A Semantics-Aware Approach to Automated Claim Verification

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Abstract

The influence of fake news in the perception of reality has become a mainstream topic in the last years due to the fast propagation of misleading information. In order to help in the fight against misinformation, automated solutions to fact-checking are being actively developed within the research community. In this context, the task of Automated Claim Verification is defined as assessing the truthfulness of a claim by finding evidence about its veracity. In this work we empirically demonstrate that enriching a BERT model with explicit semantic information such as Semantic Role Labelling helps to improve results in claim verification as proposed by the FEVER benchmark. Furthermore, we perform a number of explainability tests that suggest that the semantically-enriched model is better at handling complex cases, such as those including passive forms or multiple propositions.

1 Introduction

With the rise of digital channels that disseminate all kinds of information, misinformation has become a big challenge for a healthy society (Hermida, 2010). Fake news has been defined as a news article or message published through media that carries false information (Kshetri and Voas, 2017). Although this is not a new phenomenon, the current absence of control systems in social media facilitates the fast spreading of misinformation, arriving to a large number of users and greatly influencing their perception of real world events (Zubiaga et al., 2018). Recent work has shown that fake news spread faster in social media than factual news (Vosoughi et al., 2018), which is why researchers from different fields have proposed using automated solutions to help dealing with this situation (Zhou and Zafarani, 2020; Oshikawa et al., 2020).

Claim verification is the task of assessing the veracity of a statement by finding evidence about the claimed facts. This work is usually done manually by fact-checkers, who use their trusted sources to label the claims as true, false or other assessments. Automated Claim Verification, as proposed by Thorne et al. (2018), consists in, given a claim, finding the evidence regarding the veracity of that claim to then infer its truth-label. Systems for Automated Claim Verification have been trained both using synthetic data (Thorne et al., 2018; Jiang et al., 2020), and crawling datasets from fact-checking websites (Augenstein et al., 2019; Wang, 2017). These datasets have enabled the development of models for the three tasks involved in the claim-verification pipeline: document retrieval (Chen et al., 2017a; Nogueira and Cho, 2020), sentence retrieval (Danesh et al., 2015; Hanselowski et al., 2018), and natural language inference (Parikh et al., 2016; Chen et al., 2017b). In this work, we focus on the last module: natural language inference (NLI).

Given the right pieces of evidence, a fact-checking system will have to reason over all the utterances involved in order to determine if the claim can be supported, refuted, or whether there is not enough info to do so. In Figure 1, for instance, it should recognize that the Rodney King riots is the same entity in the claim and in evidence 1. Then, it should identify that the location of this event is Los Angeles County, and understand that evidence 2 confirms that this happens to be the most populous county in the USA.

As illustrated in Figure 1, this reasoning process requires a deep understanding of the semantics of all the utterances involved. In this work, we propose to introduce explicit semantic knowledge in order to improve the systems for Automated Claim Verification. We hypothesize that this information might guide the natural language inference model in claims that have complex semantics.

The linguistic information we use in this work is Semantic Role Labelling (SRL, Palmer et al., 2005) and Open Information Extraction (OpenIE,
Figure 1: Natural language inference reasoning example, by Zhong et al. (2020)

Etzioni et al., 2008). In our experiments, these semantic structures are used as additional input to the BERT contextualized word embeddings (Devlin et al., 2019). We integrate this information using the SemBERT architecture presented in Zhang et al. (2020a).

The contributions of this work are the following:

- We perform a qualitative analysis to compare synthetic datasets and naturally-occurring datasets for claim verification. We find that synthetic claims are semantically more simple.

- We improve the widely used BERT language model to address the inferential component of the task by adding explicit semantic information. We also make publicly available our model to the community.

- We perform explainability tests to understand the influence of the additional semantic information. The performed tests suggest that the semantically-enriched model is better at handling complex cases.

In the following sections, we introduce previous work on datasets, systems and semantic structures (Section 2), we explain our experiments (Section 3) and expose the primary results (Section 4), we perform explainability tests to qualitatively assess the influence of semantic structures (Section 5), and finally we draw our conclusions and future work (Section 6).

2 Related Work

Automated Claim Verification is a relatively new task, and a lot of effort have been put on how to develop datasets to train automated systems for this task. In the following subsections we introduce some of these efforts and the systems that have been developed on these datasets. We also present previous work using semantic structures.

2.1 Datasets

Ideally, a claim verification system should be able to take sentences from naturally-occurring texts (e.g. news articles, social media posts or political speeches) and assess their veracity. However, developing training data for this task has some complexities, such as defining the ground truth and creating a knowledge database with boundaries, which allows the annotators to know for sure that the ground truth is right. For this reason, there have been several attempts to approximate the task by creating domain-specific datasets (SciFact, Wadden et al., 2020) and synthetic datasets (FEVER and HoVer, Thorne et al., 2018; Jiang et al., 2020).

These datasets consist of a set of claims annotated with their ground truth, together with a knowledge base, in which the truth labels are based (e.g. a set of scientific abstracts or a set of Wikipedia articles). The labels are usually Supports, Refutes and NotEnoughInfo. Due to its size and popularity, FEVER has become a benchmark for Automated Claim Verification and has been used in the organization of several shared tasks.

Other datasets exist containing naturally-occurring claims (Augenstein et al., 2019; Wang, 2017). These are generally scraped from fact-checking websites, and sometimes include the justification of the fact-checker for the given label. However, these datasets do not contain a fixed database of evidence. This makes it very difficult to use them to train inference systems, as the ground truth at the moment of fact-checking can be different from the current one. Additionally, there is a high heterogeneity in the inventory of labels across different fact-checking platforms.

2.2 Systems

In the first FEVER shared task (2018), Nie et al. (2019) obtained the highest label accuracy by adding the sentence similarity score between claim and evidence to the embedding representation of evidences. Hanselowski et al. (2018) (UKP-Athene) won the task by using noun phrases to query the Wikipedia search API in the retrieval module.

After the shared task, better results were achieved using transformer-based models (Soleimani et al., 2019). Further improvements came from rethinking the interaction between the pieces of evidences. Zhou et al. (2019) (GEAR)
developed a graph approach that uses an attention layer to propagate the information within the evidences. And Zhong et al. (2020) (DREAM) used semantic information to break the evidences into arguments, which then interacted with each other in a graph approach. These two last approaches both used transformer-based models and helped to advance the state-of-the-art on this task. Finally, a recent work (Krishna et al., 2021) developed a system (ProoFVer) based on sequences of natural language logic relations, where the proofs are generated from the claims and corresponding evidence by a seq2seq model (Lewis et al., 2020) and represented as triples. The last inferential step is performed using natural logic proofs only. ProoFVer is the current state-of-the-art on the FEVER benchmark.

Finally, Augenstein et al. (2019) developed a multi-task learning system to deal with a dataset of naturally-occurring claims. They accounted for the multiple labels by creating embeddings for each of these labels, and combining those with the evidence-claim embedding.

2.3 Semantic Structures

Natural Language Inference can be framed as a relation extraction task: in order to know if a sentence is entailed by another sentence, it is necessary to identify the semantic relation between the verb and the arguments of both the premises and hypothesis. For this reason, early approaches used semantic information to approach tasks that required NLI. He et al. (2015) introduced the possibility of annotating semantic roles as a question-answering task, showing that predicate-argument structures can be extracted from natural language questions. In the same direction, Stanovsky et al. (2015) demonstrated the contribution of semantic structures, such as OpenIE, when performing text comprehension with a simple unsupervised lexical matching algorithm.

The creation of more extensive datasets (Bowman et al., 2015; Williams et al., 2018) enabled the development of systems based on neural networks (Wang and Jiang, 2016). Later, the release of transformer-based language models (Devlin et al., 2019; Liu et al., 2019; Yang et al., 2019) revolutionized the performance of many NLP tasks, which also was reflected in NLI.

Recently, a new research direction has suggested using information that had been helpful for NLI models before the arrival of deep learning, in order to guide the self-attention mechanisms (Zhang et al., 2020b). Zanzotto et al. (2020) designed a system that explicitly embeds syntax parse trees into sentence embeddings using distributed tree kernels, and can visualise the decisions made (KERMIT). Zhang et al. (2020a) introduced a modified BERT architecture (SemBERT), that maps semantic role labels (SRL) to embeddings in parallel and integrates the text representation with the contextual explicit semantic embedding to obtain a joint representation. In automated claim verification, Zhong et al. (2020) used SRL tuples to structure information graphs.

A variety of lexical resources have been developed to structure the semantics of sentences with different focus (Baker et al., 1998; Kipper et al., 2000). Semantic roles (SRL), for instance, represent the different arguments that a predicate might have. These semantic categories are relations between noun phrases and verbs. An ideal set of roles should be able to concisely label the arguments of any relation. Nonetheless, the exact set of these relations remains an open discussion inside the linguistic community (Bonial et al., 2011).

SRL in PropBank (Palmer et al., 2005) was designed to be used in automated tasks. The goal of this framework is to create a shallow but broad representation that covers every instance of every verb in a corpus to allow representative statistics to be calculated. PropBank defines semantic roles on a verb-by-verb basis: individual verb’s semantic arguments are numbered, beginning with zero. In the example in Figure 2, the agent of the verb bought is Arg0, the theme is Arg1, the location Arg2, and the price Arg3.

[Mr. Bean]Arg0 bought [the sweater]Arg1 from [the second hand store]Arg2 for [400 pounds]Arg3.

Figure 2: PropBank semantic roles example

Open Information Extraction (OpenIE) was first introduced as an extraction paradigm to tackle an unbounded number of relations (Etzioni et al., 2008). Systems based on OpenIE extract relational tuples from text by identifying relation phrases and the arguments associated to these relations (Mausam et al., 2012). Stanovsky et al. (2015) were the first to propose this task as an intermediate structure for other semantic tasks, similar to what was already being done with other linguistic
### Table 1: Number of claims in the FEVER dataset

|        | Supports | Refutes | NEI  |
|--------|----------|---------|------|
| Training | 80,035   | 29,775  | 35,639 |
| Development | 3,333    | 3,333   | 3,333 |
| Test    | 3,333    | 3,333   | 3,333 |

inference, such as semantic roles, syntactic dependencies or lexical representations. An example of the difference between SRL in PropBank and OpenIE is shown in Figure 3.

**PropBank:**

[John]_{Arg0} [refused]_{V} [to visit a Vegas casino]_{Arg1}

**OpenIE:**

[John]_{Arg} [refused to visit]_{V} [a Vegas casino]_{Arg}

Figure 3: Example of the representations extracted with OpenIE and SRL in PropBank from Stanovsky et al. (2015)

### 3 Experiments

In this work, we use the FEVER dataset (Thorne et al., 2018). We first develop a baseline using the BERT model (Devlin et al., 2019), and then introduce two types of semantic information to the model (SRL and OpenIE) by using the SemBERT architecture (Zhang et al., 2020a).

#### 3.1 Data

The FEVER dataset consists of 185,445 generated claims with its truth label and the evidence for that label, divided between a train, a development and a test set. The statistics can be seen in Table 1.

The claims were generated manually by annotators, using the June 2017 Wikipedia dump. They were given sentences at random and were asked to generate variations of the claims, altering them in ways that may or may not change their truth label. The types of mutations were: paraphrasing, negation, substitution of entity/relation, and making the claim more general or specific. In a second phase, these claims were labelled as Supports, Refutes or NotEnoughInfo (NEI), and the evidences used for the labelling were recorded (Thorne et al., 2018).

FEVER has been criticized for missing some of the complexity that naturally-occurring claims have, such as claims that contain rich semantics in long and complex sentences (Thorne and Vlachos, 2019). For this reason, we decided to perform a comparison between the claims in FEVER and MultiFC. Axis x indicates the number of verbs per claim.

Figure 4: Comparison of claim complexity between FEVER and MultiFC. Axis x indicates the number of verbs per claim.

Figure 4: Comparison of claim complexity between FEVER and MultiFC. Axis x indicates the number of verbs per claim.

### 3.2 Experimental setup

As this work focuses on the NLI module of claim verification, we do not perform evidence retrieval, and instead, we use the evidences retrieved by the system that had the highest evidence recall in the FEVER shared task (Hanselowski et al., 2018). We take the top 5 evidences for each claim.

Given that transformer-based architectures, such as BERT (Devlin et al., 2019), have given state-of-the-art results in the task of NLI (Soleimani et al., 2019), we use this architecture as our baseline, and add the semantic information to it. BERT is designed to be given plain natural text as input. However, recent work suggests that it could benefit from additional linguistic knowledge (Zanzotto et al., 2020; Zhong et al., 2020). Zhang et al. (2020a) proposed an architecture that is able to encode both natural text and semantic information: SemBERT.

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1Measured with the Universal pos-tags of the nltk package.
At a first step, SemBERT encodes text in the same way that BERT does: tokenizing the text into sub-tokens and computing contextualized embeddings for each of these sub-tokens. In parallel, SemBERT takes the semantic representation that it is given, which should have one tag per word (SRL tags in the original paper), and computes tag embeddings. Given that a single sentence can have several predicates, and consequently several argument-predicate structures (propositions), Zhang et al. (2020a) allow for up to three different representation vectors. A linear layer aggregates the three semantic representation vectors (for the three propositions per sentence allowed) into one final semantic embedding. Then, the BERT word representation and the final semantic representation are concatenated. According to the authors, SemBERT outperforms BERT in NLI tasks, increasing the final accuracy between 1 and 3 percentage points (Zhang et al., 2020a).

In this work, we adapt SemBERT to fit the requirements of Automated Claim Verification. Since we use 5 pieces of evidence per claim, the input to the model consists of 6 sentences. Given that we can have many propositions per instance, we allow up to 12 propositions per instance and implement different sets of tags. Both the SRL tags and the OpenIE tags are extracted with the AllenNLP toolkit (Gardner et al., 2018; Shi and Lin, 2019; Stanovsky et al., 2018) and mapped to the different sets.

To summarise, the model has two separate inputs of the exact same length:

1. The claim plus the 5 concatenated evidences (given to the model as represented in the left part of Figure 5).
2. The semantic tags for each word in the claim and evidences (given to the model as represented in the right part of Figure 5).

Our experiments include a BERT baseline and 5 other models that interact with different sets of semantic tags. All the models have a maximum input length of 250 tokens, and are trained for 4 epochs with a batch size of 20, an AdamW optimizer (Loshchilov and Hutter, 2019) with the learning rate set to 2e-5, and a linear scheduler.

SemBERT_base On first instance, we train a model with all the semantic roles (from now on we will call them tags) retrieved by the AllenNLP parser. This results in a tags-vocabulary of size 19, so the encoding layer contains 19 contextualized embeddings (plus 3 BERT-special tokens) of length 10 (see the tags in Appendix A).

Provided that the set of tags is quite large, the sparsity of the SRL data could be preventing the model from learning patterns. We make additional experiments reducing the set of tags by doing two different mappings.

SemBERT_tags1 One mapping reduces the amount of tags by removing the positional part of the tags, which is given in BIO notation (e.g. I- B-), and reducing the amount of modifier arguments to just temporal, location or other modifiers, leaving a total of 10 tags. The correspondence with the tags of the first model are in Appendix A.

SemBERT_DREAM The second tag set comes from using the mapping of the DREAM system (Zhong et al., 2020), which additionally reduces all the ARG tags to a single argument tag, leaving a total of 5 tags. The correspondence can be seen in Appendix A.

SemBERT_Attention The original SemBERT model uses a linear layer to squeeze all the 12 predicates into one. That is needed to remove the multiple predicates dimension and be able to concatenate the representation coming from the SRL to the one produced by BERT. We hypothesized that this linear layer could be replaced by an attention mechanism that allowed evidences to reason between them, inspired by the self-attention mechanism from Zhou et al. (2019).

This self-attention mechanism concatenates the vectors of each predicate in pairs, to then compute self-attention between them and use that information to reshape the 12 representations into one, using a linear layer. To train this model, we used the mapping of SemBERT_tags1.

SemBERT_OpenIE In order to get the OpenIE tags we have also used the AllenNLP parser (Gardner et al., 2018). Then, we have kept the tags argument, verb and O – O meaning that the word is not part of the predicate. This makes a tag vocabulary of size 3.

4 Results

Table 2 reports the accuracy of the predictions of all these models in the development set. We observe that all the SemBERT experiments have a
better performance than the BERT baseline. This difference is of 1 to 2 percentage points. Our best model is the SemBERT model with the SRL set tags1 (SemBERT_tags1).

Going back to our hypothesis that claim complexity will be better understood by using models that include SRL, we calculate the accuracy separately for claims with more (and with less) than 5 verbs. The SemBERT_tags1 model improves 6.5 points on complex claims over BERT, while it just improves 1.5 points on simple claims. However, since FEVER has few complex claims (only 62), further experiments with more complex claims should be used to confirm our hypothesis.

![Figure 5: SemBERT architecture by Zhang et al. (2020a)'](image)

Table 2. Results from all the models in the FEVER development set

| Label Accuracy | Evidence F1 | Label Acc. | Fever Score |
|----------------|-------------|------------|-------------|
| BERT_base (baseline) | 73.82 | |
| SemBERT_base | 75.06 | |
| SemBERT_tags1 | 75.37 | |
| SemBERT_DREAM | 75.12 | |
| SemBERT_Attention | 74.92 | |
| SemBERT_OpenIE | 74.34 | |

Table 3. Results on the test set of our models and previous work

|                  | Evidence F1 | Label Acc. | Fever Score |
|------------------|-------------|------------|-------------|
| UKP-Athene       | 36.97       | 65.46      | 61.58       |
| GEAR             | 36.87       | 71.60      | 67.10       |
| DREAM            | 39.45       | 76.85      | 70.60       |
| ProoFVer         | 40.03       | 79.47      | 76.82       |
| BERT_base        | 36.87       | 70.86      | 65.52       |
| SemBERT_tags1    | 72.18       | 67.16      | |

Table 3. In the unseen data, the SemBERT model also outperforms the BERT baseline by 1.3 percentage points in label accuracy. Both models drop around 3 percentage points with respect to the development set. Additionally, we also report the results on the test set of previous work such as UKP-Athene (Hanselowski et al., 2018), GEAR (Zhou et al., 2019), DREAM (Zhong et al., 2020), and ProoFVer (Krishna et al., 2021). For our model, we used the evidences extracted by UKP-Athene, and some pre-processing scripts from GEAR, which explains why all three models have (almost) the same F1 for evidence retrieval. Our model outperforms both of these models in the inference module.
Our approach is similar to the one in DREAM, as both integrate semantic information to improve the reasoning process. However, instead of using a graph-based approach, we use the SemBERT architecture to incorporate the semantic information. As observed, DREAM performs better than our model, suggesting that graph-based architectures might be a better representation for semantic information. Finally, the highest scoring system is ProoFVer\(^2\). Furthermore, both DREAM and ProoFVer rely on better evidences, as shown by the F1 in Table 3. Still, while being substantially simpler than a higher-performing work such as ProoFVer, our approach provides an effective method to integrate explicit semantic information with clear benefits in performance. Furthermore, our code and model are publicly available to facilitate research on claim verification and reproducibility of results.

5 Explainability tests

While the accuracy results allow for a comparison between models, they are not enough to understand the contribution of the semantic information to the model. For this reason, we decided to perform qualitative explainability tests based on calculating saliency scores and performing adversarial attacks.

5.1 Saliency Scores

Extracting the saliency of each of the tokens given as input is not a trivial task for deep-learning models. Simonyan et al. (2014) proposed to compute them as the gradient of the output with respect to each input. Later improvements to this technique proposed to then multiply these gradients to the input (Input\(\times\)Gradient), or to overwrite the gradients of the ReLU functions in order to prevent negative gradients from being propagated (Guided Backpropagation, Kindermans et al., 2016; Springenberg et al., 2015).

We will use the saliency scores proposed above to get a better grasp of where the model focuses in order to make its inference decisions. For an interpretable output, we want to have one saliency value for each token. Given that the last layer that we can compute the gradients for is the embedding layer, we will get one gradient for each value in the embedding of each token. In order to aggregate these values and get one single value per token we will use the L2 norm (Atanasova et al., 2020).

In Figure 6, we can see an example where both BERT and SemBERT get the output right. The instance looks like:

- **Claim:** Telemundo is an English-language television network.
- **Evidence:** Telemundo is an American Spanish-language terrestrial television network owned by Comcast through the NBCUniversal division NBCUniversal Telemundo Enterprises.

Both models output REFUTES and the saliency scores clearly point towards the words English-language in the claim, and Spanish-language in the evidence. As an opposite case we display Figure 7. In this case, the instance looks like:

- **Claim:** Easy A is directed by Bert V. Royal.
- **Evidence:** Easy A, stylized as easy A, is a 2010 American teen comedy film directed by Will Gluck, written by Bert V. Royal and starring Emma Stone, Stanley Tucci, Patricia Clarkson, Thomas Haden Church, Dan Byrd, Amanda Bynes, Penn Badgley, Cam Gigandet, Lisa Kudrow and Aly Michalka.

In this instance, BERT gets the inference wrong and outputs SUPPORTS, while SemBERT gets it right and outputs REFUTES. Based on the saliency scores, BERT tries to focus on many different tokens, while SemBERT ignores almost all of them. From this observation, we hypothesize that, with such a semantically-complicated evidence (it contains 5 predicates), SemBERT is relying on the semantic information for its decision, which is not plotted on this figure. We further investigate this hypothesis by creating manual adversarial attacks in the next section.

5.2 Adversarial Attacks

Performing adversarial attacks consists on changing the input in order to assess the influence that it has over the output. This has been done both by removing input tokens systematically (Zeiler and Fergus, 2014), and by altering the input instances to generate adversarial attacks which can show what the model actually understands (Ribeiro et al., 2018; Ebrahimi et al., 2018). In this section, we are going to create some manual adversarial attacks in order to test the capabilities of our models.
Taking the example of Easy A, we start by checking that the REFUTES label of SemBERT is not random by changing the claim to Easy A is written by Bert V. Royal. SemBERT passes this test and outputs SUPPORTS. Following the tests for semantic structure in Ribeiro et al. (2020)’s CheckList, we modify the evidence by changing the order of the propositions, creating symmetric relations and swapping them to active form. The new versions of the evidence are:

1. **Order change**: Easy A, stylized as easy A, is a 2010 American teen comedy film written by Bert V. Royal, directed by Will Gluck, and starring Emma Stone, [...]. ← **Refutes**

2. **Order change**: Easy A, stylized as easy A, is a 2010 American teen comedy film written by Bert V. Royal, starring Emma Stone, [...], and directed by Will Gluck. ← **Refutes**

3. **Symmetric relation**: Easy A, stylized as easy A, is a 2010 American teen comedy film directed by Will Gluck and Bert V. Royal and starring Emma Stone, [...]. ← **Supports**

4. **Remove the written by proposition**: Easy A, stylized as easy A, is a 2010 American teen comedy film directed by Will Gluck, and starring Emma Stone, [...]. ← **Refutes**

5. **Active form**: Easy A, stylized as easy A, is a
2010 American teen comedy film. Will Gluck directed the film, and Bert V. Royal wrote it. ← Refutes

With all the variations of the evidence presented above, SemBERT always outputs the right label, while BERT just outputs the right label in the last piece of evidence, which contains the same information but in active form. These tests suggest that SemBERT does have capabilities regarding semantic structure that are missing in BERT. However, more systematic tests should be performed in this direction.

6 Conclusion and Future Work

In this work we have investigated if semantic information could help to improve the reasoning process when inferring the truth label of a claim given some pieces of evidence. To this goal, we have used two different semantic parsers and the architecture of the pre-trained model SemBERT (Zhang et al., 2020a). For our experiments, we have used the FEVER dataset (Thorne et al., 2018), which requires building a model that, given some pieces of evidence, can output if a claim is supported, refuted, or the evidence does not give enough information.

We have performed several experiments on top of the SemBERT architecture, such as training models with different kinds of semantic information, different sets of semantic tags, and with an additional attention mechanism to represent the semantic information. In terms of label accuracy, all our experiments have outperformed the baseline, which was a BERT model with no additional semantic information. Our best model uses Semantic Role Labels and a set of 10 different tags, with an additional attention mechanism. This model achieves a label accuracy of 75.37 on the development set and 72.18 on the test set, outperforming the baseline by 1.5 and 1.3 percentage points respectively. Future work could include testing the impact of these semantic structures in models such as RoBERTa (Liu et al., 2019) or XLNet (Yang et al., 2019).

To better understand the contribution of the semantic information, we have performed some explainability tests with our best model. These have shown that the SRL knowledge might be contributing to guiding the model in semantically complex sentences that include several propositions or passive forms.

To keep moving towards systems that can contribute to the work of fact-checkers, future research on claim verification should take two directions. On the one hand, there is a need to develop large datasets that are more similar to naturally-occurring claims. On the other hand, NLI models for claim verification should output more explanatory justifications to their conclusions, which would make these systems more trust-worthy.

In this work, we have not dealt with the task of evidence retrieval. In FEVER, this task is limited by the static Wikipedia database that comes with the dataset. However, in real-world scenarios defining the boundaries of what is trust-worthy information is a challenge that goes beyond research in NLP and reaches the fields of journalism, politics and even philosophy. The non-static nature of what is a true fact is an additional challenge to evidence retrieval.

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A Appendix: Tags mapping

| All Tags | Tags1 Tags | DREAM Tags |
|----------|------------|------------|
| O        | O          | O          |
| B-V      | V          | verb       |
| I-V      | V          | verb       |
| B-ARG0   | ARG0       | argument   |
| I-ARG0   | ARG0       | argument   |
| B-ARG1   | ARG1       | argument   |
| I-ARG1   | ARG1       | argument   |
| B-ARG2   | ARG2       | argument   |
| I-ARG2   | ARG2       | argument   |
| B-ARG4   | ARG4       | argument   |
| I-ARG4   | ARG4       | argument   |
| B-ARGM-TMP | TMP        | temporal   |
| I-ARGM-TMP | TMP        | temporal   |
| B-ARGM-LOC | LOC        | location   |
| I-ARGM-LOC | LOC        | location   |
| B-ARGM-CAU | ARGM      | argument   |
| I-ARGM-CAU | ARGM      | argument   |
| B-ARGM-PRP | ARGM      | argument   |
| I-ARGM-PRP | ARGM      | argument   |

Table 4: Mapping between sets of SRL tags