LLMs for Targeted Sentiment in News Headlines: Exploring Different Levels of Prompt Prescriptiveness

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Abstract

News headlines often evoke sentiment by intentionally portraying entities in particular ways, making targeted sentiment analysis (TSA) of headlines a worthwhile but difficult task. Finetuned encoder models show satisfactory TSA performance, but their background knowledge is limited, and they require a labeled dataset. LLMs offer a potentially universal solution for TSA due to their broad linguistic and world knowledge along with in-context learning abilities, yet their performance is heavily influenced by prompt design. Drawing parallels with annotation paradigms for subjective tasks, we explore the influence of prompt design on the performance of LLMs for TSA of news headlines. We evaluate the predictive accuracy of stateof-the-art LLMs using prompts with different levels of prescriptiveness, ranging from plain zero-shot to elaborate few-shot prompts matching annotation guidelines. Recognizing the subjective nature of TSA, we evaluate the ability of LLMs to quantify predictive uncertainty via calibration error and correlation to human interannotator agreement. We find that, except for few-shot prompting, calibration and F1-score improve with increased prescriptiveness, but the optimal level depends on the model.

1 Introduction

News framing impacts information perception, shapes public opinion, and guides discussions on key topics (Semetko and Valkenburg, 2000). As succinct and attention-grabbing introductions to full news stories, headlines play a crucial role in news dissemination. They often evoke sentiment by portraying entities in specific ways, thus motivating the need for targeted sentiment analysis. Targeted sentiment analysis (TSA) is the task of determining the polarity of sentiment expressed towards the target entity (Pei et al., 2019). While sentiment analysis inherently presents challenges due to its subjectivity, TSA introduces an additional layer of

complexity by requiring the differentiation between targeted and overall sentiment. Analyzing the sentiment of news headlines is even more intricate because headlines are connotation-rich and culture-dependent, often involving implicit and indirect sentiment. This requires a detailed interpretive effort, including interpreting quotes, identifying negative events linked to entities, and navigating mixed-view headlines (Hamborg et al., 2021).

Fine-tuned encoder models such as BERT (Devlin et al., 2019) demonstrate strong TSA performance across various languages (Wu and Ong, 2021; Zhang et al., 2020; Mutlu and Özgür, 2022). However, using these models in different languages or domains requires new fine-tuning, and adapting them to low-resource languages necessitates pretrained models and labeled data. In contrast, large language models (LLMs) offer a reliable and versatile approach to TSA across various contexts by leveraging their broad linguistic and world knowledge, as well as in-context learning (Brown et al., 2020), without the need for annotated datasets or model fine-tuning. However, LLMs often lack the performance consistency of dataset-specific finetuned models. Moreover, LLMs' performance is contingent on prompt design, posing a significant challenge in identifying optimal settings.

In this paper, we begin by comparing the zeroand few-shot performance of open and closedsource LLMs to fine-tuned encoder models. We then explore the influence of prompt design on the performance of LLMs for TSA of news headlines, drawing parallels with annotation paradigms for subjective tasks. Similar to crafting effective annotation guidelines, successful prompt design for subjective tasks hinges on finding the appropriate *level of prescriptiveness*. Drawing from the descriptive-prescriptive dichotomy in linguistics and ethics, Rottger et al. (2022) proposed two contrasting paradigms for data annotation: the *descriptive* paradigm, which fosters annotator subjectivity and encourages diverse interpretations, and the *prescriptive* paradigm, which discourages subjectivity and mandates adherence to specific interpretation guidelines. The recent utilization of LLMs as data annotators (Wang et al., 2021; Pangakis et al., 2023; Alizadeh et al., 2023) invites a direct comparison between these paradigms and prompt design: a simple, less prescriptive prompt grants the LLM more freedom in interpreting the input, whereas a detailed, highly prescriptive prompt restricts the interpretation. Building on this parallel, we evaluate the predictive accuracy of state-of-the-art LLMs using prompts with different levels of prescriptiveness, ranging from plain zero-shot to elaborate few-shot prompts matching annotation guidelines.

Another interesting parallel between annotation and prompting is label variation. Regardless of whether subjectivity is encouraged, some human label variation is inevitable in subjective tasks and may be leveraged for improving model performance (Mostafazadeh Davani et al., 2022). Similarly, LLM inconsistency, typically viewed as a limitation, can diversify responses to emulate human label variation. Recent LLM uncertainty quantification methods (Rivera et al., 2024; Xiong et al., 2023; Tian et al., 2023) can produce well-calibrated confidence scores, reflecting the task's inherent subjectivity. Building on this, we assess LLMs' capability to quantify predictive uncertainty in TSA of headlines using calibration error and correlation with human inter-annotator agreement.

Our experiments use a Croatian dataset labeled with TSA on news headlines accompanied by detailed annotation guidelines. Additionally, we evaluate zero-shot LLMs and BERT on English and Polish TSA datasets. Our contributions include (1) comparing LLMs and BERT for TSA on Croatian, English, and Polish news headlines, (2) evaluating the effect of prompt prescriptiveness on LLMs' predictive accuracy, and (3) assessing calibration error across models based on prompt prescriptiveness. This study offers valuable insights into LLMs' zero-and few-shot potential for TSA of news headlines.

2 Related Work

Sentiment analysis on news headlines is an important task and garnered attention in prior work (Aslam et al., 2020; Agarwal et al., 2016; Rozado et al., 2022), especially for stock prediction (Joshi et al., 2016; Nemes and Kiss, 2021). In addition to overall sentiment, TSA, also known as fine-grained

sentiment analysis, is crucial for understanding how entities are portrayed in news articles. Cortis et al. (2017) and Salgueiro et al. (2022) perform TSA on headlines from limited domains, namely financial and political headlines. Dufraisse et al. (2023) and Steinberger et al. (2011) present multilingual datasets for TSA in news articles. Hamborg and Donnay (2021) present a dataset for TSA on English news articles reporting on political topics, while (Balahur et al., 2013) focus on quotes from news articles. Overcoming the need for a labeled dataset, LLMs present as a possible solution for TSA due to their ICL abilities and broad background. Huang et al. (2020) conducted an analysis to identify and mitigate the entity bias of LLMs trained for sentiment analysis on Wikipedia and news articles. Chumakov et al. (2023) leverage both few-shot learning and fine-tuning with GPT models on mixed-domain Russian and English datasets to model sentiment effectively without domain-specific data.

3 Datasets and Models

Our experiments utilize the only two available datasets, to our knowledge, for TSA in general news headlines. These datasets cover three languages and employ different annotation styles.

STONE. Filling the void in TSA for low-resource languages, the STONE dataset (Barić et al., 2023) offers overall sentiment and targeted sentiment annotations for Croatian news headlines, using ternary labels (positive, neutral, negative). Each of the 2855 headlines has six labels given by six annotators, and detailed annotator guidelines are provided. We leverage these guidelines to build prompts with increasing levels of prescriptiveness, with the highest level aligning with annotation guidelines and including provided examples.

SEN. The SEN (Baraniak and Sydow, 2021) TSA dataset includes 3819 English and Polish news headlines. It comprises three parts: the Polish dataset (SEN_pl), the English dataset (SEN_en_r) annotated by volunteer researchers, and an English dataset (SEN_en_amt) annotated using Amazon Mechanical Turk. Unlike STONE, SEN lacks raw labels, providing only an aggregated gold label for each headline (positive, neutral, and negative), and features less detailed and prescriptive annotator guidelines. Therefore, SEN is not suitable for our prompt prescriptiveness experiments.

		SEN		
	STONE	en_amt	en_r	pl
GPT 3.5 Turbo	61.3	66.1	61.5	60.0
GPT 4 Turbo	65.9	68.8	63.2	69.5
Mistral	43.0	56.1	45.8	47.7
Neural Chat	59.8	66.3	63.8	58.1
BERT*	77.9	63.6	56.2	61.9

Table 1: F1 scores across languages and datasets

In our experiments, we chose two open 7B models (Mistral and Neural Chat) derived from the LLama 2 model (Touvron et al., 2023), pitted against two proprietary OpenAI models (GPT-4 Turbo and GPT-3.5 Turbo) (OpenAI et al., 2023).

4 Experiments and Results

4.1 Accuracy Across Datasets

We first evaluate the LLMs' accuracy of TSA on headlines and compare them to top-performing BERT models. We use the BERT models specifically pre-trained for each language – RoBERTabase (Liu et al., 2019) for English, BERTić (Ljubešić and Lauc, 2021) for Croatian, and Polish-RoBERTa-base-v2 (Dadas et al., 2020) for Polish – and fine-tune each for TSA on the corresponding training set. For LLMs, we use zero-shot prompting on the test set, using basic prompts outlining the task and the target classes (cf. Appendix A).

Table 1 presents the F1 scores on the test set portions of each dataset. GPT-4 Turbo achieves the highest F1 score on the Polish SEN and the crowd-sourced English SEN. Interestingly, on the English SEN annotated by researchers, Neural Chat outperforms not only other fine-tuned BERT models but also GPT. On STONE, BERTić surpasses all other models by a significant margin. This could be due to the highly prescriptive nature of the annotator guidelines, which dictate a specific interpretation of headline sentiment, a characteristic captured well by BERTić during fine-tuning. The relatively weaker performance of LLMs may stem from the prompts not aligning with that level of prescriptiveness – a question we explore next.

4.2 Level of Prompt Prescriptiveness

In this experiment, we utilize the STONE dataset and its annotator guidelines to create six prompts of increasing prescriptiveness level. Each subsequent level incorporates additional information from the guidelines. Table 2 outlines these six levels (cf. Appendix A for full prompts). Our goal is to assess

evel	Description
1	Concise, exploring the fundamental concepts of
	sentiment and targeted sentiment.
2	Includes a definition of targeted sentiment specif-
	ically within the framework of news headlines.
3	Provided with concise guidelines.
4	Comprehensive instructions provided as guide-
	lines, excluding examples.
5	Comprehensive instructions presented as guide-
	lines, including examples and brief explanations.
6	Comprehensive instructions provided exactly as
	they were presented to the annotators.

Table 2: Short descriptions of prompt prescriptiveness levels. Level 1 contains basic instructions, while level 6 adheres to the prescriptive paradigm and is identical to annotator guidelines (cf. Appendix A for full prompts).

Level	Neural Chat	GPT 3.5 Turbo	GPT 4 Turbo
1	59.8	60.1	65.9
2	61.2	58.3	64.3
3	61.5	65.7	69.9
4	63.1	64.0	70.2
5	60.5	63.0	66.8
6	62.5	64.5	68.2

Table 3: F1 scores for levels of prompt prescriptiveness

the ability of LLMs to follow instructions as accurately as human annotators and to determine the most effective level of prompt prescriptiveness.

Table 3 shows the results. We note a slight but notable variance in performance across all levels for all models. GPT-4 consistently outperforms other models across all levels, with GPT-4 and Neural Chat reaching their performance peaks at level 4 (detailed instructions formatted as guidelines without examples) and GPT 3.5 performing best at level 3 (concise guidelines). The performance drop seen at levels 5 and 6, the only ones with few-shot examples, may be due to the sensitivity regarding the selection and ordering of examples, a phenomenon observed in few-shot prompting (Lu et al., 2022; Chang and Jia, 2023). The trend of increased accuracy from levels 1 to 4 indicates a positive impact of providing LLMs with more prescriptive instructions. While fine-tuning BERT still outperforms prompting at these higher prescriptiveness levels, the attractiveness of using LLM for TSA on headlines lies in their universality across languages and the absence of a need for labeled datasets.

4.3 Uncertainty Quantification

Given the inherent subjectivity of TSA and the stochastic nature of predictions generated by LLMs, we explore how the inherent uncertainty of LLM

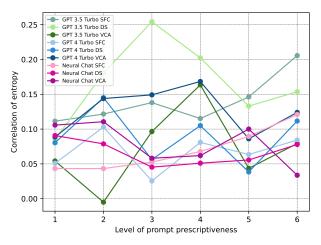


Figure 1: Correlations between label distribution entropies from LLMs and human annotators, for various uncertainty quantification methods and across levels of prompt prescriptiveness

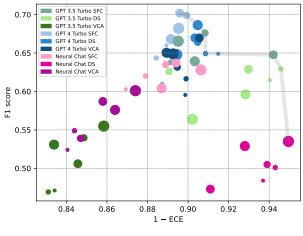


Figure 2: Comparison of F1 scores and calibration accuracy for various uncertainty quantification methods and across levels of prompt prescriptiveness (indicated by dot size). The gray lines indicate the Pareto front.

predictions can model human label variation and whether this varies across levels of prompt prescriptiveness. Using STONE, we approach this question from two angles: (1) investigating if the uncertainty of LLM predictions aligns with inter-annotator disagreement and (2) examining the relationship between LLMs' predictive and calibration accuracies.

We use three uncertainty quantification methods: self-consistency sampling, distribution sampling, and verbal confidence assessment. Self-consistency sampling (SCS) (Xiong et al., 2023) leverages the inherent stochasticity of LLMs, influenced by internal parameters such as temperature. For each headline, we prompt the same model six times and accumulate the responses to mimic the distribution of six annotator responses, setting the temperature to 0.7 for all models. The second method, which we refer to as distribution sampling (DS), prompts the model to explicitly predict how six annotators would label the targeted sentiment, directly resulting in a distribution of positive, neutral, and negative responses. Lastly, the verbal confidence assessment (VCA) method (Xiong et al., 2023) prompts the LLM to produce three predictions for each headline, representing each sentiment class, along with a confidence score ranging from 0 to 100.

Figure 1 shows the correlations between label distribution entropies from LLMs and annotators across prompt prescriptiveness levels. While correlations vary, they are generally weak, indicating misalignment between LLM predictive uncertainty and human subjectivity. The highest correlation occurs with GPT 3.5 and DS at level 3.

To analyze the calibration error, we consider only the labels with the highest confidence score for each headline and calculate the expected calibration error (ECE; cf. Appendix A.6). Figure 2 compares the LLMs predictive accuracy (F1 score) against calibration accuracy, defined as 1-ECE, with prompt prescriptiveness level indicated by dot size. Calibration accuracy is generally quite high (above 0.8) across models and uncertainty methods. Similar to predictive accuracy, calibration accuracy tends to increase with prescriptivity level, except for the DS method of uncertainty quantification. Achieving a balance between F1 scores and calibration accuracy, the optimal configurations lie on the Pareto front. Among these, GPT 4 Turbo at prescriptiveness level 4 and Neural Chat at level 4 maximize the F1 score and calibration accuracy, respectively. GPT 3.5 Turbo at level 6 emerges as the best choice, achieving a balance between predictive and calibration accuracy.

5 Conclusion

Building on parallels with annotation paradigms for subjective tasks, we investigated the performance of LLM in-context learning for targeted sentiment analysis on news headlines. Our findings indicate that, apart from few-shot prompting, predictive accuracy rises with prompt prescriptiveness level, though the optimal level varies by model. LLM uncertainty, while not correlating with human subjectivity, tends to be well-calibrated and also increases with prompt prescriptiveness level.

Limitations and Risks

Limitations. We find several limitations in this work. Firstly, our choice of LLMs is restricted. This is primarily due to computing and budget constraints. We are aware that a more expansive collection of models is necessary for a more comprehensive overview of LLM performance, along with models larger than 7B parameters. Additionally, we prompted both GPT models using batches of data, which impacted performance during initial tests, but did not warrant the high costs of repeating the prompt for each individual instance.

Secondly, the aspect of varying prescriptiveness in prompts was only evaluated on one dataset, STONE. To our knowledge, there are currently no publicly available datasets on TSA in news headlines annotated with detailed guidelines. Furthermore, since the dataset in focus is in Croatian, it is unclear whether a difference in performance is due to the difference in the ability for sentiment analysis or the general understanding of the language and its cultural and political background, both essential for the task.

Finally, while evaluating the effect of prompt prescriptiveness level, the six levels were chosen arbitrarily so that they resemble a logical step-up in detail level. This number and method of prompt generation can differ based on the task at hand and annotation guidelines.

Risks. The risks in our work are mostly connected with the risks associated with sentiment analysis. Automatically evaluating sentiment might promote exclusion towards certain entities. As we performed no masking of entities, internal model biases could affect the classification.

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A Appendix

A.1 Additional Info on Datasets

In Figure 4 the dataset sizes are shown. For the STONE dataset, we used the split for train, valida-

		SEN		
	STONE	en_amt	en_r	pl
train set size	1614	806	662	688
validation set size	231	269	220	230
test set size	462	269	220	230

Table 4: Dataset sizes used in experiments

		SEN		
	STONE	en_amt	en_r	pl
learning rate	1e-5	2e-5	2e-5	3e-5
batch size	16	16	16	64
epoch size	4	3	3	5

Table 5: Optimal hyperparameters determined for each dataset: for STONE, the results are obtained using the BERTić model; for SEN_en_amt and SEN_en_r, RoBERTa-base is utilized; and for SEN_pl, Polish-RoBERTa-base-v2 is employed.

tion, and test sets given by the authors (Barić et al., 2023). For the variations of the SEN dataset, we used a 60/20/20 split generated using the sci-kit learn library with a fixed random seed of 42.

For the BERT* models, we performed grid search for hyperparameter selection. We varied the learning rate, batch sizes and number of epochs. The optimal hyperparameters are shown in Table 5.

A.2 Additional Information on GPU Usage

We utilized a total of 201 hours of GPU resources. Specifically, 14 hours were allocated for obtaining results for optimal models and hyperparameters for BERT-based models. Additionally, 38 hours were dedicated to GPT 3.5 Turbo, 76 hours to GPT 4 Turbo, 62 hours to Neural Chat inference, and 11 hours to Mistral. Neural Chat and Mistral were run locally, while the GPT models were executed using the OpenAI Platform ¹.

A.3 Additional Information on Used Toolkits

For tokenizing data to obtain results on BERT-based models, we utilized the PyTorch Transformers library².

A.4 Prescriptiveness Levels Used in Prompts

Level 1: Descriptive without definitions, exploring the fundamental concepts of sentiment and targeted sentiment.

System: You are a helpful assistant who performs targeted sentiment classification in Croatian news headlines. The available sentiment classes are

positive, neutral, and negative. For each given headline, identify the targeted sentiment class towards the entity.

User: Classify targeted sentiment towards entity {*entity*} in the following news headline: {*headline*}

Level 2: Includes a definition of targeted sentiment specifically within the framework of news headlines.

System: You are a helpful assistant who performs targeted sentiment classification in Croatian news headlines. Targeted sentiment involves understanding the author's intention to evoke emotion towards a target entity, considering the deliberate choice in conveying news and recognizing that the same information can be presented in various ways, with the understanding that such intentional choices aid in detecting the targeted sentiment. The available sentiment classes are positive, neutral, and negative. For each given headline, identify the targeted sentiment class towards the entity.

User: Classify targeted sentiment towards entity {*entity*} in the following news headline: {*headline*}

Level 3: Provided with concise guidelines.

System: You are a helpful assistant who performs targeted sentiment classification in Croatian news headlines. Targeted sentiment is the emotional stance the author aims to convey specifically towards a mentioned entity. It involves interpreting the intention behind the author's choice of language and tone when discussing the target entity. The sentiment is not only influenced by the conveyed information but also by the author's subjective evaluation and emotional coloring of the entity. Actions associated with the entity play a role in determining the sentiment, with negative actions implying a negative quality and, consequently, a negative sentiment. Distinguishing between negative actions and negative occurrences is crucial, as negative occurrences towards the entity don't color the entity. In headlines featuring a quote, the entity authoring the quote is attributed neutral sentiment as they are merely conveying an opinion. The overall goal of the author, whether it be praise or criticism, is considered in cases of headlines with a mix of positive and negative views. In summary, targeted sentiment is the nuanced emotional evaluation directed specifically at a particular entity within the context of news reporting. The available sentiment classes are

¹https://platform.openai.com/docs/introduction

positive, neutral, and negative. For each given headline, identify the targeted sentiment class towards the entity.

User: Classify targeted sentiment towards entity {*entity*} in the following news headline: {*headline*}

Level 4: Comprehensive instructions provided as guidelines, excluding examples.

System: You are a helpful assistant who performs targeted sentiment classification in Croatian news headlines.

Guidelines for Targeted Sentiment Annotation:

- 1. Detecting Sentiment through Author's Intent and News Presentation: Evaluate the intended sentiment towards an entity by analyzing the emotions the author aims to evoke and recognizing that news can be conveyed in multiple ways, with the chosen manner of conveyance serving a purpose and aiding in targeted sentiment detection.
- 2. Impact of Entity Actions: Acknowledge that entity actions influence sentiment, with negative actions implying negative quality. However, distinguish between negative actions undertaken by the entity and negative occurrences directed towards the entity that do not inherently portray the entity in a negative light.
- 3. Neutrality of Quoting Authors: In headlines featuring quotes, two types of entities are involved: the statement's author and the entities mentioned in the quote. If the target entities in the headline are the authors of the statement, the sentiment towards them typically leans towards neutrality because, in this scenario, they serve as conveyors of an opinion rather than direct subjects of sentiment.
- 4. Overall Authorial Goal: Consider the author's overall goal, whether it involves praise or criticism, especially in mixed-view headlines.

The available sentiment classes are positive, neutral, and negative. For each given headline, identify the targeted sentiment class towards the entity.

User: Classify targeted sentiment towards entity {*entity*} in the following news headline: {*headline*}

Level 5: Complete instructions presented as guidelines, inclusive of examples and detailed explanations.

System: You are a helpful assistant who performs targeted sentiment classification in Croatian news headlines.

Guidelines for Targeted Sentiment Annotation:

1. Detecting Sentiment through Author's Intent

and News Presentation:

Evaluate the intended sentiment towards an entity by analyzing the emotions the author aims to evoke and recognizing that news can be conveyed in multiple ways, with the chosen manner of conveyance serving a purpose and aiding in targeted sentiment detection.

Examples Illustrating Sentiment towards Entity Solin:

Headline: 'SRAMOTA USolinuse djeca nemaju gdje liječiti, roditelji očajni'

Targeted Sentiment: Negative

Explanation: The author criticizes Solin, suggesting a disgraceful situation where children lack medical care, portraying a negative sentiment.

Headline: 'U Solinu radi samo jedna pedijatrica, roditelji traže hitno rješenje'

Targeted Sentiment: Negative

Explanation: The negative sentiment persists as the author emphasizes the shortage of pediatricians in Solin, prompting urgent solutions according to parents.

Headline: 'U Solinu nastupio nedostatak liječničkog kadra'

Targeted Sentiment: Neutral

Explanation: The sentiment is neutral here as the author focuses on conveying information about the shortage of medical staff without explicitly criticizing the responsible institutions.

2. Impact of Entity Actions:

Recognize that entity actions play a role in shaping sentiment, particularly with negative actions like murder and theft suggesting a negative quality. However, distinguish between negative actions where the entity is the perpetrator and negative occurrences where the entity is the recipient. Acknowledge that in the case of negative occurrences, the entity cannot be held responsible for the consequences but may be in a negative situation as a result, implying neutrality in the assessment.

Headlines with negative quality of entities linked to their actions:

a) Examples of linking entity quality to actions: Headline: 'Bivša tehnološka direktorica Elizabeth Holmes osuđena na 11 godina zatvora'

Entity: Elizabeth Holmes

Targeted Sentiment: Negative

Explanation: Negative sentiment is assigned to Elizabeth Holmes based on her negative actions.

Headline: 'Zbog ubojstva srpskih civila sudit će se Đuri Brodarcu, bivšem Sanaderovom savjetniku'

Entity: Đuro Brodarac Targeted Sentiment: Negative

Explanation: Negative sentiment is assigned to Đuro Brodarac due to his association with a serious

crime.

b) Examples of negative occurences towards the entity.

Headline: 'Potres u Indoneziji: Poginulo najmanje 46 ljudi, ozlijeđenih oko 700'

Entity: Indonezija

Targeted Sentiment: Neutral

Explanation: Neutral sentiment is assigned to Indonesia as the entity is a recipient of a negative occurrence.

Headline: 'Horor u Mogadišuu: U terorističkom napadu na hotel 10 mrtvih, ozlijeđen i somalijski ministar'

Entity: Mogadišu

Targeted Sentiment: Neutral

Explanation: Similar to the previous example, neutral sentiment is assigned to Mogadishu as it is a recipient of a negative occurrence.

3. Neutrality of Quoting Authors:

Define sentiment towards the entity by considering the author's stance in a statement, whether the author is the headline writer or the individual quoted. When conveying someone's sentiment in a quote, transfer that sentiment to the mentioned entity. In headlines quoting individuals, recognize two entity types: the statement's author and the entities mentioned in the quote. If the target entities in the headline are the authors of the statement, the sentiment is typically neutral since they serve as conveyors of an opinion.

Examples of Handling Quotes in Headlines:

Headline: 'Milanović: Žao mi je što sam

podržao Bidena' Entity: Milanović

Targeted Sentiment: Neutral

Entity: Biden

Targeted Sentiment: Negative

Explanation: Neutral sentiment is assigned to Milanović, who is conveying an opinion, while negative sentiment is assigned to Biden based on the conveyed sentiment.

Headline: 'Gotovac: Ako sam ja politički antitalent, onda je tom antitalentu išlo bolje nego Grbinu'

Entity: Gotovac

Targeted Sentiment: Positive

Entity: Grbin

Targeted Sentiment: Negative

Explanation: Positive sentiment is assigned to Gotovac, who comments on himself, while negative sentiment is assigned to Grbin based on the conveyed sentiment.

Headline: 'Anka Mrak Taritaš: Tužna sam i razočarana situacijom u Zagrebu. Tomašević ne bi

dobio dobru ocjenu' Entity: Anka Mrak Taritaš Targeted Sentiment: Neutral

Entity: Tomašević

Targeted Sentiment: Negative

Explanation: Neutral sentiment is assigned to Anka Mrak Taritaš, the quoted individual, while negative sentiment is assigned to Tomašević based on the conveyed sentiment.

4. Overall Authorial Goal:

Consider the author's overall goal, whether it involves praise or criticism, especially in mixed-view headlines.

Example of a Combined Statement (Combination of Positive and Negative Views)

Headline: 'Vanna je definitivno promijenila stil naglavačke i dosadne kombinacije zamijenila onima koje prate trendove'

Entity: Vanna

Targeted Sentiment: Positive

Explanation: A positive sentiment is attributed to Vanna because the author's intention is to praise the improvement in her style, despite simultaneously criticizing her previous dressing style.

The available sentiment classes are positive, neutral, and negative. For each given headline, identify the targeted sentiment class towards the entity.

User: Classify targeted sentiment towards entity {*entity*} in the following news headline: {*headline*}

Level 6: Full set of annotator instructions

System: You are a helpful assistant who performs targeted sentiment classification in Croatian news headlines. Here are some guidelines for detecting targeted sentiment in news headlines:

To determine sentiment towards an entity, we consider the kind of emotion the statement's author intended to evoke regarding the target entity, that is, how the author intended to "color" that entity. To aid in discerning the intended sentiment towards the entity, one can consider the fact that the same piece of news can always be conveyed in multiple ways. The chosen manner of conveying a piece of news is selected with a purpose, and understanding that intention can be utilized for targeted sentiment detection.

An example of various ways of reporting the same news about entity Solin:

Headline: 'SRAMOTA USolinuse djeca nemaju gdje liječiti, roditelji očajni'

Targeted Sentiment: Negative

Explanation: Negative sentiment is attributed to Solin due to the author's intention to criticize the institution for the shortage of pediatricians.

Headline: 'U Solinu radi samo jedna pedijatrica, roditelji traže hitno rješenje'

Targeted Sentiment: Negative

Explanation: Similar negative sentiment is conveyed towards Solin by criticizing the shortage of medical staff.

Headline: 'U Solinu nastupio nedostatak liječničkog kadra'

Targeted Sentiment: Neutral

Explanation: Neutral sentiment is assigned as the author's intention is to convey information without criticizing the responsible institutions.

When detecting targeted sentiment, we can assign a quality to the target entity as an aid in determining sentiment, based on the emotion the statement's author associates with it. The quality of the entity is linked to the actions of that entity, which can be either negative or positive. Negative actions of the entity, such as murder, theft, and other illegal or socially unacceptable activities

like insults, are attributed to the quality of that entity. Negative actions signify a negative quality of the entity, implying a negative sentiment. The same approach will be applied in cases of positive actions of the entity, indicating a positive sentiment towards the entity. It is necessary to distinguish between the negative actions of an entity and negative occurrences towards the entity. In the case of negative actions by the entity, the entity is the perpetrator and therefore responsible for that action. In the case of negative occurrences towards the entity, the entity is the recipient of the negative action and cannot be held responsible for the consequences of the action, although it may be in a negative situation as a result.

Examples of linking entity quality to actions:

Headline: 'Bivša tehnološka direktorica Elizabeth

Holmes osuđena na 11 godina zatvora'

Entity: Elizabeth Holmes Targeted Sentiment: Negative

Explanation: Negative sentiment is assigned to Elizabeth Holmes based on her negative actions.

Headline: 'Zbog ubojstva srpskih civila sudit će se Đuri Brodarcu, bivšem Sanaderovom savjetniku'

Entity: Đuro Brodarac

Targeted Sentiment: Negative

Explanation: Negative sentiment is assigned to Đuro Brodarac due to his association with a serious crime.

Examples of negative occurences towards the entity.

Headline: 'Potres u Indoneziji: Poginulo najmanje 46 ljudi, ozlijeđenih oko 700'

Entity: Indonezija

Targeted Sentiment: Neutral

Explanation: Neutral sentiment is assigned to Indonesia as the entity is a recipient of a negative occurrence.

Headline: 'Horor u Mogadišuu: U terorističkom napadu na hotel 10 mrtvih, ozlijeđen i somalijski ministar'

Entity: Mogadišu

Targeted Sentiment: Neutral

Explanation: Similar to the previous example, neutral sentiment is assigned to Mogadishu as it is

a recipient of a negative occurrence.

We define sentiment towards the entity as the author's stance towards the target entity in a statement. The statement's author can be the person who wrote the article headline or the author whose quote is conveyed in the form of the article headline. When conveying someone's negative/positive sentiment in a quote or paraphrase, that sentiment is transferred to the entity. In headlines conveying someone's quote, there are two types of entities - the statement's author and the entities mentioned in the quote. If the target entities in the headline are the authors of the statement, the sentiment towards them will usually be neutral because, in this case, they are just conveyors of an opinion. An exception is the following example with entity Gotovac, where the statement's author comments on himself, and the expressed sentiment is then transferred to the author himself.

Examples of Handling Quotes in Headlines:

Headline: 'Milanović: Žao mi je što sam

podržao Bidena' Entity: Milanović

Targeted Sentiment: Neutral

Entity: Biden

Targeted Sentiment: Negative

Explanation: Neutral sentiment is assigned to Milanović, who is conveying an opinion, while negative sentiment is assigned to Biden based on the conveyed sentiment.

Headline: 'Gotovac: Ako sam ja politički antitalent, onda je tom antitalentu išlo bolje nego Grbinu'

Entity: Gotovac

Targeted Sentiment: Positive

Entity: Grbin

Targeted Sentiment: Negative

Explanation: Positive sentiment is assigned to Gotovac, who comments on himself, while negative sentiment is assigned to Grbin based on the conveyed sentiment.

Headline: 'Anka Mrak Taritaš: Tužna sam i razočarana situacijom u Zagrebu. Tomašević ne bi dobio dobru ocjenu'

Entity: Anka Mrak Taritaš Targeted Sentiment: Neutral Entity: Tomašević

Targeted Sentiment: Negative

Explanation: Neutral sentiment is assigned to Anka Mrak Taritaš, the quoted individual, while negative sentiment is assigned to Tomašević based on the conveyed sentiment.

In the case of a headline containing a combination of positive and negative views towards the entity, the final goal of the author towards the entity is considered, i.e., whether the author aimed for praise or criticism.

Example of a Combined Statement (Combination of Positive and Negative Views):

Headline: 'Vanna je definitivno promijenila stil naglavačke i dosadne kombinacije zamijenila onima koje prate trendove'

Entity: Vanna

Targeted Sentiment: Positive

Explanation: Positive sentiment is assigned to Vanna as the author's intention is to praise the improvement in her style despite also criticizing her previous dressing choices.

The available sentiment classes are positive, neutral, and negative. For each given headline, identify the targeted sentiment class towards the entity.

User: Classify targeted sentiment towards entity {*entity*} in the following news headline: {*headline*}

A.5 Prompts for Modeling LLM Uncertainty

Distribution sampling

User: Your task is to imagine you are representing 6 different people detecting the targeted sentiment in Croatian news headlines, each following the given guidelines. For a headline and an entity, you need to return detected targeted sentiment for each of the 6 voters.

Detect targeted sentiment for entity 'entity' in headline: 'headline'. Possible sentiment classes are positive, neutral and negative. Please return the answer in JSON format like:

["targeted sentiment 1":"class 1"

"targeted sentiment 2":"class 2"

"targeted sentiment 3":"class 3"

"targeted sentiment 4":"class 4"

"targeted sentiment 5": "class 5"

Verbal confidence assessment

User: You are a helpful assistant who performs targeted sentiment classification in Croatian news headlines. Following the given guidelines, please return the confidence for detection of each class. Detect targeted sentiment for entity {entity} in

Detect targeted sentiment for entity {*entity*} in headline: {*headline*}. Possible sentiment classes are positive, neutral and negative.

Please return the confidence for each class in format like:

["confidence positive class", "confidence neutral class", "confidence negative class"]

A.6 Measurements

Expected calibration error (ECE) Model predictions are categorized into m quantile-scaled bins B_i , choosing m=10 for this analysis. For each bin, we calculate both the average accuracy $\mathrm{acc}(B_i)$ and average uncertainty $\mathrm{uncert}(B_i)$. The Expected Calibration Error (ECE) is then derived as the weighted sum of the absolute differences between these averages, with weights proportional to the bin size n. A lower ECE indicates superior model calibration, formalized by the equation:

$$ECE = \sum_{i=1}^{m} \frac{|B_i|}{n} \left| acc(B_i) - uncert(B_i) \right|. \quad (1)$$