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Research paper

ConSPro: Context-Aware Stance Detection Using Zero-Shot Prompting

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Abstract

Stance detection is the process of identifying and classifying an author's point of view or stance towards a specific target in a given text. Most of previous studies on stance detection neglect the contextual information hidden in the input data and as a result lead to less accurate results. In this paper, we propose a novel method called ConSPro, which uses decoder-only transformers to consider contextual input data in the process of stance detection. First, ConSPro applies zero-shot prompting of decoder only transformers to extract the context of target in the input data. Second, in addition to target and input text, ConSPro uses the extracted context as the third type of parameter for the ensemble method. We evaluate ConSPro on SemEval2016 and the empirical results indicate that ConSPro outperforms the non-contextual approaches methods, on average 9% with respect to f-measure. The findings of this study show the strong capabilities of zero-shot prompting for extracting the informative contextual information with significantly less effort comparing to previous methods on context extraction.

1. Introduction

This In the era of digital communication, the proliferation of user-generated content on social media platforms has necessitated advanced methods for understanding and analyzing public opinion. Stance detection, a critical task in natural language processing (NLP), aims to determine an individual's position regarding a specific target based on the text they produce [1, 2]. This task is pivotal for applications such as sentiment analysis, fake news detection, and opinion mining, where understanding the stance of a text provides deeper insights into the underlying sentiments and intentions of the author [3].

By analyzing perspectives and opinions on various topics, stance detection enables more precise analyses across different domains. The target of stance detection can pertain to events, ideas, topics, or politics, with outputs typically categorized as: 1) Agree, 2) Disagree, or 3) Neutral [4]. Recent advancements in machine learning, particularly the development of transformer-based models, have significantly enhanced the capabilities of stance detection systems. These models, leveraging techniques such as zero-shot prompting, have demonstrated remarkable efficacy in extracting nuanced contextual information with minimal manual effort [5]. This paper aims to explore the current state of stance detection, highlighting the challenges, methodologies, and future directions in this rapidly evolving field. Stance detection has diverse applications, including identifying misinformation, analyzing public opinions, understanding user sentiments, and predicting election outcomes [6]. Additionally, it is crucial for analyzing user feedback related to products, services, or brand identities. This evolving research field has garnered significant attention from both industry and academia in recent years, driven by societal needs [5].

Our innovation is ConSPro. ConSPro stands for contextualizing input data in stance detection task using decoder-only transformers. Decoder-only transformers have gained significant attention in recent years due to their ability to generate coherent and contextually relevant text. Unlike encoder-decoder architectures, which use separate mechanisms for encoding input and generating output, decoder-only transformers utilize a single mechanism to handle both tasks. This approach simplifies the architecture and allows for more efficient processing of input data. recent studies have demonstrated the effectiveness of decoder-only transformers in various natural language processing (NLP) tasks [7-9]. In the context of stance detection, decoder-only transformers can be particularly advantageous. By using the self-attention mechanism, these models can capture intricate relationships within the input data, allowing for a more detailed understanding of the text's stance. This capability is crucial for accurately identifying the writer's position, especially when dealing with complex or ambiguous statements.

One of the most well-known decoder-only transformers is GPT (Generative Pre-trained Transformer). GPT models, developed by OpenAI, have set new benchmarks in various NLP tasks, including text generation, translation, and summarization. The ability of GPT to generate contextually appropriate responses makes it an ideal candidate for tasks like stance detection, where understanding the context is paramount. By using GPT or similar models, we can effectively contextualize input data, leading to more accurate and reliable stance detection outcomes. By leveraging GPT, we can extract additional information and improve stance detection [10, 11].

In our proposed method, we use the SemEval-2016 Task 6 dataset as input, which includes both targets and tweets. We have employed data augmentation prompts to enhance the dataset. A key aspect of our work is the use of a decoder-only transformer (GPT-4) as a novel component in our ensemble method. We leveraged GPT-4 to contextualize each tweet, then extracted features using BERT and RoBERTa, and finally predicted the stance of the tweet towards the target using ensemble learning. To better evaluate our approach, we compared it with WordNet-based contextualization and a baseline stance detection method without contextualization. The results demonstrated that our proposed method outperforms the alternative approaches, highlighting its effectiveness in stance detection.

The paper is structured as follows: Section 2 reviews prior work on stance detection. Section 3 details the proposed method and main contribution. Section 4 presents empirical results, and Section 5 discusses findings and future research directions.

2. Background

Please In this section, we delve into the existing body of research on stance detection. Stance detection, also referred to as stance classification [12-16], stance identification [17-19], or stance prediction [20, 21], has garnered significant attention in recent times. Researchers have explored various input data sources for stance detection, including social media [3, 5, 22], news articles [23, 24], Wikipedia entries [25], and other textual data. In the following discussion, we highlight some of the recent advancements in the field of stance detection.

In their influential study, Gómez-Suta and colleagues [26] introduced a robust two-phase classification system for tweet stance detection. Their primary focus was on identifying fake information circulating on social media platforms. Leveraging advanced topic modeling features, their approach not only secured second place in the SemEval-2016 task 6 but also outperformed deep learning-based methods. What sets their study apart is the provision of detailed explanations for stance labels. By linking relevant terms in tweet topics to specific stances, they enhanced the interpretability of their results. Moreover, the flexibility of their approach allows it to adapt to vocabulary variations using topic information, further contributing to its effectiveness.

Reveilhac et al. [27] explored innovative techniques for enhancing stance detection in tweets. Leveraging named entity recognition (NER) and part-of-speech (POS) tagging, they extracted novel features from tweet content. Their approach involved applying logistic regression to predict the stance of texts using the SemEval-2016 dataset. By incorporating NER and POS information, Reveilhac et al. aimed to improve the accuracy and interpretability of stance detection. These additional features allowed them to capture context-specific cues and linguistic patterns associated with different stances. The results of their study shed light on effective strategies for identifying stance in social media text.

Glandt et al. [28] focused on stance detection of tweets related to the COVID-19 pandemic. They examined over 70,000 user tweets under four topics: "Stay at Home," "Wear Masks," "Keep Schools Closed," and "Anthony Fauci – Senior Medical Advisor to the President of the United States." Their proposed method utilized BiLSTM, CNN, and BERT models.

Fu and colleagues [29] explored stance detection on Twitter using a BiLSTM-based architecture. Their method extracted semantic vectors from input text and target pairs, leveraging bidirectional context and semantic representations. This approach showed promising results, advancing stance analysis in social media.

Vychegzhanin et al. [30] presented a new method for stance detection in Twitter data. In their proposed approach, the input text underwent preprocessing, and parallelly, features were extracted using N-gram and word embedding from the input text. Additionally, sentiment and linguistic features were considered in this study. Finally, based on the extracted features, a group learning architecture was trained for stance detection.

Al-Ghadir et al. [5] proposed a three-phase method for detecting stance in tweets. Their three-stage method involved preprocessing the input text, feature extraction, and, finally, employing six different classification methods for stance detection. Al-Ghadir et al.'s fusion of TFIDF-based ranked lists and sentiment features demonstrates promising results in stance detection on Twitter.

Alam et al. [31] annotated a dataset of German news articles on migration for stance detection and sentiment analysis.

Their evaluation, compared with four baseline systems, revealed negative stances in the news regarding refugees and migration. They used TFIDF models, Word2Vec, and Transformer networks in their proposed systems. Mascarell et al. [32] addressed stance detection in German news articles using a dataset of around 3,700 articles. They employed a pre-trained BERT model for the German language, achieving better results compared to word embedding-based methods. Sun et al. [33] introduced a novel approach to stance detection by incorporating sentiment information to enhance algorithm performance. They proposed a joint neural network model that simultaneously predicts both stance and sentiment, addressing the issue of error propagation in traditional models. Their method utilized an LSTM network, which is commonly used in stance detection tasks.

Liu et al. [34] sought to improve stance detection using knowledge graphs. They presented a hybrid approach combining feature extraction from a knowledge graph and input text for stance detection. Clark et al. [35] combined transformer networks and knowledge graphs for stance detection on Twitter.

They used the SpaCy entity linker to build a knowledge graph from Wikipedia entities and their descriptions. By integrating the RoBERTa model [36] with this knowledge graph, they performed stance detection on Twitter data.

Yan Luo et al. [37] utilized the ConceptNet knowledge graph for stance detection. They extracted a subgraph with specific labels and used the GCN network [38] to derive features for each node. For each input text, they combined semantic vectors from the BERT method with subgraph-related features and used an attention-based network for stance prediction.

Zhang et al. [39] utilized the RoBERTa model and constructed a graph of entities present in the text for stance detection. In their proposed method, they first extracted semantic features from the input text using the RoBERTa model.

3. Methodology

In this section, we aim to introduce the proposed method of this article. Our proposed process for stance detection is illustrated in Figure 1. We will explore the details of each of these stages in the following sections.

3.1. Problem Definition

Our innovation, ConSPro, stands for Contextualizing Input Data in the Stance Detection Task using Decoder-Only Transformers. As illustrated in Figure 1, we begin by using the SemEval2016 Task 6 dataset, extracting tweets and targets as inputs. These are then fed into a data augmentation prompt.

For the given text in the Target, the prompt generates up to three sentences that fully describe the text in detail. This prompt is processed by a decoder-only transformer (GPT-4), from which context is extracted and added as a new component to our ensemble method. Consequently, the context, along with the target and tweet, is provided to the ensemble method, resulting in stance detection. Further details are provided in subsequent sections.

3.2. Contextual Input Data

Our primary focus has been on decoder-only transformer. We aim to enrich the text using decoder-only transformer. However, for comparative purposes, WordNet has also been utilized. In the following sections, we will discuss both WordNet and decoder-only transformer (GPT-4) in detail.

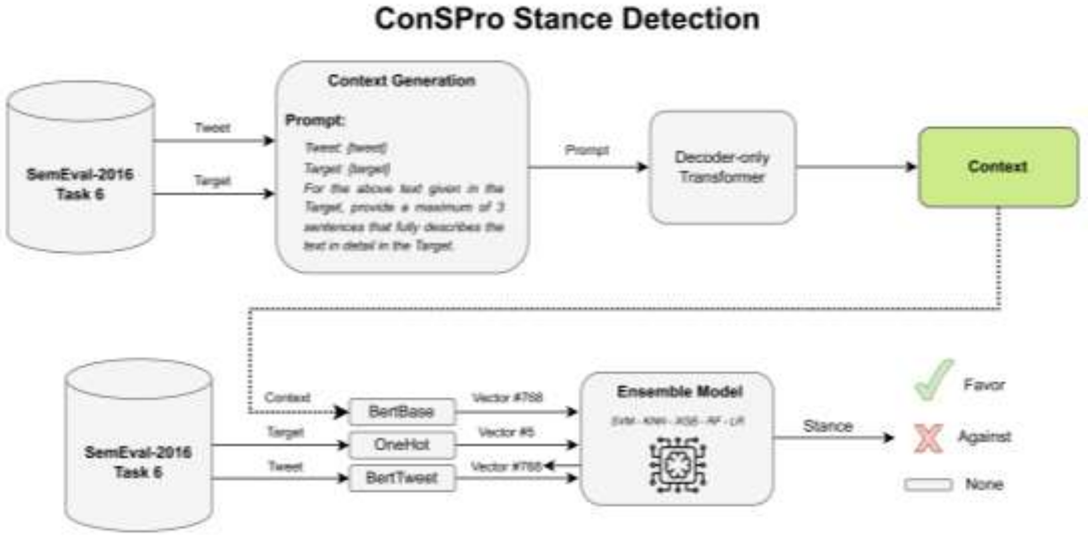

Figure 1. Overview of ConSPro's Enhanced Stance Detection Method Using Contextual Input and Zero-Shot Prompting.

3.2.1. WordNet
WordNet is a comprehensive lexical database that enhances text by providing semantic relationships between words. For text enrichment, WordNet is utilized to extract semantic information from the text, transforming words into weighted concept terms that form a semantic frequency vector. This process involves semantic disambiguation techniques to ensure accurate representation of word meanings. By integrating these semantic vectors with text embeddings, such as word2vec, the enriched text captures deeper semantic relationships, improving the performance of natural language processing tasks. In this section, the following tasks were performed:

1) The tweet column from the SemEval2016 test dataset was utilized.
2) Each tweet was preprocessed and tokenized.
3) The tokens were fed into the WordNet model to enrich the text.
4) Definitions for the target words were extracted from the WordNet output, if available.
5) The extracted definitions were considered as the enriched text in addition to the original text.

3.2.2. Decoder-only Transformers Model
In recent years, the research on Large Language Models (LLMs) has significantly advanced, particularly focusing on models based on the transformer architecture. Among these, decoder-only transformers have garnered considerable attention due to their efficiency and performance in various natural language processing tasks. The decoder-only architecture, as opposed to the traditional encoder-decoder setup, simplifies the model by using a single stack of transformer layers to generate outputs directly from the input sequence. This approach has been shown to be highly effective in tasks such as language generation, translation, and summarization [40-44]. One prominent example of these models is GPT-4.

GPT-4 is a state-of-the-art Transformer-based model developed by OpenAI. It has been pre-trained on a diverse range of internet text and fine-tuned for specific tasks, resulting in improved performance on measures of factuality and adherence to desired behavior. In our study, we utilize the ChatGPT API with the GPT-4o model to enrich text by generating contextually relevant expansions and refinements, thereby enhancing the overall quality and depth of the textual data. We used the API with default settings and did not modify any hyperparameters, providing only our custom prompt.

In the proposed model, we utilize the SemEval-2016 training data by separating tweets and their corresponding targets, which are then processed using the GPT-4 model. The same procedure is applied to the SemEval-2016 test data to generate contextual text. For each instance, a prompt is generated in the format of Figure 2 based on the tweet text and target, and it is sent as a single paragraph to the ChatGPT-4o API. The generated output is then considered as the context for that instance. From these generated contexts, we construct feature vectors, which, along with tweet vectors, are fed into ensemble models to produce the final predictions.

"""
Text: {text}
Target: {target}
For the above text given in the Target, provide a maximum of 3 sentences that fully describes the text in detail in the Target.
"""

Figure 2. Prompt template for ChatGPT-4o to extract tweet Context.

In our study, we utilized the GPT-4 API, which eliminates the need for high-end hardware but incurs financial costs. On average, each request to the API took approximately 1.2 seconds, though this duration depends on internet speed. To assess whether the financial cost is justified, we compared our proposed method with a non-LLM approach using WordNet and a baseline method. This comparison allows us to evaluate the accuracy improvements against the associated costs, providing insights into the trade-off between performance and computational efficiency.

3.3. Features Construction

Feature construction is a crucial step in enhancing the performance of machine learning models. By creating new features from the original data, we can capture more complex patterns and relationships, leading to improved model accuracy and robustness.

In this approach, we performed several steps to process and analyze the data effectively:

- **Processing Tweets with BERT-Tweet or RoBERTa-Tweet:** Each tweet was processed using either the BERT-Tweet or RoBERTa-Tweet model. BERT-Tweet is specifically designed for handling informal and noisy text in tweets, making it well-suited for social media data. On the other hand, RoBERTa-Tweet, with its optimized pretraining and improved contextual representations, is also effective in capturing the nuances of tweet data.
- **Using BERT-Base or RoBERTa-Base for Context:** For text generated by GPT (Generative Pre-trained Transformer), we used either the BERT-Base or RoBERTa-Base model. BERT-Base is a general-purpose model that effectively processes formal and structured text, while RoBERTa-Base's optimized pretraining enhances its ability to capture contextual meanings more accurately.
- **One-Hot Encoding for Targets:** For the target labels, we used one-hot encoding, which converts categorical labels into a binary vector representation. This resulted in a 5-dimensional vector, corresponding to the five possible stance categories.

The combination of the three sets of features together will form the feature vector of each sample. These features are fed as input to the Ensemble model.

3.4. Features Construction

We extract features for both the training and test samples using two methods: WordNet-based and Decoder-only Transformers Model. These approaches enhance the textual data, enabling the extraction of more informative features, which are then fed into various classifiers. The classifiers are evaluated both individually and in combination through an Ensemble Classification approach, which helps improve the overall prediction performance by leveraging the strengths of multiple models.

Table 1. Hyperparameters for Each Model in the Ensemble Classification.

Classifier	Hyperparameters
KNN	n_neighbors: [1, 2, 3, 4, 5, 6, 7, 8, 9, 10] weights: ['uniform', 'distance'] algorithm: ['ball_tree', 'kd_tree', 'brute', 'auto'] metric: ['euclidean', 'manhattan', 'minkowski', cosine_distance]
SVM	C: [0.1, 1, 5, 10] gamma: [0.001, 0.05, 0.01, 0.1]
LR	C: [0.1, 1, 10] solver: ['liblinear', 'lbfgs']
RF	n_estimators: [100, 200, 500] max_depth: [5, 10, 20, 30, 50]
XGB	n_estimators: [100, 200, 500] learning_rate: [0.01, 0.1, 0.2] max_depth: [3, 6, 9, 12]

In the ensemble setup, multiple machine learning models—including SVM, KNN, Logistic Regression, XGBoost, and Random Forest—are trained on the extracted feature vectors. To optimize performance, we apply Grid Search to determine the best hyperparameters for each classifier. The ensemble method combines the predictions from these models, leveraging their strengths to improve overall accuracy and robustness. The hyperparameters for each model, obtained through Grid Search, are detailed in Table 1.

4. Results

In this section, we evaluate the performance of our model and examine its results.

4.1. Dataset

In this article, we utilize the SemEval2016 Task6 dataset [44], which is one of the most commonly used datasets in previous works. This dataset comprises 5 targets: Atheism, Climate Change is Concern, Feminist Movement, Hillary Clinton, and Legalization of Abortion. The dataset includes three labels: Favor, Against, and Neither, with 70% of the samples allocated for training and 30% for testing. The complete information of the SemEval2016 Task6 dataset is presented in Table 2.

4.2. Evaluation metrics

In this article, we evaluate using the F1-Score metric, which averages across the two labels: Favor and Against. Formulas 1, 2, and 3 detail the calculation.

$$F_{Favor} = \frac{2P_{Favor}R_{Favor}}{P_{Favor} + R_{Favor}} \quad (1)$$

$$F_{Against} = \frac{2P_{Against}R_{Against}}{P_{Against} + R_{Against}} \quad (2)$$

$$F_{avg} = \frac{F_{Favor} + F_{Against}}{2} \quad (3)$$

Here, F_{Favor} and $F_{Against}$ correspond to the F1-Score values for the Favor and Against labels, while P and R denote Precision and Recall.

4.3. Numerical Results

In this section, we analyzed our results using the specified evaluation metric for both individual and ensemble methods. We present the results for the baseline, WordNet, and our proposed method (ConSPro model). Examples of the outcomes of these methods are summarized in

Table 3.

The following points present the analysis of

Table 3:

- **Baseline Methods:** Baseline methods like KNN and Logistic Regression show moderate performance. The best performance among the baseline methods is from the combination of KNN, LR, and XGB with an F-Measure of 65.25.
- **Using WordNet:** Using WordNet for text enrichment yields poorer results compared to baseline methods. For example, WordNet with KNN only achieves an F-Measure of 41.81.
- **Our Proposed Method:** Our proposed method using Decoder-only Transformers (GPT-4) shows significantly better performance. The best performance is from the ensemble of SVM, RF, and XGB with an F-Measure of 74.73.
- **Overall Comparison:** Our proposed method generally outperforms both the baseline methods and the use of WordNet.

We evaluated our approach against the top-performing methods on the SemEval2016 Task6 dataset. The results are summarized in Table 4. Notably, our model achieved approximately a 9% improvement over the methods that do not incorporate contextual input data.

Table 2. Statistical Information of the SemEval Dataset.

Targets	# Train			# Test			# Total
	Favor	Against	Neither	Favor	Against	Neither	
Hillary Clinton	118	393	178	45	172	78	**984**
Feminist Movement	210	328	126	58	183	44	**949**
Climate Change is a Real Concern	212	15	168	123	11	35	**564**
Atheism	92	304	117	32	160	28	**733**
Legalization of Abortion	121	355	177	41	169	40	**933**
All	753	1395	766	299	695	225	**4133**
	2914			1219			

Table 3. Examples of Baseline, WordNet, and Proposed Methods for Individual and Ensemble Approaches.

Approach	Features	Classifier	Precision	Recall	FMeasure
Baseline	BERT	KNN	61.22	62.28	61.75
Baseline	BERT	LR	63.13	63.81	63.46
Baseline	BERT	KNN, LR, XGB	64.47	66.05	65.25
Baseline	BERT	SVM, KNN, XGB	64.42	66.05	65.22
Baseline	RoBERTa	KNN, LR, XGB	63.57	64.05	63.81
WordNet	BERT	KNN	46.31	38.11	41.81
WordNet	BERT	LR	58.47	60.12	59.29
WordNet	BERT	KNN, LR, XGB	55.96	54.44	55.19
WordNet	BERT	SVM, KNN, XGB	54.98	52.42	53.66
WordNet	RoBERTa	LR	57.36	59.72	58.51
Our Method	BERT	KNN	69.43	68.93	69.18
Our Method	BERT	SVM	73.13	72.69	72.91
Our Method	BERT	LR	67.69	65.89	66.78
Our Method	BERT	RF	69.01	69.65	69.33
Our Method	BERT	XGB	71.55	71.41	71.48
Our Method	BERT	KNN, SVM, LR, RF, XGB	72.2	72.08	72.14
Our Method	**BERT**	**SVM, RF, XGB**	**74.79**	**74.68**	**74.73**
Our Method	RoBERTa	SVM, RF, XGB	72.29	72.64	72.46

The following points present the analysis of Table 4:

- **Comparison with Other Studies:** Our proposed method (Ensemble with SVM, RF, and XGB) achieved an F-measure of 74.73, demonstrating strong performance and outperforming many previous studies.
- **Best Performance:** The best performance is from the study by Al-Ghadir et al. with an F-Measure of 76.45.
- **Conclusion:** Our proposed method is among the top-performing methods in the field, demonstrating the high efficiency of our approach in stance detection using Decoder-only Transformers (GPT-4).

Table 4. Results of the Proposed Method and Previous Approaches on the SemEval 2016 Dataset.

Method	FMeasure
Sun and et al [10]	69.22
Mohammad and et al [37]	68.98
Reveilhac et al [24]	72.00
Fu and et al [26]	73.71
Gómez-Suta et al [23]	74.63
Our Method - Ensemble (SVM, RF, XGB)	74.73
Al-Ghadir and et al [6]	76.45

4.4. Non-numerical Results

In this section, we examine our non-numerical results. We provided a tweet and a target to our decoder-only transformer, which returned enriched text as output. Subsequently, stance detection was performed. Examples of this process can be seen in Table 5. As observed, our model, ConSPro, has achieved significant and satisfactory results.

5. Conclusions and Future Work

In recent years, stance detection has garnered significant attention due to the rise of fake news and the need for accurate opinion mining on social media platforms. Stance detection is the process of identifying and classifying a writer's point of view or stance towards a specific target in a given text. The typical labels for stance are 'Favor', 'Against', and 'Neutral'. To the best of our knowledge, most of the studies on stance detection neglect the contextual information hidden in the input data and as a result, lead to less accurate results.

In this paper, we proposed a method called ConSPro in which we use zero-shot prompting to make the task of stance detection context-aware. ConSPro uses the strong capabilities of zero-shot prompting for extracting the informative contextual information of target and input text. We evaluated ConSPro on SemEval-2016 and we succeeded in outperforming the baseline methods by an average of 9% with respect to the f-measure. As a future work, we could extend ConSPro’s context generation capability by applying few-shot prompting and use this capability of context generation in other NLP-related domains. Additionally, we plan to explore and evaluate ConSPro on a broader range of datasets to further assess its generalizability and robustness across different domains.

Table 5. Examples of Output from Our Model Using a Decoder-Only Transformer.

Tweet	Target	Context	Label
Many doctrines have been created so Christians could save face #truth #theology #SemST	Atheism	The text suggests that various doctrines within Christianity were developed as a strategy for Christians to maintain their dignity or credibility, possibly in light of challenging or contradictory evidence against their beliefs. The hashtags #truth, #theology, and #SemST (likely referring to "Seminary Twitter") indicate that the statement is making a pointed comment about the nature of theological practices or beliefs within the religious community, particularly in an academic or knowledgeable discourse about religion. The target 'Atheism' implies that this perspective may resonate with or originate from atheistic viewpoints, which often critique religious doctrines as human-made constructs.	Favor
@diistantecho Your wee sister believes in both Santa Claus and feminism. Think harder about what that means. #SemST	Feminist Movement	The text is a tweet that draws a comparison between believing in Santa Claus, often seen as a childhood fantasy, and believing in feminism, suggesting a critical or dismissive attitude towards the feminist movement. By stating that the individual's younger sister believes in both, it implies that feminism is similarly a naive or unreal belief. The hashtag "#SemST" could indicate that this message is part of a wider discussion or debate about social, ethical, or moral theories relating to feminism.	AGAINST
@Chris_1791 @newsbusters 2 years ago #Hillary never answered whether she used private email #Liberal media passed on reporting #SemST	Hillary Clinton	The text addresses an issue from two years ago involving Hillary Clinton's use of a private email, noting that she never responded to inquiries about it. It criticizes the liberal media for not reporting on this issue. The text also includes specific Twitter handles and a hashtag related to political and media criticism.	AGAINST
A needed, safe medical procedure is available to women. Unfortunately, RW men say they should make women's decisions. Sad, huh? #SemST	Legalization of Abortion	The text discusses the topic of abortion as a necessary and safe medical procedure accessible to women, indicating a conflict where right-wing men believe they should control women's healthcare decisions. The tone of the text expresses disapproval and disappointment regarding the imposition by some men on women's autonomy in making health-related choices. The use of "Sad, huh?" emphasizes the author's dismay at the situation and invites the reader to consider the inappropriateness of such interference in personal health matters.	Favor

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ConSPro: تشخیص موضع آگاه از زمینه با استفاده از Zero-Shot Prompting

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چکیده:

تشخیص موضع فرآیند شناسایی و طبقه‌بندی دیدگاه یا موضع نویسنده نسبت به یک هدف خاص در متن داده‌شده است. بیشتر مطالعات پیشین در این حوزه، اطلاعات زمینه‌ای پنهان در داده‌های ورودی را نادیده گرفته‌اند و در نتیجه به دقت کمتری دست یافته‌اند. در این مقاله، روشی نوین به نام ConSPro ارائه می‌شود که از ترنسفورم‌ها برای در نظر گرفتن اطلاعات زمینه‌ای در فرآیند تشخیص موضع استفاده می‌کند. در مرحله اول، ConSPro از روش zero-shot prompting برای استخراج زمینه مرتبط با هدف در داده‌های ورودی بهره می‌برد. سپس، علاوه بر متن ورودی و هدف، از زمینه استخراج‌شده به عنوان پارامتر سوم در روش رده‌بندی گروهی استفاده می‌کند. این روش بر روی مجموعه داده‌های SemEval2016 ارزیابی شده و نتایج تجربی نشان می‌دهد که ConSPro به طور میانگین ۹ درصد از نظر معیار F-measure نسبت به روش‌های غیرزمینه‌ای عملکرد بهتری دارد. یافته‌های این مطالعه نشان می‌دهد که zero-shot prompting توانایی بالایی در استخراج اطلاعات زمینه‌ای مفید با تلاش بسیار کمتر در مقایسه با روش‌های پیشین استخراج زمینه دارد.

کلمات کلیدی: تشخیص موضع، زمینه‌سازی داده‌های متنی، شبکه‌های ترنسفورمر.