the models; and finally, (iv) *MedExpQA* presents the only available multilingual benchmark for Medical Question Answering, plus a Mistral 7B fine-tuned model evaluated on the benchmark [3].

2 Argument Mining in the Medical Domain

AM aims to aid evidence-based decision-making in medicine. More precisely, AM aims to identify argument components (i.e., claims and premises) and argument relations (i.e., attack or support) to then reason upon the extracted arguments to deliberate.

2.1 ACTA 3.0

ACTA is an online tool⁵ for the detection of argument components and their relations, the detection of PICO (Patient, Intervention, Comparison, Outcome) elements, and the effects of interventions on outcomes (i.e., Increased, Decreased, Improved, No Occurrences, No Difference). We refactored and revisited the ACTA pipeline [18], improving and updating technical aspects of the original code to increase its overall stability, documentation, and compatibility, especially with newer models available on Hugging Face [33]. The module was released as an open-source library⁶. We updated and relaunched the ACTA 2.0 demo [22], keeping its core functionality but also adding an open and documented REST API. ACTA 3.0 includes:

Search on PubMed PubMed⁷ is a free search engine accessing primarily the MEDLINE database of references and abstracts on life sciences and biomedical topics. In ACTA, we included the possibility of searching for a set of abstracts directly on the PubMed catalog through their API, integrated as a search bar to enter queries in the PubMed format. The abstracts of the queried publications can be subject to argument mining analysis with our models.

¹ <http://antidote.i3s.unice.fr>

² <https://youtu.be/ZJFWAwuimVA>

³ <https://gitlab.com/wimmics-antidote/antidote-server>

⁴ <https://univ-cotedazur.eu/antidote>

⁵ <http://antidote.i3s.unice.fr/acta/>

⁶ <https://gitlab.com/wimmics-antidote/antidote-acta>

⁷ <https://pubmed.ncbi.nlm.nih.gov/>

Argumentative Analysis From a medical argumentative text, the system identifies the argumentative components and relations. The extracted argumentation graph is browsable in the demo, with the highlighted components and the graph of relations among them. The component detection model is DEBERTa-v3 [14], achieving a macro f1-score of 0.81, 0.82, and 0.82 for the AbstRCT-Neoplasm, AbstRCT-Glaucoma, and AbstRCT-Mixed tests sets respectively [20]. The relation classification model is SciBERT [4] uncased base model, which achieves a macro f1-score of 0.70 for the AbstRCT-Neoplasm test set [20]. Both model are fine-tuned on the AbstRCT dataset [19].

PICO Element Detection The system also extracts the PICO elements which are highlighted in the browsable demo. The model used here is trained on the EBM-NLP dataset [23] with coarse labels following the set-up in [20]. The f1-score on the test set is 0.69.

Effects on Outcome The last module of ACTA aims to identify the effects that interventions have on outcomes. The identified effects are also highlighted in the browsable demo. The module was trained on the part of AbstRCT containing outcomes. The task is addressed as a two-step pipeline: (i) outcome detection, and (ii) effect classification [20]. The outcome detection and effect classification tasks together reach a macro f1-score of 0.80.

REST API To foster versatility and re-usability, we also enhance the ACTA tool so that the full pipeline and each of the processing steps can be executed as independent units via our publicly available REST API. The API is documented and provides examples to run it.

Browsing Data The processed argumentative text is available for visualization via our web user interface. The browser shows the different elements (i.e., argument components, PICO elements, and effects on outcomes) highlighted in the analyzed text with different colors and displayed in a table with the text and their corresponding label. The argument relations are displayed in a graph that differentiates premises from claims by color, visualizing relations (i.e., attack or support) as directed edges. It is possible to download the analyzed data as a JSON file that has the metadata and the annotated text, both via the REST API and the browser UI. We also provide the user with pre-computed examples to visualize the outcome of ACTA.

2.2 Multilingual Argument Component Detection

Transfer learning and pre-trained language models are closely related, as the knowledge learned for one or more tasks in one specific language can be applied to other tasks or languages [31]. Given that the only existing dataset manually annotated with argumentative structures is currently available only for English, exploring this idea is particularly interesting for AM in the medical domain. A detailed study of a variety of techniques for cross-lingual transfer learning [37] has allowed us to conclude that *data-transfer*, i.e., translating the data and projecting the required annotations to a given target language, outperforms other alternatives. Furthermore, it also helps to improve results over training with the original English data only [20].

We provide the best performing mBERT model fine-tuned on the *data-transfer* approach to address the task of argument component detection in four languages: English, French, Italian, and Spanish⁸. The model can be easily integrated into applications via the HuggingFace API. Furthermore, the model card comes with an inference API that allows to test it with various examples in the four languages. The dataset used to train and evaluate the model is publicly available⁹.

⁸ <https://huggingface.co/HiTZ/mbert-argmining-abstract-multilingual>

⁹ <https://huggingface.co/datasets/HiTZ/multilingual-abstract>

2.3 Dual-tower Multi-scale Convolution Neural Network (DMON)

DMON [29] is a model for Argument Structure Learning (ASL), i.e., the classification of relations between arguments. The model has four components that work as follows: first, an encoder extracts pairwise argument representations. The relationships are represented as an asymmetric relationship tensor. During training, a cropping strategy selects sub-tensors from the relationship tensor. Then, a bidirectional learning mechanism is applied to the cropped relationship tensors to capture contextual arguments and their relationships. Finally, the model employs label fusion to merge two predicted label matrices into one label matrix. During evaluation, the full relationship tensor is fed into the model. DMON was obtained by fine-tuning BioLinkBERT [36] for the AbstRCT dataset [19] and LinkBERT [36] for the SciDTB [35] and CDCP [25] datasets. DMON achieved macro F1-scores of 0.763, 0.742, 0.741, 0.484, and 0.681 on AbstRCT-Neoplasm, AbstRCT-Glaucoma AbstRCT-Mixed, SciDTB, and CDCP datasets, respectively.

3 Explanation Extraction and Generation

In this section, we present the two tools for the extraction and generation of argument-based natural language explanations.

3.1 SymExp

SymExp, i.e., Symptomatic Explanation, is an online tool¹⁰ that provides natural language explanations for clinical cases and is used to train medical residents. The tool provides both a user interface and an REST API for consultation.

Explanation Generation The UI asks for a clinical case, the correct diagnosis for that clinical case, and up to 4 incorrect diagnoses. The result is a template-based explanation of why the correct diagnosis is the correct one and why the other diagnoses cannot be good for this precise clinical case. The tool provides a set of functionalities:

Entities detection Patient’s symptoms in clinical cases are often described in layperson terms and can be missed by traditional medical Named Entity Recognition (NER) systems [26]. For example, occurrences of the symptom “Dyspnea” can be expressed as “shortness of breath” or “difficulty breathing”. To tackle this, we provided a system to detect instances of these layperson terms (symptoms) as well as medical findings (blood tests, vital signs, ...). The model was trained using the MEDQA-USMLE-Symp dataset [16], and the best results were obtained using the biomedical domain-specific SciBERT [4] uncased transformer model initialized with its respective pre-trained weights, obtaining a macro f1-score of 0.86.

Findings to symptom conversion In addition to symptoms, medical explanations often rely on the results of additional tests known as medical findings, such as blood tests and vital sign measurements. The system employs the findings extracted through entity detection and converts them into symptoms. An example of this would be replacing the measure “platelets count is 50000 mcL” with “Thrombocytopenia”, which is the term (i.e., concept) more commonly used in medical ontologies. A database of findings matched to symptoms, manually curated by experts, is used to make the conversion, and an option allows the user to use an LLM in an Input-Output Zero-Shot Prompting [32] setting if no corresponding symptom is found in the database. ChatGPT-4 [24] was the best performing for the findings to

¹⁰ <http://antidote.i3s.unice.fr/symexp/>

symptoms conversion task. Under a few-shot setting [5], an accuracy of 0.64 was obtained.

Ontology alignment The alignment module associates, whenever possible, the detected symptoms and converted findings mentioned in the clinical case description with a term (concept) found in the Human Phenotype Ontology (HPO) [15].

Template-based explanations The system also incorporates a template-based explanation generation module. The goal is to explain why a patient is given a diagnosis based on her symptoms, and to discard alternative diagnoses by explaining why they are not viable. To support these explanations, we employ the previously converted findings and detected symptoms, as well as statistical information present in HPO, such as the frequency of these symptoms' incidence. Additionally, the module is able to identify symptoms that are key to a diagnosis but are not invoked in the given explanation. Finally, references to the original terms used in the clinical case description (i.e., layperson terms and findings) are kept as a reference in the produced explanations.

REST API Like in ACTA, we provide a publicly available documented REST API. This API provides examples for each of the modules in the tool.

3.2 Correct Answer Explanation Extraction

We provide a mDeBERTa model¹¹ fine-tuned for a novel extractive task consisting of *identifying the explanation of the correct answers* in medical exams commented with gold reference explanations [11]. In other words, the model is trained to answer medical questions regarding the correct answer in a multiple-choice setting *by providing the piece of text in the context that explains why a given answer is correct*. The model is fine-tuned using the CasiMedicos dataset [2, 11] for English, French, Italian, and Spanish¹², and it can be easily accessed using the HuggingFace API. The model card setup for this model in HuggingFace provides a demo to test it in inference mode. The model obtained a 0.746 f1-score (partial match) averaged across the four languages, showing the feasibility of our approach.

4 Medical mT5

Medical mT5 [10] is an encoder-decoder model developed by continuing the training of publicly available mT5 [34] checkpoints on medical domain data for English, Spanish, French, and Italian. The model was tested on different medical tasks, including two new multilingual sequence labeling (argument component detection¹³) and generative question answering¹⁴ datasets for the evaluation of multilingual LLMs in the medical domain.

We distribute the base¹⁵ and a fine-tuned version¹⁶ of the models for multitask and multilingual sequence labeling in the medical domain. The models can be used via Hugging Face and tested using the available demo in their respective model cards.

A comprehensive experimental evaluation showed that Medical mT5 outperforms similarly-sized text-to-text models for the Spanish, French, and Italian benchmarks while being competitive in English with respect to the current state-of-the-art text-to-text [34, 6] and encoder-only models [14, 20].

¹¹ <https://huggingface.co/HiTZ/mdeb-erta-expl-extraction-multi>

¹² <https://huggingface.co/datasets/HiTZ/casimedicos-squad>

¹³ <https://huggingface.co/datasets/HiTZ/multilingual-abstract>

¹⁴ <https://huggingface.co/datasets/HiTZ/Multilingual-BioASQ-6B>

¹⁵ <https://huggingface.co/HiTZ/Medical-mT5-large>

¹⁶ <https://huggingface.co/HiTZ/Medical-mT5-large-multitask>

5 MedExpQA - Multilingual Medical QA

MedExpQA [3] is the first multilingual benchmark (EN, ES, FR, IT) based on medical exams to evaluate LLMs in Medical Question Answering. To the best of our knowledge, MedExpQA includes, for the first time, reference gold explanations written by medical doctors¹⁷. Comprehensive experimentation using both gold reference explanations and Retrieval Augmented Generation (RAG) methods demonstrate that high performance in LLMs in this benchmark remains a challenge, especially for Spanish, French, and Italian. In addition, we also release the best-performing model in MedExpQA, a Mistral 7B model fine-tuned with maximum RAG, which obtained 0.6 in accuracy averaged across the four languages¹⁸, through Hugging Face.

6 Concluding remarks

In this paper, we presented ANTIDOTE, a suite of tools and services for Argument Mining (AM) and explainable Artificial Intelligence (XAI) in the medical domain. With the growing interest in AM, our work addresses the critical need for transparent and understandable AI systems in a sensitive domain. Among the different functionalities offered by ANTIDOTE, we present tools for (i) AM on medical data: the updated ACTA demo, a full pipeline for AM in the medical domain, support for multilingual component detection, and a state-of-the-art model for argument structure learning; (ii) explanation extraction and generation: the SymExp demo that provides explanations, in natural language, based on diagnoses from clinical cases, as well as a multilingual model for the novel task of identifying the explanation of the correct answers; (iii) a Large Language Model fine-tuned for multiple multilingual medical tasks; and (iv) a new multilingual benchmark for evaluation of LLMs in medical question answering. All these modules aim at supporting evidence-based clinical decision-making and enhancing the interpretability of AI systems through natural language argument-based explanations. Additionally, experimental results showcase the efficacy of the tools presented across all of these tasks, highlighting the potential of ANTIDOTE as a valuable asset in medical research and training, offering transparency and comprehensibility that are crucial for facilitating informed decision-making in healthcare.

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¹⁷ <https://huggingface.co/datasets/HiTZ/MedExpQA>

¹⁸ <https://huggingface.co/HiTZ/Mistral-7B-MedExpQA-EN>

Ethical Statement

We acknowledge the development of ANTIDOTE has ethical implications. The broader impact of this work lies in its potential to improve the medical and linguistic research communities. However, it also raises ethical considerations in the risks that come with applying LLMs, given the likelihood of incorrect inferences as the information is automatically generated. Furthermore, we are committed to transparency and fairness in our models' development and evaluation to reduce biases; and commit to open source of our models, data and code, promoting collaboration within the research community.

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