Abstract

Stance detection deals with the identification of an author’s stance towards a target and is applied on various text domains like social media and news. In many cases, inferring the stance is challenging due to insufficient access to contextual information. Complementary context can be found in knowledge bases but integrating the context into pretrained language models is non-trivial due to their graph structure. In contrast, we explore an approach to integrate contextual information as text which aligns better with transformer architectures. Specifically, we train a model consisting of dual encoders which exchange information via cross-attention. This architecture allows for integrating contextual information from heterogeneous sources. We evaluate context extracted from structured knowledge sources and from prompting large language models. Our approach is able to outperform competitive baselines (1.9pp on average) on a large and diverse stance detection benchmark, both (1) in-domain, i.e. for seen targets, and (2) out-of-domain, i.e. for targets unseen during training. Our analysis shows that it is able to regularize for spurious label correlations with target-specific cue words.

1 Introduction

Given a text and the target the text is directed at, the goal of stance detection (Küçük and Can, 2020) is to predict whether the text contains a positive or negative stance towards the target, or is not related at all. We provide an example in Figure 1. In contrast to formal polls, stance detection (SD) provides a scalable alternative to assess opinions expressed in unstructured texts. However, in contrast to predicting the polarity of a text (i.e. sentiment analysis), SD requires to establish the relation towards a target which is rarely mentioned in the text. Further, to infer the correct stance, often the text alone is not sufficient. Humans are capable of commonsense reasoning and often have contextual information about the target which helps them to infer the missing context to deduct the stance.

In contrast, most stance classification models are expected to make a correct classification given the text and target only, which can lead to overly relying on label correlations with target-specific vocabulary (Thorn Jakobsen et al., 2021). In our example §1, it is challenging to follow the reasoning of the text if the meaning of school spirit is left unclear.

| Target: School Uniforms |
|-------------------------|
| Label: Pro |
| Text: Creates a sense of school spirit. |
| Context: ['school spirit is the enthusiasm and pride felt by the students of a school', 'a strong sense of school spirit is a positive and uplifting influence on the school and its students'] |

Figure 1: Example for Stance Detection from the UKP ArgMin dataset (Stab et al., 2018). The context is not part of the original dataset and was extracted from a large language model.

Consequently, providing external knowledge as an additional signal to stance classification has been proposed as a remedy. However, in lack of a general solution, previous work applies knowledge integration only for a specific text domain like social media (Allaway et al., 2021; Clark et al., 2021). But stance detection (SD) algorithms are applied on a multitude of different text sources like social media (ALDayel and Magdy, 2021), news (Hanselowski et al., 2019) or debating fora (Hasan and Ng, 2013; Chen et al., 2019) and on diverse targets such as persons (Sobhani et al., 2017; Li et al., 2021), products (Somasundaran and Wiebe, 2010), or controversial topics (Stab et al., 2018; Jo et al., 2021a), inter alia. In addition, ex-
isting approaches are often dependent on the structure of the external knowledge source which is used (Zhang et al., 2020). However, most likely a single source of knowledge will not suffice for all different scenarios and adapting the model architecture to the structure of a specific knowledge source (e.g. graph-based) limits its applicability.

In this work we propose a flexible approach to integrate external knowledge (or any contextual information) by encoding it as text. We argue that it is better aligned to the encoding schema of the language model and does not introduce a dependency on the structure of a particular knowledge source. It also allows for usage of any context source which fits best the text domain of the data. Finally, it even allows mixing contextual information from multiple sources.

In detail, we propose a dual-encoder architecture (INJECT), which encodes the input text and context information separately while facilitating information exchange between both via cross-attention. We investigate extracting contextual information from various sources using different extraction strategies and evaluate our approach across a benchmark of 16 stance detection datasets exhibiting different characteristics with regards to text source, size, and label imbalance. Our experimental setup involves experiments both (1) in-domain, i.e. the targets of the test dataset are seen during training, and (2) cross-domain, i.e. the test targets are unseen. We observe statistical significant improvements when comparing to competitive baselines and provide an analysis which demonstrates the effectiveness of our approach.

In summary, we make the following contributions:

• We propose the INJECT architecture to integrate contextual information for stance detection based on cross-attention. We see performance improvements using our approach across a large and diverse benchmark of 16 stance detection datasets.

• A comparison of different sources for extracting contextual information and their effectiveness for stance detection. We extract context from traditional knowledge bases and by prompting a large pretrained language model.

• An analysis highlighting the benefits of our approach compared to a more direct integration via appending the context to the input.

We observe our approach regularizing the influence of topic-specific spurious correlations and thereby enhancing out-of-domain stance detection.

2 Background And Related Work

Many tasks in NLP benefit from access to external knowledge such as natural language inference (Chen et al., 2018), machine translation (Shi et al., 2016) or argument mining (Jo et al., 2021a; Al Khatib et al., 2021; Lauscher et al., 2021). Within the era of pretrained language models, many approaches rely on extensive pretraining using data from knowledge bases (Peters et al., 2019; Zhang et al., 2019; Lauscher et al., 2020) or supervision from knowledge completion tasks (Wang et al., 2021; Rozen et al., 2021).

In SD, early works leveraged sentiment lexicons (Bar-Haim et al., 2017b) or combinations thereof (Zhang et al., 2020) to improve classification performance. Similarly to aforementioned approaches, the focus has also shifted towards combining information from structural KBs and PLMs. Kawintiranon and Singh (2021) identify label-relevant tokens and prioritize those during masked language modeling. This approach risks overfitting on target-specific tokens because stance is often expressed using target-specific terminology - an issue which is particularly problematic for SD of argumentative sentences (Thorn Jakobsen et al., 2021; Reuver et al., 2021). Clark et al. (2021) apply a knowledge infusion method for PLMs by filtering Wikipedia triplets for contextual knowledge. Jo et al. (2021b) present a variant of BERT pretrained using a variety of supervised tasks resembling logical mechanisms. Paul et al. (2020) extract relevant concepts from ConceptNet using graph-based ranking methods and integrate them into model training for argument relation classification. Likewise, Liu et al. (2021) use ConceptNet to identify relevant concept-edge pairs and integrate them during training via a graph neural network. Finally, Hardalov et al. (2022) recently showed that sentiment-based pretraining improves multi-lingual stance detection.

In summary, most of the existing approaches integrate knowledge by extensive pretraining on knowledge-rich data which does not guarantee improvement of the downstream task they are intended for and requires additional experiments. Another line of work introduces architectural depen-
dependencies on the structure of the external knowledge source in use, thereby limiting their usage to tasks and domain for which the knowledge source is applicable. In contrast, our approach does not require any pretraining, but directly learns to integrate contextual information during supervised training. The usefulness of the context is therefore directly measurable. Further, our proposed approach integrates context in natural language, thereby decoupling it from the structure of the context source. This is better aligned with the encoding mechanism of pretrained language models and allows for integration of contextual information from various sources.

3 Methodology

We see having contextual information as a necessity for stance detection. Our goal is twofold: (1) we aim to integrate contextual information independent of the context source and (2) in a way that does not amplify spurious correlations with target-specific vocabulary. Therefore, we propose INJECT, a dual encoder approach to integrate contextual sentences using the cross-attention mechanism introduced by Vaswani et al. (2017). The general idea is that the information can flow from input to context and vice versa, thereby regularizing the attention in both encoders. Thus, the context provides further information to reweigh the prediction importance of individual tokens in the input. It is inspired by recent work (Borgeaud et al., 2022) on injecting knowledge from large corpora into autoregressive language modeling which has been proven to be an effective post-hoc method for updating knowledge in pretrained language models without retraining from scratch.

3.1 Preliminaries

Task In stance detection, given an input text \( x_i \in X \) and its corresponding target \( t_i \in T \), the goal is to identify the correct label \( y_i \in Y \) from a predefined set of stance descriptions. Different variations have been proposed where the number of unique labels varies from a binary setting (Hasan and Ng, 2013) to a more fine-grained differentiation of relevance to the target (Qazvinian et al., 2011).

Context Our notion of contextual information encloses any text which provides additional information on the input text (or its constituents) to understand its implied meaning. The context for each input instance is retrieved beforehand and is provided as text to the model. Formally, we describe context \( c_i \in C \) where \( c_i \) is a list containing \( m \) texts which provide contextual information on the input text \( x_i \). See Figure 1 for an example with \( m = 2 \). The length of these texts is upper bounded by the maximum sequence length of the encoder model.

3.2 Context Integration via INJECT

Figure 2 provides a high-level visualization of our proposed INJECT architecture. It consists of two modules - input encoder and context encoder. The context encoder is used to encode contextual information and both encoders are interwoven using one INJECT-block based on the cross-attention mechanism (Vaswani et al., 2017).
The output layer produces a new hidden state $h_i^X$ by processing the cross-attention output $e(X, c)$.

Finally, we add a classification head to the input encoder which consists of a pooling layer, dropout and a linear classification layer. The parameters of both modules are optimized using the standard cross-entropy loss.

An alternative approach would be to append contextual information to the input text. However, it is limited in length by the maximum sequence length of the model in use. Our architecture is flexible with regard to the number of context sentences which can be encoded. In the case of multiple sentences, we average the cross-attention for all of them with regard to the input.

### 3.3 Context Retrieval

The INJECT model expects the context in natural language form and is therefore flexible with regards to the source of contextual information. We evaluate different sources for extracting contextual information: (1) a structured knowledge base which stores knowledge as entity-relationship triplets, (2) a set of causal relations extracted from an encyclopedia, and (3) prompting a large pre-trained language model (PLM) using predefined question templates. The latter provides an intuitive interface to prompt for relevant sample-specific context, especially in the absence of suitable knowledge bases.

In the following we describe our approach to extract contextual information. Examples are provided in Figure 3.

#### ConceptNet

ConceptNet (Speer et al., 2017) is a directed graph whose nodes are concepts and whose edges are assertions of commonsense about these concepts. For every edge, ConceptNet provides a textual description of the type of node relationship along with a weight which is based on the frequency that type of connection between words was detected in the corpus ConceptNet was trained on.

For our approach, we use the English subset of ConceptNet to get context sentences. We filter out concepts which are part of English stopwords 2 and ignore relations without descriptions. In total, we consider 400k nodes connected through approximately 600k edges. To retrieve the context, we use all tokens of the input text to search for string matches within the ConceptNet concepts. Finally, we sort the paths based on their weight (provided by ConceptNet) and convert every path into a context candidate by joining the descriptions of all its edges. A comparable approach of knowledge graph linearization was also used in previous work (Lauscher et al., 2020).

#### CauseNet

CauseNet (Heindorf et al., 2020) is a KB of claimed causal relations extracted from the ClueWeb12 corpus as well as from Wikipedia. We use the causal relations contained in the high-precision subset of CauseNet, consisting of 80,223 concepts and 199,806 relations. We ignore concepts which are shorter than 3 characters or consisting of a modal verb (see Appendix A.3.1).

We encode all relations using a sentence encoder (Reimers and Gurevych, 2019) using BERT-base-uncased weights. For each sample in a dataset, we retrieve the most relevant relations by ranking based on the cosine similarity between the encoded sample and all relations.

#### Pretrained Language Model

It has been shown that (large) PLMs store facts and can be queried as a KB using natural language prompts (Petroni et al., 2019; Heinzerling and Inui, 2021). We adopt this paradigm and generate context candidates by prompting a PLM to provide more information on either the target, parts of the input or a combination of both. Specifically, we extract noun-phrases from the input sentence of length of up to three words using the Stanford CoreNLP tool (Manning et al., 2014), ignoring stopwords and filtering noun-phrases which are equal to the target. Then, we create prompts using the following templates for

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2 As in NLTK (Bird, 2006)

3 see https://causenet.org/
single inputs \( a \) (e.g. target or noun-phrase)

\[
P_1(a) = \text{define } a \\
P_2(a) = \text{what is the definition of } a \\
P_3(a) = \text{explain } a
\]

and combination of inputs \((a, b)\).

\[
P_4(a, b) = \text{relation between } a \text{ and } b \\
P_5(a, b) = \text{how is } a \text{ related to } b \\
P_6(a, b) = \text{explain } a \text{ in terms of } b
\]

The single-input approach is referred to as INJECT-T0pp-NP, the second approach as INJECT-T0pp-NP-Targ. We found those prompts to generate the most meaningful contexts across different targets and noun-phrases (see Appendix A.3.2 for more details). The prompts can then be used to generate outputs using any pre-trained sequence-to-sequence model.

We make use of T0pp (Sanh et al., 2022) which is based on a pretrained encoder-decoder (Raffel et al., 2020) and was fine-tuned using multiple diverse prompts generated using a large set of supervised datasets\(^4\). We set the output sequence length to 40 words and sort the generated outputs by length in descending order because we observe T0pp to degenerate into producing single words in some cases. Further, we filter those candidates where more than half of the generated words are repetitions. Finally, we remove all special tokens from the candidates (<\s> and <pad>). In preliminary experiments, we found using two context sentences \((m = 2)\) to be most beneficial.

4 Experiments

We design our experiments to answer the following research questions:

**RQ1** Can we improve SD performance by including contextual information using the INJECT architecture?

We combine INJECT with contextual information extracted from each context source (§3.3) individually. We compare its performance with a model where the context is appended directly to the input to evaluate the effectiveness of INJECT. We control for out-of-domain variance by conducting experiments in the in-target setting, i.e. samples related to a specific target are contained in each dataset split.

**RQ2** How does INJECT generalize in a cross-target setting?

To answer RQ2, we use a cross-target evaluation setup (Stab et al., 2018; Reimers et al., 2019) where targets are exclusively contained in either the training, development or test split of each individual dataset. This setup is more truthful towards a real-world scenario where a stance detection model is applied on texts from targets which were not observed during training.

**RQ3** Can we use large pretrained PLMs to generate contextual knowledge?

We evaluate large PLMs as a source of contextual knowledge by prompting for relevant information, as an alternative to a standard knowledge base. We apply our method described in §3.3 to generate contextual sentences for benchmark datasets and evaluate their integration within INJECT.

4.1 Datasets

Schiller et al. (2021) proposed a benchmark dataset collection for stance detection research which was extended by Hardalov et al. (2021) to cover altogether 16 datasets in English for research on (cross-domain) stance detection. We use this benchmark because it shows a large diversity with regards to text sources, the number of targets, the number of annotated instances, and class imbalance. Thus, it provides a suitable testbed to evaluate the effectiveness of our context injection approach. Due to space limitations, we provide information about the target types, text sources and label distributions in the Appendix A.2.

4.2 Experimental Details

**Evaluation** For our experiments, we differentiate between the in-target (RQ1) and cross-target (RQ2) evaluation setup. For each dataset, the in-target evaluation setup is defined such that each target is contained in each data split. The instances for each target are split into training, development and test sets.

In contrast, the cross-target (Augenstein et al., 2016) setup organized all instances of one target either in the training, development or test split. This setting is better aligned with a real-world application scenario of a SD model but it is more challenging due to the lack of target-relevant training...
### 5 Results

The results for the in-target and cross-target evaluation settings are displayed in Table 1. First, we see a large performance boost (+8.5pp) when including information about the target when comparing BERT and BERT+Target. While it has been shown that integrating target information is beneficial for individual stance detection datasets (Reimers et al., 2019), we generalize this finding for 15 out of 16 SD datasets. We refer to BERT+Target as baseline.

#### 5.1 Context Integration via INJECT

To answer our first research question RQ1, we look at the results in the in-target evaluation setting across all 16 benchmark datasets (upper part of Table 1). Considering direct context integration via appending to the input (BERT+ConceptNet), we make use of the standard splits given in the Appendix A.1.

The results for the in-target and cross-target evaluation setups. We highlight best performance per evaluation setting and dataset in bold. Statistically significant prediction differences compared to best performing baseline without access to context (BERT+Target) are indicated by †.

### Table 1: Overview of the results across the benchmark datasets for both the in-target and cross-target evaluation settings. We highlight best performance per evaluation setting and dataset in bold. Statistically significant prediction differences compared to best performing baseline without access to context (BERT+Target) are indicated by †. Numbers are macro-$F_1$ scores averaged over three runs with differently initialized seeds.

|         | arc | iac | perspective | polarus | scd | engment | fact | snopes | mrid | rumor16 | rumor17 | wirt | begin |thumbs | vart | micro-$F_1$-
|---------|-----|-----|-------------|--------|-----|---------|------|--------|------|--------|--------|-----|-------|-------|-----|----------------|
| **BERT** | 63.0±0.6 | 51.4 | 50.8 | 75.5 | 60.8 | 62.3 | 80.5 | 54.4 | 72.5 | 53.5 | 81.3 | 67.1 | 57.5 | 83.3 | 74.5 | 68.7 | 44.6 |
| **BERT+Target** | 71.5±0.5 | 61.4 | 51.1 | 88.7 | 63.2 | 61.7 | 81.5 | 96.7 | 82.7 | 66.8 | 81.0 | 69.0 | 57.5 | 83.7 | 75.1 | 77.8 | 45.5 |
| **BERT+ConceptNet** | 79.0±0.7 | 62.0 | 52.5 | 88.2 | 65.0 | 64.9 | 81.1 | 96.0 | 81.2 | 66.2 | 81.0 | 67.5 | 56.2 | 83.4 | 75.2 | 80.6 | 45.2 |
| **BERT+CauseNet** | 70.9±1.9 | 61.0 | 52.2 | 87.2 | 61.0 | 58.2 | 81.4 | 95.1 | 79.7 | 64.4 | 74.7 | 63.5 | 58.0 | 83.2 | 74.6 | 70.1 | 46.2 |
| **INJECT+ConceptNet** | 52.1±0.5 | 63.0 | 54.1 | 88.9 | 64.3 | 60.9 | 83.1 | 97.5 | 82.0 | 68.0 | 81.7 | 69.2 | 58.4 | 83.8 | 75.5 | 78.5 | 44.7 |
| **INJECT+CauseNet** | 71.4±0.8 | 63.7 | 50.7 | 89.5 | 62.6 | 60.6 | 83.1 | 97.2 | 81.4 | 68.5 | 81.1 | 68.7 | 59.3 | 83.7 | 76.1 | 79.9 | 45.7 |
| **INJECT+Topp-NP** | 72.2±0.3 | 61.8 | 53.2 | 89.1 | 62.5 | 59.7 | 83.1 | 97.0 | 82.0 | 67.9 | 81.8 | 68.4 | 58.4 | 83.5 | 75.7 | 78.6 | 45.3 |
| **INJECT+Topp-S0-Targ** | 71.8±0.2 | 63.0 | 53.3 | 88.8 | 62.9 | 59.7 | 83.1 | 97.2 | 82.8 | 67.9 | 79.8 | 68.7 | 58.2 | 83.7 | 75.6 | 77.7 | 45.1 |
| **INJECT+Topp-S0-Targ** | 48.9±0.9 | 21.5 | 34.8 | 64.6 | 51.3 | 56.7 | 78.3 | 72.2 | 68.7 | 40.4 | 44.6 | 63.5 | 53.3 | 25.5 | 59.6 | 50.7 | 46.2 |
| **BERT+Target** | 56.1±0.2 | 61.6 | 36.4 | 76.4 | 49.1 | 57.8 | 78.1 | 73.1 | 69.0 | 42.6 | 64.2 | 64.8 | 53.3 | 54.1 | 60.2 | 52.8 | 35.9 |
| **BERT+ConceptNet** | 55.4±0.8 | 60.8 | 39.5 | 71.5 | 49.1 | 57.5 | 75.6 | 72.0 | 69.4 | 41.2 | 45.4 | 62.7 | 53.3 | 39.1 | 61.2 | 52.6 | 34.2 |
| **BERT+CauseNet** | 53.9±1.4 | 61.4 | 34.6 | 74.2 | 48.4 | 57.2 | 74.1 | 69.9 | 68.9 | 41.9 | 32.0 | 61.6 | 55.1 | 41.0 | 60.0 | 46.2 | 35.0 |
| **INJECT+ConceptNet** | 55.0±1.0 | 62.7 | 36.6 | 75.1 | 48.9 | 56.3 | 77.1 | 74.4 | 69.6 | 42.0 | 49.4 | 65.2 | 54.5 | 55.4 | 61.3 | 53.2 | 39.8 |
| **INJECT+Topp-NP** | 57.6±0.3 | 62.1 | 36.5 | 76.1 | 49.7 | 58.3 | 78.0 | 73.7 | 67.9 | 41.0 | 51.3 | 65.5 | 54.8 | 57.5 | 59.4 | 50.8 | 37.3 |
| **INJECT+Topp-S0-Targ** | 57.9±0.4 | 63.3 | 38.5 | 76.4 | 49.5 | 57.4 | 78.0 | 73.5 | 69.5 | 40.9 | 56.2 | 65.5 | 55.3 | 53.2 | 60.4 | 51.7 | 37.2 |

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data (Reimers et al., 2019) and because models tend to overly rely on label correlations with target-specific vocabulary (Thorn Jakobsen et al., 2021). It has been referred to as cross-target (Wei and Mao, 2019), cross-topic (Stab et al., 2018) or zero-shot stance detection (Augenstein et al., 2016; Hardalov et al., 2021) - by including the target via concatenation to the input (BERT+Target). Further, we evaluate appending the retrieved context to the input (BERT+C) where C can either be ConceptNet or CauseNet.

### Training Setup

For in-target evaluation, we use stratified training, development, and test splits with a ratio of 70:15:15. For the cross-target evaluation, we make use of the standard splits given in the benchmark (Hardalov et al., 2021) where possible or create our own (see Appendix A.1).

We use macro-$F_1$ as evaluation metric and average across three runs with different seeds. Performance is measured after the best-performing epoch based on the development set. To test statistical significance, we use the Bhapkar test (Bhapkar, 1966) with $p < 0.05$. It is a generalized version of the McNemer’s test (McNemer, 1947) for multi-class classification tasks.

For all experiments, we use the uncased BERT-base model (Devlin et al., 2019) as the backbone model. For INJECT, we use the same model architecture for both input encoder and context encoder.

We use the same set of hyperparameters for all model setups. The only hyperparameter we tune for INJECT is the layer for context integration. We tested layer 3, 6, 9 and 12 and found 12 to perform the best according to the average benchmark-performance on the development set using three random seeds. We use context integration on layer 12 for all reported results. More details can be found in the Appendix A.1.
BERT+CauseNet), we observe it cannot outperform the baseline on average and achieves better performance in only three cases - none of them are statistically significant (sig.). However, injecting context via INJECT outperforms the baseline on average and performs the best on 13 datasets. In detail, INJECT+ConceptNet performs on average 0.6pp better than the baseline. INJECT+CauseNet performs on average on par with the baseline and outperforms it on 10 tasks.

5.2 Generalization across targets

To answer RQ2 we investigate the results of the cross-target evaluation setting which measures a model’s capability to generalize SD on unseen targets. The lower part of Table 1 displays the results. The difficulty of this setup is evident in the overall lower scores compared to the in-target setting.

Similar to in-target, BERT+ConceptNet and BERT+CauseNet do not improve performance on average. Again, both INJECT variations outperform the baseline on average with +1.4pp and +1.9pp. INJECT+ConceptNet outperforms the baseline in nine datasets (sig. in four cases) and achieves best performance in four cases, while INJECT+CauseNet outperforms the baseline in eleven datasets (six of them sig.) and performs the best on four tasks. Notably, INJECT+CauseNet achieves the best performance for SD datasets based on argumentative texts (argmin, ibmcs, vast). Causal relations bear information especially relevant for argumentative reasoning which is one of the goals CauseNet was created for.

5.3 Language Model as Context Source

The results to answer RQ3 are provided in Table 1, denoted with INJECT+T0-NP for integration of context sentences using prompts $P_{1-3}$ and INJECT+T0-NP-Target when using $P_{4-6}$ (see §3.3). On average, both perform similarly or better compared to experiments where (structured) knowledge bases are used (i.e. INJECT+ConceptNet or INJECT+CauseNet).

For in-target performance, we find noun-phrase information (INJECT+T0-NP) to be more beneficial reaching the highest average performance with best performance in three datasets. For cross-target experiments, INJECT+T0-NP-Target performs second best with the overall best performance in four datasets.

5.4 Quantitative Analysis

Although provided with the same contextual information, we observe large performance differences when integrating via appending to the input (BERT+ConceptNet, BERT+CauseNet) and the INJECT architecture. Therefore, we examine internal processes in the model architecture by analyzing six tasks from the cross-target setting which exhibit different performance characteristics. In detail, we analyze the attribution of single tokens with regards to the predictions and correlate them with their different properties to unwanted spurious correlations. In particular, we consider the relevance of a token towards a given label or target.

**Token Attributions** To approximate a token’s attribution, we calculate the vector-norms (Kobayashi et al., 2020) for the output of the self-attention on the 12th layer.

**Token Properties** We characterize single tokens using different properties. As properties, we consider the relevance of a token with regards to the annotated label or the given target. In detail, we calculate the ratio of observing a token within one value $p$ of a property $P$ (i.e. within the target abortion) compared to all other property-values - all other targets. A higher value indicates that a token is more likely to occur along this property-value and vice-versa.

In detail, we first calculate the relevance as the maximum log-odds-ratio $r_{t,P}^c$ (Kawintiranon and Singh, 2021) over all possible values $p$ of a property $P$ for a given token $t$. For instance when we consider the target as property, we calculate $o_{t,p}$ for every single target $p$ and take maximum values as a representation of $t$’s target relevance.

We define $o_{t,p} = \frac{c(t,p)}{c(-t,p)}$ as the odds of finding a token $t$ withing the property $p$, where $c(t,p)$ describes the raw counts of $t$ in $p$. E.g. in case of the target, this is the odds of observing a token in a specific target $p$ and not in the others. Then, we calculate the log-ratio of the odds as $r_{t,P} = \max_{p \in P}(\log(\frac{o_{t,p}}{o_{t,-p}}))$. This tells us how specific is this token for a property $P$.

**Baseline Comparison** First, we compare token attributions of the best baseline model BERT+Target with BERT+CauseNet and INJECT+CauseNet. We calculate the Pearson correlation of the self-attention with target- and label-relevance.
Figure 4: Two examples of the argmin dataset. The first is an argument against gun control while the second one is supporting. It shows the token-level attribution for BERT, BERT+Target, BERT+CauseNet, and INJECT+CauseNet.

Table 2: Correlation between self-attention (self) and the target- and label-specific tokens for the best baseline model BERT+Target and the best model overall INJECT+CauseNet. Larger correlation indicates more dependence on spurious correlations which impede cross-target generalization capacities, i.e. scores closer to zero are better.

| model                  | argmin correlation | mtsd correlation | rumor correlation | wtwt correlation |
|------------------------|--------------------|------------------|-------------------|------------------|
| BERT+target            | self  \times target -11.2 | 20.6             | 14.5              | -12.7            | 16.8             | 13.4             |
| BERT+CauseNet          | self  \times target -14.2 | 23.4             | 16.0              | -5.1             | 14.5             | 15.7             |
| INJECT+CauseNet        | self  \times target -14.8 | 19.5             | 14.5              | -12.6            | 12.9             | 5.7              |
| BERT+Target            | self  \times label 10.3  | 22.9             | 13.5              | -1.1             | 14.4             | 13.7             |
| BERT+CauseNet          | self  \times label 9.1   | 25.5             | 15.3              | -2.0             | 1.4              | 14.6             |
| INJECT+CauseNet        | self  \times label 7.9   | 21.9             | 13.7              | -1.6             | 10.4             | 6.6              |

In Table 2, we note a positive correlation (for argmin, mtsd, rumor, or wtwt) with the self-attention when there are a small number of clearly semantically separated targets - like Nuclear Energy and Marijuana Legalization from argmin. While we see a slightly smaller negative correlation when there are many targets which are not clearly distinguishable - as in perspectrum and arc. In addition, there is a positive correlation of self-attention with label-relevance for argmin, mtsd, rumor, and wtwt - an indicator for spurious correlations.

Further, we see INJECT reducing the importance of target-specific words when it performs better than BERT+Target while keeping untouched or increasing when it has a worse performance (mtsd, perspectrum). Similarly, it reduces the importance for label-specific tokens when it succeeds - as for argmin or arc which are known to include spurious correlations (Niven and Kao, 2019; Thorn Jakobsen et al., 2021). Similarly, we see that BERT+CauseNet tends to increase the correlation with label or target specific tokens. This indicates its lower performance, as it gives more importance to spurious correlations. We conclude that injecting contextual information via cross-attention adjusts the attributions of single tokens. It increases the importance of less target- or label-specific tokens while reducing the importance of tokens with high relevance.

5.5 Qualitative Analysis

We provide anecdotal examples in Figure 4 along with their token-level attribution of the 12th layer from (BERT, BERT+Target, BERT+CauseNet) and INJECT+CauseNet. For the first three, we use the self-attention and for the latter one the cross-attention. In the first example, INJECT+CauseNet made the right prediction while all BERT-based models failed and vice-versa for the second one. In both examples, we see lower attribution for target-specific terms like firearms or arms and higher attribution for terms with general use like besides, cause, or to. INJECT+CauseNet makes the correct prediction while BERT+Target failed due to its high attribution to firearms - an example of a spurious correlation. However, in some cases this can also lead to erroneous predictions as in the second example where INJECT+CauseNet gives less importance to the specific - and in this case important - tokens of the sentences (right to bear arms).

6 Conclusion

We propose INJECT, a dual-encode approach to integrate contextual information for stance detection based on cross-attention. Across a large and diverse benchmark, we observe improvements compared to competitive baselines using three different sources for extracting contextual information. We show
that the context integrated via INJECT improves stance detection and is beneficial for generalization on targets not seen during training. As future work we plan to evaluate a larger variety of knowledge bases and explore more sophisticated ways of prompting large pretrained language models for helpful context.

Ethical Considerations and Limitations

Quality of the context The performance improvement for contextual information injection is bounded by the quality of the context source. Independently of the source in use, it is possible to introduce additional noise into the training procedure. While this is a rather generic problem, we observe that our proposed architecture seems to be better at filtering noisy context compared to a direct integration via appending to the input.

Quality of context source Most of the existing knowledge bases provide high-quality and curated knowledge. In contrast, when prompting a large language model for knowledge, we are additionally exposed to the risk that we extract the biases (e.g. false facts or stereotypical biases) which the model has learned during pretraining. In our experiments we make use of the T0pp language model where biases have been reported\(^5\). These biases have the potential to influence the prediction performance in unintended ways, especially as in many SD datasets the annotated targets are often of controversial nature. While the investigation of such effects is out of scope for this work, we consider such an evaluation as inevitable before deploying our proposed model to any data outside of (academic) research context.

Limitations As described in §3, our proposed approach makes use of two parallel encoder models (input and context). It thus requires twice as much parameters as the baseline model we compare to and thereby enforcing additional hardware demands. We consider our approach as a proof-of-concept on how to integrate contextual knowledge without amplifying a model’s exploitation of spurious correlations. We plan to make our architecture more parameter-efficient by investigating more recent approaches for parameter sharing, e.g. with the use of adapters (Houlsby et al., 2019).

Moreover, we acknowledge the strong influence of wording in prompts on the output of a language model, as has been reported in the literature (Jiang et al., 2020; Schick and Schütze, 2021). We experienced similar effects during preliminary experiments and point out that we did not find a one-size-fits-all solution which works equally well across the diverse set of SD benchmark datasets. Therefore, special care must be taken when extracting contextual information from large language models using prompting.

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A Appendix

A.1 Experimental Details

• We use for most hyperparameters fixed values (5 epochs, batch size of 16, learning rate of 0.00002, warmup-up ratio of 0.2 with linear scheduling, and AdamW as optimizer). The hyperparameters which are tuned during training are described in the main paper (see §4.2).

• We use CUDA 11.6, Python v3.8.10, torch v1.10.0, and transformers v4.13.0 as software environment and the NVIDIA A6000 as underlying hardware.

• For all pretrained language models, we use the HuggingFace library.

• We use the captum library (v0.5.0) to calculate the vector-norms for approximating token-attributions (Kobayashi et al., 2020) in §5.4.

• We use the statsmodel library (v0.13.2) to calculate statistical significant differences using the Bhapkar test (Bhapkar, 1966) with $p < 0.05$.

• We measured the average training runtime of models on the argmin dataset as reference. BERT+Target and BERT+ConceptNet needed 618 seconds whereas INJECT needed 400 seconds.

• We use the seeds $[0, 1, 2]$. 
A.2 Datasets

We provide an overview of the benchmark datasets we use in Table 3 and provide details about the individual split proportions, for the cross-target evaluation setup in Table 5 and for the in-target setting in Table 4. For more information on each individual dataset, we refer to Schiller et al. (2021) and Hardalov et al. (2021).
Table 3: Stance Detection Benchmark datasets and their characteristics (sorted by source, then alphabetically). This table is based on Hardalov et al. (2021).

| Dataset          | Target | Context | Labels                                      | Source     |
|------------------|--------|---------|---------------------------------------------|------------|
| arc (Habernal et al., 2018) | Headline | User Post | unrelated (75%), disagree (10%), agree (9%), discuss (6%) | Debates    |
| iact (Walker et al., 2012) | Topic | Debating Thread | pro (55%), anti (35%), other (10%) | Debates    |
| perspectrum (Chen et al., 2019) | Claim | Perspective Sent. | support (52%), undermine (48%) | Debates    |
| poldeb (Somasundaran and Wiebe, 2010) | Topic | Debate Post | for (56%), against (44%) | Debates    |
| scd (Hasan and Ng, 2013) | None (Topic) | Debate Post | for (60%), against (40%) | Debates    |
| emergent (Ferreira and Vlachos, 2016) | Headline | Article | for (48%), observing (37%), against (15%) | News       |
| fncl (Pomerleau and Rao, 2017) | Headline | Article | unrelated (73%), discuss (18%), agree (7%), disagree (2%) | News       |
| snopes (Haneloskowsi et al., 2019) | Claim | Article | agree (74%), refute (26%) | News       |
| mtsd (Sobhani et al., 2017) | Person | Tweet | against (42%), favor (35%), none (23%) | Social Media |
| rumor (Quervain et al., 2011) | Topic | Tweet | endorse (35%), deny (32%), unrelated (18%), question (11%), neutral (4%) | Social Media |
| semeval2016t6 (Mohammad et al., 2016) | Topic | Tweet | against (51%), none (24%), favor (25%) | Social Media |
| semeval2019t7* (Gorrell et al., 2019) | None (Topic) | Tweet | comment (72%), support (14%), query (7%), deny (7%) | Social Media |
| wtwt (Conforti et al., 2020) | Claim | Tweet | comment (41%), unrelated (38%), support (13%), refute (8%) | Social Media |
| argmin (Stab et al., 2018) | Topic | Sentence | argument against (56%), argument for (44%) | Various     |
| ibmcs (Bar-Haim et al., 2017a) | Topic | Claim | pro (55%), con (45%) | Various     |
| vast (Allaway and McKeown, 2020) | Topic | User Post | con (39%), pro (37%), neutral (23%) | Various     |

Table 4: Number of examples per data split for the in-target evaluation setting. For datasets marked with *, not all tweets could be downloaded or we discovered empty instances which we excluded (in comparison to the numbers provided by Hardalov et al. (2021)); for mtsd, we received the full dataset by the original authors; the original number of tweets is in parentheses.

| Dataset | Train | Dev | Test | Total |
|---------|-------|-----|------|-------|
| arc     | 12,382| 1,851| 3,559| 17,792|
| argmin  | 6,845 | 1,568| 2,726| 11,139|
| emergent| 1,638 | 433  | 524  | 2,595 |
| fnc1    | 42,476| 7,496| 25,413| 75,385|
| iact*   | 4,221 | 453  | 923  | 5,597 |
| ibmcs   | 935   | 104  | 1,355| 2,394 |
| mtsd    | 6,227 | 1,317| 1,366| 9,900 |
| perspectrum | 6,978 | 2,071| 2,773| 11,822|
| poldeb  | 4,753 | 1,151| 1,230| 7,134 |
| rumor*  | 6,093 | 299  | 505  | 7,106| 10,237|
| scd     | 3,251 | 624  | 964  | 4,839 |
| semeval2016t6 | 2,497 | 417  | 1,249| 4,163 |
| semeval2019t7* | 5,205 | 1,478| 1,756| 8,439| 8,529|
| snopes  | 14,416| 1,868| 3,154| 19,438|
| vast    | 13,477| 2,062| 3,006| 18,545|
| wtwt    | 25,193| 7,897| 18,194| 51,284|

Table 5: Number of examples per data split for the cross-target evaluation setting. For datasets marked with *, not all tweets could be downloaded or we discovered empty instances which we excluded (in comparison to the numbers provided by Hardalov et al. (2021)); for mtsd, we received the full dataset by the original authors; the original number of tweets is in parentheses.

| Dataset | Train | Dev | Test | Total |
|---------|-------|-----|------|-------|
| arc     | 12,854| 2,269| 2,669| 17,792|
| argmin  | 8,047 | 1,421| 1,671| 11,139|
| emergent| 1,874 | 331  | 390  | 2,595 |
| fnc1    | 54,465| 9,612| 11,308| 75,385|
| iact*   | 4,043 | 714  | 840  | 5,597 |
| ibmcs   | 1,728 | 306  | 360  | 2,394 |
| mtsd*   | 6,437 | 1,136| 1,337| 8,910 |
| perspectrum | 8,540 | 1,508| 1,774| 11,822|
| poldeb  | 5,153 | 910  | 1,071| 7,134 |
| rumor*  | 5,134 | 906  | 1,066| 7,106| 10,237|
| scd     | 3,496 | 617  | 726  | 4,839 |
| semeval2016t6 | 3,007 | 531  | 625  | 4,163 |
| semeval2019t7* | 6,097 | 1,076| 1,266| 8,439| 8,529|
| snopes  | 14,043| 2,479| 2,916| 19,438|
| vast    | 13,398| 2,365| 2,782| 18,545|
| wtwt    | 37,052| 6,539| 7,693| 51,284|
### A.3 Knowledge

The information about the average length of the retrieved contextual knowledge is given in Table 6. We observe substantially longer paragraphs extracted from CauseNet which is not surprising as CauseNet consists of passages extracted from Wikipedia.

#### A.3.1 CauseNet

We ignore concepts which are shorter than 3 characters or consist of one of the following modal verbs ("must", "shall", "will", "should", "would", "can", "could", "may", "might").
| Prompt                                | Usage |
|--------------------------------------|-------|
| define $a$                           | ✓     |
| what is $a$                           | ✓     |
| describe $a$                         | ✓     |
| what is the definition of $a$        | ✓     |
| explain $a$                          | ✓     |
| relation between $a$ and $b$         | ✓     |
| how is $a$ related to $b$            | ✓     |
| explain $a$ in terms of $b$          | ✓     |

Table 7: Prompts which have been evaluated for generating contextual knowledge for stance detection.

**A.3.2 Prompts**

We manually evaluated the following prompts for both single and combination inputs. As reported in related work (Jiang et al., 2020; Schick and Schütze, 2021), the generated text is sensible to wording and punctuation in the prompt. We made similar experiences and removed all punctuation at the end of the prompt to prevent the model from generating outputs of short length.