ABSTRACT

We propose a new uniform framework for text classification and ranking that can automate the process of identifying check-worthy sentences in political debates and speech transcripts. Our framework combines the semantic analysis of the sentences, with additional entity embeddings obtained through the identified entities within the sentences. In particular, we analyse the semantic meaning of each sentence using state-of-the-art neural language models such as BERT, ALBERT, and RoBERTa, while embeddings for entities are obtained from knowledge graph (KG) embedding models. Specifically, we instantiate our framework using five different language models, entity embeddings obtained from six different KG embedding models, as well as two combination methods leading to several Entity-Assisted neural language models. We extensively evaluate the effectiveness of our framework using two publicly available datasets from the CLEF’ 2019 & 2020 CheckThat! Labs. Our results show that the neural language models significantly outperform traditional TF.IDF and LSTM methods. In addition, we show that the ALBERT model is consistently the most effective model among all the tested neural language models. Our entity embeddings significantly outperform other existing approaches from the literature that are based on similarity and relatedness scores between the entities in a sentence, when used alongside a KG embedding.

Keywords Knowledge graph embeddings · Language models · Entity embeddings · fake news detection

1 Introduction

Politics is an important part of our daily lives. The general public has the right to hold politicians accountable, when they are providing information through debates with their opponents, or when giving speeches. However, general citizens usually do not have enough time to fact check every claim a politician makes, and the vast amount of possible claims made by politicians during their debates and speeches may overwhelm even professional journalists or the fact-checkers of fact-checking organisations (such as Snopes.com and Politifact.org). Indeed, it is common for political debates and speeches to include a mix of factual and non-factual information together, making it possible for the fact-checkers and targeted audiences to be deceived, while making it harder for systems to identify the fake information from the entire debate transcript. To reduce the time and effort required for fact-checking, it is common for fact-checkers and systems to focus their efforts on those dubious claims most likely to matter to the targeted audience. This paper describes an automatic system, that analyses a debate, or a speech, by extracting and ranking all sentences that are worth checking before flagging them to the users by order of their likelihood of being suspicious or fake.

Recently, the identification of these so-called most check-worthy sentences has gained increased attention. For example, the ClaimBuster system [1] was trained to label sentences in a news article as “non-factual”, “unimportant factual”, or “check-worthy factual”. Moreover, the recent CLEF’ 2019 & 2020 CheckThat! Labs [2][3] were introduced as shared evaluation forums where participants were tasked to rank sentences based on their estimated check-worthiness. While CLEF’ 2020 CheckThat! Lab also includes a task that aims to identify suspicious tweets on Twitter platform, in this work we focus on the debates and speeches. The reasons being tweets have distinct text features compared to speeches and debates, and social network features that speeches and debates do not have. Thus, we consider the identifying check-worthy tweets outside the scope of our task. As is common in recent years, the top-performing
participants applied neural language models (LMs), including long short memory models (LSTM) using pre-trained word embedding approaches [4][5][6], to represent sentences.

On the other hand, to make a claim is to assert that something is true, while assertion has a common form of $X$ verb $Y$ [7], we therefore define a claim as conveying $\langle X$ verb $Y \rangle$ is true, where the object of the claim is often an entity [8]. Moreover, claims made by politicians during debates often contain information about established entities (for instance, entities that are documented in Wikipedia) [9]. Thus, we focus on established entities in the claim in our check-worthiness identification task, as established entities can be verified with documented information, such as knowledge graphs. Knowledge graphs (KGs) are a useful source of information about entities, particularly how they relate to each other. Typically, in a knowledge graph, entities and their relationships are represented using a triplet structure $(\text{entity}_1, \text{relation}, \text{entity}_2)$. An example of such a triplet is $(\text{Arizona}, \text{a_state_of}, \text{the_United_States})$.

Su et al. [10] demonstrated that enriching the sentence representation with the similarities and relatedness scores of the entities in that sentence, can significantly improve the identification of the check-worthy sentences than using text representation alone. Recent works [11, 12, 13] have shown that learned embeddings can be derived from KGs, allowing for the advantages of word embeddings to be applied to the entities found in the KGs.

Motivated by advances in both language modelling and KG modelling, a recent model, ERNIE [14], demonstrated that by jointly training the language representation and the entity representation, it is possible to leverage the information from both the language representation and entities, thus benefiting a wide range of tasks that require both text and entity information. Building on this work, we hypothesise that the embedded entity vectors obtained from KG embeddings (which we call entity embeddings) can improve the identification and ranking of check-worthy sentences. For example, Figure 1 demonstrates an example, where the two entities highlight the important components of the sentence, thus helping to identify the sentence as check-worthy. We propose a novel framework, which combines recent neural language models with an entity pair representation for each pair of entities in the sentence, where the entity pair representation is obtained by adequately combining two entity embeddings extracted from an embedded Knowledge Graph (KG). Our proposed framework allows us to capture rich information about both the language and the entities present in each sentence thereby allowing to better predict their likelihood of being check-worthy. Our framework can be uniformly instantiated to tackle the check-worthiness task either as a text classification or ranking task thereby providing a general and flexible solution for identifying sentences of interest to users. Compared to previous work, our proposed framework has three salient aspects:

1. We represent sentences using language models that go beyond the bag of words and LSTM methods, by leveraging the latest developments in deep neural language models (BERT [15], ALBERT [16], or RoBERTa [17]);

2. We extend the method of incorporating entity information within sentences, from using the simple similarity and relatedness scores between the entities in a sentence [10] to a more sophisticated entity representation obtained from KG embeddings.

3. Our proposed framework does not require the joint training of the language model and the entity representations (for example as done in ERNIE [14]), thereby providing greater flexibility for instantiating and deploying the framework in fact-checking tasks.
We instantiate our proposed framework into several Entity-Assisted neural language models, by concatenating the language representation obtained from a state-of-the-art pre-trained language model (e.g. BERT [15], ALBERT [16], or RoBERTa [17]), with embedded representations for each pair of entities present in a sentence, to represent the sentence’s semantic information as well as its entity-related information. Thus, the contributions of this paper are four-fold:

1. We propose a simple yet powerful framework to represent sentences with rich entity information, by concatenating together a text model representation with entity pair representations.
2. Using the CLEF 2019 and 2020 CheckThat! Lab datasets, we show that our generated Entity-Assisted neural language models significantly outperform the existing state-of-the-art approaches in the classification task, as well as outperform the participating groups on the CLEF CheckThat! leader board in the ranking task.
3. We show that representing entity pairs with embeddings is significantly more effective than an existing recent technique from the literature that leverages the similarities and relatedness of the entities.
4. Finally, our findings show that among the various knowledge graph embedding models, ComplEx [13] leads to the best results, for instance, achieving results as good as the best performing system submitted to the CLEF 2019 CheckThat! Lab, without the need for labour-intensive feature engineering.

The rest of the paper is structured as follows: We review the literature related to language representation models, knowledge graph embeddings, as well as the claim check-worthiness task in Section 2. In Section 3 we state the task problem, along with our proposed model to address the task. We present our experimental setup in Section 4 and show the results of the experiments in Section 5. Finally, we provide concluding remarks in Section 6.

2 Related Work

In the following, we provide an overview of the key related approaches in language models (Section 2.1), knowledge graph embeddings (Section 2.2) and check-worthiness identification (Section 2.3).

2.1 Language Models

There are several commonly used methods for representing text, including bag-of-words (BoW) (e.g. TF.IDF) [18], parts-of-speech (POS) [19], and word embeddings (e.g. Word2Vec) [20] representations. Building upon word embeddings, deeper long short term memory (LSTM) neural networks (NN), are now commonly used to represent text in a sequential manner, capturing the semantic meaning of the text based on previous tokens. LSTMs encapsulate information about previous tokens, whereas Word2Vec representations are usually based on small skip-grams or windows of tokens. Such models do not take the future context into account when learning to predict language. To address this disadvantage, researchers have developed bidirectional LSTMs (BiLSTMs) and attention-based neural network models (such as BERT [15], ALBERT [16], and RoBERTa [17]) that not only capture both previous and future tokens in a sentence, but also use the attention mechanism to identify relevant contexts within or between sentences. Moreover, the aforementioned models combine the advantages of a large complex neural network given their pre-training on a large corpus, to create pre-trained neural language models (e.g. BERT is trained on Wikipedia, BookCorpus, and Common Crawl [15]), where the subjective bias from any small training data is minimised. Being based on a state-of-the-art pre-trained language model architecture that can be modified and that has been shown to consistently outperform other models in many tasks [21, 22], we use BERT-related language models (i.e., BERT, ALBERT, and RoBERTa) as the base language models in our experiments.

2.2 Knowledge Graph Embedding Models

A knowledge graph (KG) usually contains entities (nodes) and finite types of relationships (different types of edges) between each two entities, and can be viewed as a multi-relational graph. Each edge in the KG is represented by a triplet $e = (e_h, r, e_t)$, indicating that the head entity $e_h$ and tail entity $e_t$ are connected by relation $r$, e.g., $\langle Donald-Trump, NomineeOf, United_States_presidential_election_2016 \rangle$. Such a representation of the structured data is effective at representing factual and trackable relationships, and thus can facilitate the fact-checking processes (e.g. [23]). However, a KG is relatively hard to embed into a lower dimensional vector space. There are many existing approaches [12, 24, 25, 26] that learn embeddings from KGs, by training an unsupervised model based on the co-occurrence of entity pairs and relations. Generally, there are two types of models that are widely used to train KG embeddings: distance-based KG embeddings with “facts alone” models [12, 26, 27] trained on a semantic triplet graph alone (such as FB15k [12]), while semantic-based entity embeddings [24, 25] also use the information contained in the corresponding entity descriptions (e.g. Wikipedia pages). We describe these two types of models in turn in the next two subsections.

3
2.2.1 Facts Alone KG Embedding

There are two facts alone knowledge bases that are widely used in training KG embeddings, namely FB15k and WN18 [12]. The structure of a pure triplet (i.e., a triplet of the form $e = (e_h, r, e_l)$), without any additional descriptions for $e_h, r, e_l$ in such knowledge bases enables KG to represent information in a hierarchical and graphical manner. Such representation can be represented in a lower dimension space using graph embeddings, where the learning of the scoring functions is generally based on distances between entities and relationships. Specifically, the Euclidean distance between entities, is used to project the entities based on their relationship with one another, whether these entities and relationships are translated into the same vector space (e.g., TransE [12]), or into different spaces (e.g., TransR [28]); or projected into different vector spaces with tensor factorisation (e.g., RESCAL [25], DistMult [29]). The advances in deep neural networks also encouraged researchers to deploy deep neural networks on graph-structured data, such as data encapsulated in a KG. For example, Li and Madden [30] combined a graph embedding method node2vec [31] with the cascade embedding method, achieving a better performance at predicting triplets, than using TransE alone. Recently, complex space embedding has also been applied to KG embeddings (e.g., ComplEx [13], RotateE [32], QuatE [33]), where the complex valued embedding allows the binary relationship embeddings to represent both symmetrical and asymmetrical relationships (e.g., $(Stanley Kubrick, directed, Dr.Strangelove)$ (asymmetrical) cannot be represented as $(Dr.Strangelove, directed, Stanley Kubrick)$, while $(Barack Obama, married to, Michelle Obama)$ (symmetrical) can also be represented as $(Michelle Obama, married to, Barack Obama)$). Finally, the hyperbolic space, with the ability to represent discrete trees in a continuous analogue, has been used for modelling a KG (e.g., MuRP, RotE and RotH [27]), where the multiple possible hierarchical relations of one entity can be modelled simultaneously, resulting in a fewer dimensions of hyperbolic embeddings thereby achieving better performances than those obtained by the Euclidean distance methods. Aside from the general knowledge bases, specific knowledge bases have been developed to facilitate the KG embeddings of special knowledge. For example, museum information and other unregimented data can be converted into $e = (e_h, r, e_l)$ triplets [34], while crime-related information can be extracted from newspapers, to build a speciality knowledge base for criminology [35].

2.2.2 Semantic-based KG Embeddings

Some knowledge bases (e.g., DBpedia) contain more information than just triplets of entities and relationships (e.g. text descriptions for entities, relationships, and their possible features, such as $(Stanley Kubrick, directed, Dr.Strangelove, a comedy/war movie)$). Hence, a semantic analysis of the available descriptive texts allows algorithms to better capture each entity and its meaning, where a hyperlink between entities serves as a relationship between the two linked entities. To this end, joint training an entity embedding with semantic embeddings can benefit one another. Researchers have explored traditional machine learning methods on jointly trained embeddings, such as random walk [36], He et al. [11] used deep neural networks to compute representations of entities and contexts of mentions from the KB, while Yamada et al. [11] used a skip-gram method, and trained it on Wikipedia data to obtain the entity embeddings and the associated word embeddings.

More recently, some researchers (e.g., ERNIE [14], KnowBERT [38]) have explored the use of joint training knowledge graph embeddings along with a BERT language model, and showed promising results in several downstream tasks. Bosselut et al. [39] explored whether using the attention mechanism (similar to that for training the BERT model) to enrich a knowledge base embedding with “common sense knowledge” embedded in text content is beneficial for more complete KG embeddings. The resulting model, named Comet, puts more emphasis on general information represented as entities (e.g., $(nap, having sub-event, dosing off)$).

2.2.3 Conclusions

The question of whether the embedded entities are beneficial to suspicious claim detection and/or fake news has not yet been studied. For example, the aforementioned Comet model focuses on representing common knowledge instead of entities, which is not suitable for our task. Hence, we do not experiment with this KG embedding model in our present study. However, deploying a joint training of the KB embeddings with the language model may result in less accurate entity embedding information, as well as increase the needed training effort. Hence, in this paper, we propose to combine KG embeddings with both neural and BoW language representations, to ascertain whether using additional entity information from text enhances the identification of suspicious claims for fact-checking. In the following, we review existing related work about fact-checking and suspicious claim identification.

2.3 Check-Worthiness

Identifying check-worthy sentences is a task that identifies the most suspicious and potentially damaging sentences, from a given news article or a political debate that has been divided into sentences. The identified check-worthy
Table 1: Methods used by the top five performing groups in CLEF’ 2019 & 2020 CheckThat! lab.

| Model       | Learning models                                      | Features                        |
|-------------|------------------------------------------------------|---------------------------------|
|             | Model(s)                                             | word embeddings                |
|             |                                                      | syntactic dependence embeddings |
|             |                                                      | SUSE\(^1\)                     |
|             |                                                      | Bag of (NE, POS, Words, n-grams) |
|             |                                                      | hand-crafted features\(^2\)    |
| 2019        | Copenhagen, TheEarthIsFlat                            | ✓                               |
|             | IPIAN                                                | ✓                               |
|             | Terrier                                              | ✓                               |
|             | UAICS                                                | ✓                               |
| 2020        | NLP&IR@UNED, UAICS, TOBB ETU P                       | ✓                               |

sentences should then be prioritised in fact-checking process. The ClaimBuster system\(^1\) was the first work to target the assessment of the check-worthiness of sentences. It was trained on data manually labelled as “non-factual”, “unimportant factual”, or “check-worthy factual”, and deployed SVM classifiers with features such as sentiment, TF.IDF, POS, and named entity linking (NEL). Focusing on debates from the US 2016 Presidential Campaign, Gencheva et al.\(^40\) found that if a sentence is an interruption by one participant in the middle of a long speech by another participant, that was more likely to be selected as check-worthy by at least one news organisation. There are many follow-up works\(^41,42,43\) that have focused on deploying different learning strategies (e.g. neural networks, SVM with various features) in reproducing the check-worthy sentences selection process of a news organisation.

In the 2019 and 2020 editions of the CLEF’2019 CheckThat! Lab, datasets of check-worthy sentences from the 2016 US presidential debate were provided – these were used for 2019 Task 1\(^2\) and 2020 Task 5\(^3\). The top 5 performing groups in the official leader board of the CLEF’ 2019 CheckThat! Lab are Copenhagen\(^4\), TheEarthIsFlat\(^6\), IPIAN\(^44\), Terrier\(^10\), and UAICS\(^45\). The 3 groups in the official leader board of the CLEF’2020 CheckThat! Lab task 5 are NLP&IR@UNED\(^46\), UAICS\(^47\), and TOBB ETU\(^48\). Table 1 provides an overview of the approaches and techniques used by these top performing groups.

Among the groups and systems mentioned in Table 1, the approach deployed by the Terrier group as reported by Su et al.\(^10\) is the closest work to our proposed framework in that they also addressed named entity linking, albeit their approach made use of a KG for only the similarity and relatedness between two entities, which we will also be adopting in our experiments. However, Su et al.\(^10\) calculated the similarity and relatedness – in terms of KG structures – between pairs of entities in the sentences. In contrast, our work here uses recent advances in dense entity embeddings\(^11,12,28,29,13\) to provide richer information for suspicious claim identification. We hypothesise that by integrating entity pair representations, we can improve the performance of pure neural language models such as BERT or ALBERT, when identifying check-worthy sentences. It is of note that the best 2019 performing team (Copenhagen) achieved only a mean average precision (MAP) of 0.1660 using the 2019 dataset, while the top 2020 performing team (NLP&IR@UNED) achieved a MAP of 0.0867, indicating the difficulty of the task. For a fair comparison with existing models on this challenging task, our present work also uses the CLEF’2019 & 2020 CheckThat! datasets. In the following section we describe the task of check-worthiness prediction, and our proposed entity-assisted language models to address it.

3 Check-Worthiness Prediction using Entity-Assisted Language Models

Given a document \(d\), we aim to estimate the check-worthiness of each sentence \(s_i \in d\). This can be formulated as a classification task, aiming to predict (denoted \(\hat{y}_i\)) for each sentence if a human would label that sentence as check-worthy or not (c.f. \(y_i\)). The task can also be formulated as a ranking task, such that the predicted most check-worthy sentences are ranked highest – indeed, this is the task formulation taken by the CLEF’ 2019 and 2020 CheckThat! Labs\(^2,49\). In our present study, we propose a uniform framework, which addresses the estimation of check-worthiness both as classification and ranking tasks, when measuring the effectiveness of our models.

Our proposed uniform framework for tackling the identification of the check-worthiness of each sentence consists of two components: text representation through the use of language models, and an entity pair\(^1\) representation obtained from entity embeddings – discussed further in Section 3.1. Each sentence is represented by a language model (denoted

1Standard Universal Sentence Encoder
2Readability, sentence context, subjectivity, Sentiment
3We also experimented with sentence representation combined with a single entity, and sentence combined with three entities, and neither performs well in this task. For the ease of reading, we do not present the equations and experiments for such structure.
An ABC News poll shows that 77% of Americans have health care coverage.

Figure 2: Our proposed Entity-Assisted Language model framework.

by \( l_{rep} \), which is discussed further in Section 3.2. There are three steps involved in representing a pair of entities appearing in a sentence:

1. Resolving all entities that appear in each sentence to the corresponding entity using entity linking [50];
2. Transforming the resolved entities into dense entity embeddings through the application of KG embeddings (denoted by \( m_{ent} \)) – we discuss the choice of KG embeddings in Section 3.3.
3. Each pair of entity embeddings are combined through a combination method (denoted by \( e_{com} \)) to form a single representation for the entity pair. Note that, for sentences that contain more than two entities, every two entities form an entity pair.

3.1 Overall Structure of Proposed Framework

In order to leverage the semantic representation of various language models, as well as the entities in sentences, for each sentence, we propose to combine its language representation along with an entity pair representation for each pair of entities in the sentence using a neural network framework.

Firstly, considering a sentence \( s_i \) in which a set of entities \( E(s_i) \) have been identified through application of an entity linker. Our model is based on pairs of entities, thus we consider input instances \( x_i \), based on pairs of distinct entities:

\[
  x_i \in \{ (s_i, e_h, e_t) \mid (e_h, e_t) \in E(s_i) \times E(s_i) \}
\]

where \( e_h \) and \( e_t \) are the head and tail entities. For ease of notation, let \( x_i \in s_i \) denote a particular instance \( x_i \) obtained from \( s_i \) using Equation (1). Then, given an input instance \( x_i \), we develop two separate models: \( f_{cls}(x_i) \) for sentence classification and \( f_{rank}(x_i) \) for ranking. Furthermore, for combining the embeddings of a given entity pair, we use two different methods as explained below.

In particular, Figure 2 shows the architecture of our proposed framework, including the two different methods of entity evidence combination. In the input stage, we use the sentence as input to a language model, so as to obtain the text representation of the input sentence at a semantic level, i.e.:

\[
  l_{rep} = LanguageModel(s_i)
\]

For each entity pair in an input instance, we represent the relationship (\( e_{rep} \)) between \( e_h \) and \( e_t \) in a high dimensional space. Thus, we firstly use an existing KG embedding model \( m_{ent} \) to extract entity embeddings \( \overrightarrow{e_h} \) and \( \overrightarrow{e_t} \) for entities \( e_h \) and \( e_t \). Next, we use a combination method \( e_{com} \) to obtain the entity pair representation (\( e_{rep} \)). Specifically, as combination methods, we use the element-wise product operation (denoted by \( \text{emb\_prod} \)), and the concatenation operation (denoted by \( \text{emb\_concat} \)). This process can be represented as follows:

\[
  \overrightarrow{e_h} = m_{ent}(e_h), \overrightarrow{e_t} = m_{ent}(e_t)
\]

\[
  e_{com} \in \{ \text{emb\_prod}, \text{emb\_concat} \}
\]

\[
  e_{rep} = e_{com}(\overrightarrow{e_h}, \overrightarrow{e_t})
\]

It is of note that we select \( \text{emb\_prod} \) and \( \text{emb\_concat} \) because of their wide use as neural operators for combining two vectors (e.g., \( \text{[1,1,1]} \), \( \text{[1,0,0]} \), resp.).

We combine the text representation and entities pair together, to form the input instance representation \( x'_i \), by concatenating the language representation (\( l_{rep} \)) with the entity pair representation (\( e_{rep} \)):

\[
  x'_i = l_{rep} \oplus e_{rep}
\]

\(^2\)We use a uniform \([-1, \ldots, -1]\) vector to represent any entity not having any embedding in the pre-trained KG embeddings.
We aim to understand the robustness of using entity embeddings across a number of language models. In particular, we focus on using pairs of entities, following [52, 10]. Thus, we instead propose to obtain the entity representations using KG embedding models – such as those introduced in Section 2.2 (e.g. [11, 12, 13, 28, 25, 29]). This allows us to acquire the implicit and hidden KG-based relationships between two entities that are encoded in the embedding vectors that have been learned by a particular model. Indeed, in Section 2.2 (e.g. [11, 12, 13, 28, 25, 29]). This allows us to acquire the implicit and hidden KG-based relationships between two entities that are encoded in the embedding vectors that have been learned by a particular model. Indeed, we focus on using pairs of entities, following [52, 10].

Different KG embedding models can return varying results when given the same entity and task. For example, Table 2 shows the four most similar entities for the President of the United States ⟨Barack Obama⟩ obtained using six different KG embedding models that we use in this study. Specifically, Wikipedia2Vec returns the entities that appear closer to the entity Barack Obama in the sentence, while the other 5 models show a variety of very specific entities that Barack Obama has a relationship with (e.g., the law he passed, the article he wrote, the person he attended the same school with). Such differences in the output provided by the KG embedding models are due to the varying datasets and data structures used to train the models.

Therefore, the key argument of this paper is that by including the entity embeddings $\overrightarrow{e}$ for each entity $e$ (appearing in the sentence) into our models, we are able to consider the KG-based network relationships of entities in a sentence.
Table 2: Examples of the most similar entities to Barack Obama, using each of the KG embedding models.

| KG embedding model | Most similar entities to Barack Obama, in descending order from left to right |
|---------------------|--------------------------------------------------------------------------------|
| Wikipedia2Vec       | Michelle Obama, John McCain, US presidential election, George W. Bush          |
| TransE              | Women’s History Month, A Child’s History of ... Thickness network ... Benito Pérez Galdós |
| TransR              | Executive Order 13654, BODY SIZES OF ... yniscu kigomensis, hypothetical protein ... |
| RESCAL              | Neural representation ... Natalie Grinczer, Octavia E. Butler, Giuseppe Pozzobonelli |
| DISTMult            | live preview, Neonatal peripherally ... KSC - STS-3 Rollout ... A large sex difference on ... |
| ComplEx             | Peter B. Olney, James Willard Hurst, Robert H. McKercher, William Schwarzer     |

when making predictions about the check-worthiness of a sentence. Indeed, entities that are far apart on a simpler word embeddings space may be closer on the entity embedding space, and combining the word embeddings and entity embeddings may be able to bring these two types of information together. Overall, this provides more evidence about the expected co-occurrence of different types of entities within a sentence for identifying those sentences requiring fact-checking.

4 Experimental Setup

Our experiments address the following research questions:

- **RQ1:** Do BERT-related language models outperform the TF.IDF and BiLSTM baselines in identifying check-worthy sentences?
- **RQ2:** Does the use of entity embeddings improve the language models’ accuracy in identifying check-worthy sentences?
- **RQ3:** Which combination method \( e_{comb} \) performs the best in improving the performance of text representations at identifying check-worthy sentences?
- **RQ4:** Which KG embedding model \( m_{ent} \) provides entity embeddings that best assists the language models?

Moreover, from Section 3, the identification of check-worthy sentences can be considered either as a classification task, or instead as a ranking task (as defined by the CLEF’ CheckThat! Lab organisers). Hence, in the following experiments, we provide conclusions for all RQs from both the classification and ranking perspectives. In the remainder of this section, we describe the experimental setup used to address our four research questions.

4.1 Dataset

All our experiments use both the CLEF’2019 & 2020 CheckThat! datasets. The CLEF’2019 & 2020 datasets consist of transcripts of US political debates and speeches in the time period 2016-2019, collected from various news outlets[^4]. Each sentence has been manually compared with factcheck.org by the organisers. If the sentence appeared in factcheck.org and is fact checked, it is labelled as a check-worthy claim. Table 3 shows a dataset extracted from a speech by Senator Ted Cruz. The CLEF’ 2019 & 2020 CheckThat! Labs provided data split for training and testing purposes, which we also use in this paper. Table 4 shows the statistics of the training and testing sets. In particular, we observe that the prevalence of check-worthy sentences is reduced in the 2020 dataset compared to the 2019 dataset.

Next, as our approach makes use of entity occurrences, in Figure 3a we show the proportion of each entity type appearing in the 2019 dataset[^5]. In particular, it can be seen that the Person and Location types are the most commonly identified in the dataset, and together they account for 90% of all the entities detected. Figure 3b shows the number of entities appearing in each sentence. We observe that sentences with 0-2 entities account for more than 40% of the sentences, while sentences with 3 entities account for ~15% of sentences. The observation of the distributions of the number of entities present in each sentence further strengthens the reasons for using entity pairs (described in Section 3).3.

4.2 Models and Baselines

In this section, we describe the tools and methods we use in our experiments, along with the baseline approaches.

[^4]: ABC, Washington Post, CSPAN, etc [49], in English only.
[^5]: Similar distributions were observed for the 2020 dataset, and hence are omitted.
Table 3: A debate transcript from the CLEF’2019 CheckThat! dataset. Sentences are labelled check-worthy (1) or not (0).

| Speaker | Sentence                                                                 | Label |
|---------|--------------------------------------------------------------------------|-------|
| Cruz    | You know, in the past couple of weeks the Wall Street Journal had a very interesting article about the state of Arizona. | 0     |
| Cruz    | Arizona put in very tough laws on illegal immigration, and the result was illegal immigrants fled the state, and what’s happened there – it was a very interesting article. | 1     |
| Cruz    | Some of the business owners complained that the wages they had to pay workers went up, and from their perspective that was a bad thing. | 0     |
| Cruz    | But, what the state of Arizona has seen is the dollars they’re spending on welfare, on prisons, and education, all of those have dropped by hundreds of millions of dollars. | 1     |

Table 4: Statistics of the CLEF’2019 & 2020 CheckThat! datasets.

|          | Training | Testing |
|----------|----------|---------|
| 2019     |          |         |
| # of debates/speeches | 19       | 7       |
| # of total sentences   | 16,421   | 7,079   |
| # of check-worthy sentences | 433     | 110     |
| % of check-worthy sentences | 2.637%  | 2.554%  |
| 2020     |          |         |
| # of debates/speeches | 50       | 20      |
| # of total sentences   | 42,776   | 21,514  |
| # of check-worthy sentences | 487     | 136     |
| % of check-worthy sentences | 1.138%  | 0.632%  |

Pre-processing: To allow a fair comparison with previous methods, we follow the pre-processing procedure of Su et al. [10], which includes first person resolution and co-reference resolution\(^6\). In doing so, we aim to ensure that any implied entities in the text are therefore explicitly available for analysis by the later stages of our framework (e.g. the language models and entity linking). In particular, we replace the first person pronouns with the speaker’s name, and use the coreference resolution package\(^7\) implemented by Lee et al. [53].

\(^6\)the co-referent resolution considers two sentences at a time, align with that of [10].
\(^7\)https://github.com/kentonl/e2e-coref

Figure 3: Distribution of the entity types, and the number of entities per sentence, in the CLEF CheckThat! 2019 dataset. Entities are detected using DBpedia Spotlight. Note that we omit the figures for 2020 dataset, since we observe similar distributions.
Entity-Assisted Language Models for Identifying Check-worthy Sentences

Named entity linking: To explicitly address the entities that occur in each sentence, we deploy a named entity linking method to extract entities from each sentence. In our experiments, we use DBpedia Spotlight\(^7\) to extract entities from each pre-processed sentence, with the confidence threshold set to 0.35, following Su et al.\(^10\)

Entity embeddings: We use six sources of entity embeddings to represent the embedded entity pair\(^11\) as follows:

- Wikipedia2Vec uses the extended skip-gram methods with a link-based measure\(^54\) and an anchor context model to learn the embeddings of entities. We use pre-trained Wikipedia embeddings (window size=10, iteration=10, negative=15, dimensions=300)\(^11\)
- TransE\(^12\) aims to embed a triplet \(e = \langle e_h, r, e_t \rangle\) into the same lower dimensional space, where \(\overrightarrow{e_h} + \overrightarrow{r} = \overrightarrow{e_t}\).
- TransR\(^28\) is built upon TransE, where the relation embedding is projected into a separate relation space, in order to more accurately represent the rich and diverse information between entities and relations.
- RESCAL\(^25\) uses a three-way tensor learning method to model the triplet of \(e = \langle e_h, r, e_t \rangle\), for more flexible representation of the relationship and entities.
- DISTMult\(^29\) uses a single vector to represent both entities and the relation by simplifying the bi-linear interaction between the entity and the relation, where the relation vector is represented using the diagonal matrix of the interaction.
- ComplEx\(^13\) uses complex embeddings and the Hermitian dot product to represent the relation between two entities, and achieved a better performance than its predecessors on the entity-linking task.

For the TransE, TransR, RESCAL, DistMult and ComplEx models, we use triplets extracted from Freebase (FB15K)\(^12\) as training data. These models are trained using code provided by Zheng et al.\(^55\).

Language representations: We use five different text representation models to represent each sentence, as follows:

- TF.IDF is a commonly used BoW model to represent the text based on the word frequencies. We include TF.IDF as a baseline.
- BiLSTM+attention (denote as BiLSTM+att) is widely used in the literature to learn a language model from the training data. It appeared in several solutions\(^4\), which were deployed in the CLEF’2019 CheckThat! Lab, and demonstrated that an LSTM-based language model can effectively represent the sentences in the check-worthiness identification task. Thus, in this paper, we use BiLSTM+att as a non-pretrained language model baseline, in order to obtain a fair comparison among all the language representation methods.
- BERT\(^15\) is a state-of-the-art pre-trained language model that has been shown to be effective in many information retrieval and natural language processing tasks\(^56\)\(^57\)\(^22\). In this study, we are also interested in determining if the BERT model also performs well on the very specific task of check-worthy sentence identification, or if it can be enhanced by supplementary information such as entity embeddings (as discussed in the next section).
- ALBERT\(^16\) is a derivative of the original BERT model that aims to reduce the number of parameters. Specifically, ALBERT uses a factorised embedding parameterisation method to decompose the vocabulary size and the hidden layer size, by projecting the vocabulary twice rather than once. Moreover, cross-layer parameter sharing and inter-sentence coherence loss are used to further reduce the need of parameters updating. ALBERT achieved a new SOTA performance with less parameters and shorter training time, compared to the original BERT model.
- RoBERTa\(^17\) aims to improve over BERT by training the model for more iterations, using longer sentence sequences, with bigger batches over more data. RoBERTa also removes the next sentence prediction objective in training. Similar to the ALBERT model, RoBERTa results in improved performance over the standard BERT model.

We use the HuggingFace language model implementations\(^58\). Specifically, we use the BERT-Based English model (12-layer, 768-hidden, 12-heads, 110M parameters); the Albert-base-v2 English model (12-layer, 128-hidden, 12-heads, 1M parameters); and the RoBERTa-base English model (12-layer, 768-hidden, 12-heads, 125M parameters). We fine-tune all the BERT-related language models on the training datasets. All other parameters remain at their recommended settings.

Baselines: We compare our generated Entity-Assisted models to the following baselines:

- BiLSTM+attention
- TF.IDF
- BERT
- ALBERT
- RoBERTa

\(^7\)https://www.dbpedia-spotlight.org/
\(^8\)https://github.com/huggingface/transformers
\(^9\)https://wikipedia2vec.github.io/wikipedia2vec/pretrained/
\(^10\)https://github.com/awslabs/dgl-ke
\(^11\)https://github.com/huggingface/transformers
Table 5: Classification performances on CheckThat! 2019 dataset, alternating language models $l_{rep}$ only. **Bold** indicate the best performance; Numbers in the Significance column indicate that the model is significantly better than the numbered model (McNemar’s Test, $p<0.01$).

| # | $l_{rep}$ | P  | R  | F1  | Significance |
|---|-----------|----|----|-----|--------------|
| 1 | Random Classifier | 0.01 | 0.01 | 0.01 | - |
| 2 | SVM(TF.IDF) | 0.01 | 0.01 | 0.01 | - |
| 3 | BiLSTM+att | 0.12 | 0.07 | 0.09 | 1,2 |
| 4 | BERT | 0.12 | 0.09 | 0.10 | 1-3 |
| 5 | ALBERT | 0.14 | 0.11 | 0.12 | 1-4 |
| 6 | RoBERTa | 0.14 | 0.11 | 0.11 | 1-4 |

- **TF.IDF + SVM** (denoted by SVM(TF.IDF)): We apply a SVM text classifier using TF.IDF feature vectors. We select our hyperparameters by applying cross validation on the training data. Specifically, we use the sci-kit learn SVM implementation with an RBF kernel, a C penalty of 10, and a $\gamma$ of 0.1 in our trained SVM classifier. We use class weights based on the training data to prevent the imbalanced data from compromising our experimental results. For the classification task we obtain the predicted class label for each sentence from $f_{cls}$ (as per Equation (7)), while for the ranking task we obtain a score for each sentence in the range (0, 1) from $f_{rank}$ (as per Equation (8)). We use the same functions for SVM(TF.IDF) similarity (introduced below).
- **SVM(TF.IDF) + Entity Similarity and Relatedness** (denoted by similarity): Following Su et al. [10], we append two graph-based entity similarity and relatedness scores – obtained using Sematch [59] – as well as a feature denoting the number of entities, to the TF.IDF feature vectors of the SVM model.
- **BiLSTM + Att**: We deploy a BiLSTM + Att model (100 hidden units) with an attention mechanism, implemented using Tensorflow. We initialise the embedding layer of BiLSTM using the pre-trained GloVe embeddings (300 dimensions).
- **CLEF’2019 & 2020 CheckThat! Lab leaderboards**: For the ranking task, we additionally compare with the runs of the top three groups on the official CLEF’2019 & 2020 leader board.[14]

### 4.3 Evaluation Metrics

For evaluating the classification accuracy, we use the standard classification metrics (Precision, Recall, F1). Significant differences are measured using the McNemar’s test. On the other hand, for evaluating the ranking effectiveness, we apply the ranking metrics used by the CheckThat! Lab organisers, namely Mean Average Precision (MAP), Reciprocal Rank (RR), and Precision at rank $k$ ($P@k$, $k\in\{1,5,10,20,50\}$). Means are calculated over the seven and twenty debates and speeches in the CheckThat! 2019 and 2020 test sets, respectively - therefore, due to the small number of rankings being evaluated, significance testing is not meaningful. Finally, note that it is not possible to evaluate the CLEF’2019 & 2020 CheckThat! Lab participants’ approaches using the classification metrics – this is because the participants’ runs have scores rather than predicted labels, and do not contain predictions for all sentences in the dataset. Further, it is also not possible to combine our approach with the participants’ runs, since we do not have the predicted scores of the participants’ runs on the training sets.

### 5 Experimental Results

In this section, we present the results of the experiments that address RQs 1 - 4. In particular, for both the check-worthy sentence classification and ranking tasks, Sections 5.1 - 5.4 respectively address: the effectiveness of the BERT-related language models; the usefulness of entity embeddings; the most effective combination method for representing entity pairs; and the most effective KG embedding model from which to obtain the entity embeddings. Tables 5, 7, and 9 presents the attained classification results obtained on the CLEF CheckThat! 2019 dataset, to address RQ 1, RQs 2-3, and RQ 4 respectively. Similarly, Tables 6, 8, and 10 present the attained ranking performances on both the CLEF CheckThat! 2019 & 2020 datasets, for RQ 1, RQs 2-3, and RQ 4 respectively. Furthermore, Tables 12 & 13 summarise the performance of a salient subset of approaches on the classification and ranking tasks, respectively. In order to obtain further insights of this study, we conduct failure analysis and case studies in Section 5.5. Finally, in Section 5.6 we summarise and discuss our main findings.

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14From https://github.com/apepa/clef2019-factchecking-task1 for 2019 results, and https://github.com/sshaar/clef2020-factchecking-tasks for 2020 results.

15We evaluate the classification task with only the CLEF’2019 CheckThat! Lab dataset, as our prior results found that it is not possible to derive meaningful results from the 2020 dataset, due to the small number of positive data in the test set.
Table 6: Ranking performances on CheckThat! 2019 and 2020 dataset, alternating language models $l_{rep}$ only. **Bold** indicate the best performance in each group.

| #  | $l_{rep}$                  | MAP  | MRR  | P@1  | P@5  | P@10 | P@20 | P@50 |
|----|----------------------------|------|------|------|------|------|------|------|
|    | CLEF'2019 CheckThat! Experimental results |      |      |      |      |      |      |      |
| 1  | SVM(TF.IDF)            | 0.1193 | 0.3513 | 0.1429 | **0.2571** | 0.1571 | 0.1714 | 0.1086 |
| 2  | BiLSTM+att              | **0.1453** | 0.2432 | 0.1429 | 0.1429 | **0.1857** | **0.1343** |      |
| 3  | BERT                     | 0.0715 | 0.2257 | 0.1429 | 0.2000 | 0.1286 | 0.0857 | 0.0600 |
| 4  | ALBERT                   | 0.1332 | **0.4176** | **0.3098** | 0.2000 | 0.1429 | 0.1286 | 0.0929 |
| 5  | RoBERTa                  | 0.1011 | 0.3158 | 0.2286 | 0.2000 | 0.1429 | 0.1286 | 0.0929 |
|    | CLEF'2019 CheckThat! Submitted Runs |      |      |      |      |      |      |      |
| 6  | Copenhagen-primary      | 0.1660 | 0.4176 | **0.2857** | **0.2571** | 0.2286 | 0.1571 | 0.1229 |
| 7  | Copenhagen-contr.-1     | 0.1496 | 0.3098 | 0.1429 | 0.2000 | 0.2000 | 0.1429 | 0.1143 |
| 8  | Copenhagen-contr.-2     | 0.1580 | 0.2740 | 0.1429 | 0.2286 | **0.2429** | 0.1786 | 0.1200 |
| 9  | TheEarthIsFlat-primary  | 0.1597 | 0.1953 | 0.0000 | 0.2286 | 0.2143 | 0.1857 | **0.1457** |
| 10 | TheEarthIsFlat-contr.-1 | 0.1453 | 0.3158 | **0.2857** | 0.1429 | 0.1429 | 0.1357 | 0.1171 |
| 11 | TheEarthIsFlat-contr.-2 | 0.1821 | **0.4187** | **0.2857** | 0.2286 | 0.2286 | **0.2143** | 0.1400 |
| 12 | IPIPAN-primary           | 0.1332 | 0.2865 | 0.1429 | 0.1430 | 0.3158 | 0.1500 | 0.1171 |
|    | CLEF'2020 CheckThat! Experimental results |      |      |      |      |      |      |      |
| 13 | SVM(TF.IDF)            | **0.0946** | 0.1531 | 0.0000 | 0.0600 | 0.0400 | 0.0450 | 0.0240 |
| 14 | BiLSTM+att              | 0.0151 | 0.0320 | 0.0000 | 0.0100 | 0.0150 | 0.0075 | 0.0090 |
| 15 | BERT                     | 0.0262 | 0.0819 | 0.0500 | 0.0300 | 0.0250 | 0.0125 | 0.0110 |
| 16 | ALBERT                   | 0.0537 | **0.2145** | **0.2000** | 0.0800 | **0.0500** | **0.0250** | **0.1600** |
| 17 | RoBERTa                  | 0.0424 | 0.1315 | 0.1000 | 0.0600 | 0.0400 | 0.0200 | 0.1400 |
|    | CLEF'2020 CheckThat! Submitted Runs |      |      |      |      |      |      |      |
| 18 | NLP_IR@UNED-primary      | **0.0867** | **0.2770** | **0.1500** | **0.1300** | **0.0950** | **0.0725** | **0.0390** |
| 19 | NLP_IR@UNED-contr.-1    | 0.0849 | 0.2590 | **0.1500** | 0.1200 | 0.0900 | 0.0675 | 0.0370 |
| 20 | NLP_IR@UNED-contr.-2    | 0.0408 | 0.1170 | 0.0500 | 0.0700 | 0.0450 | 0.0275 | 0.0180 |
| 21 | UAICS-primary           | 0.0515 | 0.2247 | **0.1500** | 0.0700 | 0.0500 | 0.0375 | 0.0270 |
| 22 | UAICS-contr.-1          | 0.0431 | 0.1735 | 0.1000 | 0.0500 | 0.0550 | 0.0450 | 0.0250 |
| 23 | UAICS-contr.-2          | 0.0328 | 0.1138 | 0.0500 | 0.0300 | 0.0350 | 0.0175 | 0.0190 |
| 24 | TobbEtuP-primary        | 0.0183 | 0.0326 | 0.0000 | 0.0200 | 0.0100 | 0.0100 | 0.0060 |
| 25 | TobbEtuP-contr.-1       | 0.0417 | 0.0784 | 0.0500 | 0.0300 | 0.0150 | 0.0150 | 0.0180 |

5.1 RQ1: BERT-related Language Models vs. Baselines

We firstly consider Table 5 which reports the attained accuracies when treating check-worthy sentence identification as a classification task, on the CLEF CheckThat! 2019 dataset. Firstly, in terms of F1, we note the relative weak performance of a classical SVM classifier with TF.IDF features (row 2), which performs equivalently to a random classifier. Indeed, while the SVM classifier has been trained using class weights to alleviate the issue of class imbalance, the low performance of SVM illustrates the difficulty of this task, and underlines that simply matching on what is being said by the speakers is insufficient to attain high accuracies on this task. Next, the BiLSTM+att classifier (row 3) markedly outperforms the random classifier, demonstrating that the deployment of pre-trained (i.e., GloVe) word embeddings allows a more flexible classifier not tied to the exact matching of tokens. Moreover, the use of the attention mechanism in BiLSTM also emphasises the importance of the context of each word. Finally, the state-of-the-art BERT-related models (BERT model, row 4; ALBERT model, row 5, and RoBERTa model, row 6) significantly outperform the random classifier, the SVM classifiers, and the BiLSTM+att classifiers. Thus, we conclude that, when treating the task as a classification task, all of the BERT-related language models can significantly outperform the SVM and BiLSTM+att classifiers. Among all the BERT-related models, ALBERT exhibits the highest performance.

Moving next to the ranking task on the 2019 dataset, Table 6 shows that the BERT model (row 3) performance is less than that of a classical SVM classifier using TF.IDF features (row 1). Both ALBERT (row 4) and RoBERTa (row 5) outperform SVM(TF.IDF) and BiLSTM+att (rows 1, 2) in terms of MRR. However, in terms of MAP, both ALBERT and RoBERTa only outperform SVM(TF.IDF) (row 1), and still underperform compared to BiLSTM+att (row 2). Next, when considering the results of the ranking task on the 2020 dataset, BERT (row 15), ALBERT (row 16) and RoBERTa (row 17) models all outperform BiLSTM+att (row 14) and SVM(TF.IDF) (row 13) on both MAP and MRR.

While the contrast between the F1 classification and the ranking results on the 2019 dataset is notable, the low classification recall for all models suggests that BERT, ALBERT, and RoBERTa (c.f. rows 4, 5, 6 in Table 5) cannot retrieve the most difficult check-worthy sentences, and hence also exhibit low MAP performances in the ranking task. From Table 5, we observe the inconsistent performances for the same language model across the 2019 and 2020 ranking datasets (i.e., row 1 vs. 16, row 4 vs. 18, row 7 vs. 20, row 10 vs. 22, row 13 vs. 24), we postulate that this may be
Table 7: Classification performances on CheckThat! 2019 dataset, alternating language models \(l_{rep}\) and entity embedding models \(m_{ent}\), and entity representation combination models \(e_{com}\). **Bold** indicate the best performance; Numbers in the Significance column indicate that the model is significantly better than the numbered model (McNemar’s Test, \(p<0.01\)).

| \# | \(l_{rep}\) | \(m_{ent}\) | \(e_{com}\) | P  | R  | F1  | Significance |
|----|-------------|-------------|-------------|----|----|-----|--------------|
| 1  | SVM(TF.IDF) | -           | similarity  | 0.01 | 0.01 | 0.01 | -            |
| 2  | SVM(TF.IDF) | Wikipedia2Vec | similarity | 0.04 | 0.03 | 0.03 | 1            |
| 3  | SVM(TF.IDF) | Wikipedia2Vec | emb_concat  | 0.06 | 0.05 | 0.05 | 1.2          |
| 4  | SVM(TF.IDF) | Wikipedia2Vec | emb_prod    | 0.05 | 0.04 | 0.04 | 1.2          |
| 5  | BiLSTM+att  | -           | similarity  | 0.12 | 0.07 | 0.09 | 1-4          |
| 6  | BiLSTM+att  | Wikipedia2Vec | similarity | 0.12 | 0.08 | 0.1  | 1-5          |
| 7  | BiLSTM+att  | Wikipedia2Vec | emb_concat  | 0.13 | 0.1  | 0.11 | 1-6          |
| 8  | BiLSTM+att  | Wikipedia2Vec | emb_prod    | 0.12 | 0.09 | 0.1  | 1-5          |
| 9  | BERT        | -           | similarity  | 0.12 | 0.09 | 0.1  | 1-5          |
| 10 | BERT        | Wikipedia2Vec | similarity | 0.12 | 0.1  | 0.11 | 1-6          |
| 11 | BERT        | Wikipedia2Vec | emb_concat  | 0.19 | 0.11 | 0.14 | 1-10, 13     |
| 12 | BERT        | Wikipedia2Vec | emb_prod    | 0.18 | 0.11 | 0.13 | 1-10, 13     |
| 13 | ALBERT      | -           | similarity  | 0.14 | 0.11 | 0.12 | 1-10         |
| 14 | ALBERT      | Wikipedia2Vec | similarity | 0.14 | 0.14 | 0.14 | 1-10, 13     |
| 15 | ALBERT      | Wikipedia2Vec | emb_concat  | 0.22 | 0.15 | 0.18 | 1-14, 17-20  |
| 16 | ALBERT      | Wikipedia2Vec | emb_prod    | 0.20 | 0.14 | 0.16 | 1-14, 17-20  |
| 17 | RoBERTa     | -           | similarity  | 0.14 | 0.11 | 0.12 | 1-10         |
| 18 | RoBERTa     | Wikipedia2Vec | similarity | 0.14 | 0.13 | 0.13 | 1-10         |
| 19 | RoBERTa     | Wikipedia2Vec | emb_concat  | 0.21 | 0.15 | 0.17 | 1-14, 17, 18 |
| 20 | RoBERTa     | Wikipedia2Vec | emb_prod    | 0.19 | 0.14 | 0.16 | 1-14, 17, 18 |

Table 8: Ranking performances on CheckThat! 2019 dataset, alternating language models \(l_{rep}\) and entity embedding models \(m_{ent}\), and entity representation combination models \(e_{com}\). **Bold** indicate the best performance.

| \# | \(l_{rep}\) | \(m_{ent}\) | \(e_{com}\) | MAP | MRR | P@1 | P@5 | P@10 | P@20 | P@50 |
|----|-------------|-------------|-------------|-----|-----|-----|-----|------|------|------|
| 1  | SVM(TF.IDF) | -           | -           | 0.1193 | 0.3513 | 0.1429 | 0.2571 | 0.1571 | 0.1714 | 0.1086 |
| 2  | SVM(TF.IDF) | Wikipedia2Vec | similarity | 0.1263 | 0.3254 | 0.2857 | 0.2000 | 0.2000 | 0.1286 | 0.0915 |
| 3  | SVM(TF.IDF) | Wikipedia2Vec | emb_concat  | 0.1332 | 0.3361 | 0.3254 | 0.2000 | 0.2000 | 0.1286 | 0.0915 |
| 4  | SVM(TF.IDF) | Wikipedia2Vec | emb_prod    | 0.1332 | 0.3361 | 0.3254 | 0.2000 | 0.2000 | 0.1286 | 0.0915 |
| 5  | BiLSTM+att  | -           | -           | 0.1453 | 0.2432 | 0.1429 | 0.1429 | 0.1429 | 0.1857 | 0.1343 |
| 6  | BiLSTM+att  | Wikipedia2Vec | similarity | 0.0715 | 0.2857 | 0.2432 | 0.1429 | 0.1286 | 0.0714 | 0.0314 |
| 7  | BiLSTM+att  | Wikipedia2Vec | emb_concat  | 0.0659 | 0.3361 | 0.2857 | 0.1429 | 0.1429 | 0.0714 | 0.0314 |
| 8  | BiLSTM+att  | Wikipedia2Vec | emb_prod    | 0.0659 | 0.3158 | 0.2000 | 0.1429 | 0.1286 | 0.0714 | 0.0314 |
| 9  | BERT        | -           | -           | 0.0715 | 0.2257 | 0.1429 | 0.2000 | 0.1286 | 0.0857 | 0.0600 |
| 10 | BERT        | Wikipedia2Vec | similarity | 0.1011 | 0.6196 | 0.3361 | 0.1714 | 0.1429 | 0.0929 | 0.0686 |
| 11 | BERT        | Wikipedia2Vec | emb_concat  | 0.0826 | 0.3361 | 0.3361 | 0.1429 | 0.1429 | 0.0929 | 0.0929 |
| 12 | BERT        | Wikipedia2Vec | emb_prod    | 0.1332 | 0.4176 | 0.3098 | 0.2000 | 0.1429 | 0.1286 | 0.0929 |
| 13 | ALBERT      | -           | -           | 0.1332 | 0.4176 | 0.3098 | 0.2000 | 0.1429 | 0.1286 | 0.0929 |
| 14 | ALBERT      | Wikipedia2Vec | similarity | 0.1453 | 0.4176 | 0.3361 | 0.2286 | 0.2000 | 0.1286 | 0.0929 |
| 15 | ALBERT      | Wikipedia2Vec | emb_concat  | 0.1580 | 0.6196 | 0.3361 | 0.2857 | 0.2571 | 0.2286 | 0.2286 |
| 16 | ALBERT      | Wikipedia2Vec | emb_prod    | 0.1332 | 0.4187 | 0.3361 | 0.2571 | 0.2571 | 0.2000 | 0.1286 |
| 17 | RoBERTa     | -           | -           | 0.1011 | 0.3158 | 0.2286 | 0.2000 | 0.1429 | 0.1286 | 0.0929 |
| 18 | RoBERTa     | Wikipedia2Vec | similarity | 0.1263 | 0.4176 | 0.3361 | 0.2286 | 0.2000 | 0.1286 | 0.0929 |
| 19 | RoBERTa     | Wikipedia2Vec | emb_concat  | 0.1453 | 0.4176 | 0.3361 | 0.2857 | 0.2571 | 0.2000 | 0.2286 |
| 20 | RoBERTa     | Wikipedia2Vec | emb_prod    | 0.1332 | 0.4187 | 0.3361 | 0.2571 | 0.2571 | 0.2000 | 0.2286 |

cased by the markedly different proportion of positive examples in the two test sets (as illustrated by the percentage of the check-worthy sentences in Table 7). Overall, in answer to RQ1, we conclude that while the BERT, ALBERT, and RoBERTa models perform well at classifying check-worthy sentences, for ranking they are most effective at higher rank sentences. On both tasks, ALBERT performs the best among the BERT-related language models.

### 5.2 RQ2: Using Entity Embeddings

We now examine the impact of entities at improving the classification accuracy. Firstly, from Table 7 we note that the F1 performance of the SVM classifier is improved by adding the entity similarity scores (row 2 vs row 1), echoing our earlier observations for ranking, on the 2019 dataset. Similarly, adding entity emb Prod (row 4) element-wise
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The product operation between language representation and entity pair representation and entity emb_concat (row 3) concatenating language representation and entity pair representation also improve the SVM classifier’s performance, using the 2019 dataset, in terms of precision, recall and F1 compared to SVM(TF.IDF) without entity information. Next, we observe that all of the neural language models (i.e., BiLSTM+att, BERT, ALBERT, RoBERTa) also exhibit a significantly improved accuracy when combined with entity embeddings (rows 7 & 8 vs. 5; rows 11 & 12 vs. 9; rows 15 & 16 vs. 13; rows 19 & 20 vs 17). On the contrary, even though we do observe an improvement when the neural models are combined with entity similarities (row 6 vs. 5; row 10 vs. 9, row 14 vs. 13; row 18 vs. 17), the improvement is not significant. Moreover, combining the neural models with the entity embedding information, both entity combination methods significantly outperform the corresponding language model when combined with simpler entity similarities. Indeed, our proposed entity-assisted ALBERT classifiers using the emb_concat method (row 16) attains the highest overall classification performance (an F1 score of 0.18). Table further shows that almost all neural models with all types of entity embeddings outperform the corresponding language models alone, in terms of F1. Thus, we conclude that the entity information (the entity similarity and embedding for the SVM classifier, the entity embeddings in the neural language models) can indeed improve the classification accuracy in the identification of check-worthy sentences.

Turning to the ranking task, in Table we observe that the use of entities (i.e., entity similarities, emb_concat, and emb_prod) enhances most of the approaches: the effectiveness of the SVM classifier is enhanced on MAP, P@1, and P@10. On the other hand, while BiLSTM+att is enhanced for MRR and P@1, when combined with any type of entity information, the MAP performances are damaged by the entity embeddings (rows 6-8 vs. 5). Finally, the BERT-related models (i.e., BERT, ALBERT, RoBERTa) are enhanced by all three types of entity information, regardless of the entity embedding combination model used, in terms of MAP, MRR, and P@1 (rows 10-12 vs. 9; rows 14-16 vs. 13; rows 18-20 vs. 17). When tested on the 2020 dataset, Table further shows that the ComplEx KG embedding model together with the emb_concat method, consistently improves all the neural networks’ performance on all metrics. Thus, we conclude that entity embeddings can consistently enhance the BiLSTM+att models for ranking on high precision metrics such as MRR and P@1, as well as enhance the SVM(TF.IDF) and neural language models (i.e., BERT, ALBERT, RoBERTa) across the evaluation metrics.

Therefore, in response to RQ2, we conclude that using entity embeddings – regardless of the KG embedding model from which the entity embeddings are obtained – does help to improve the BERT-related language models’ performance, on both precision and recall for the classification task, and on MAP, MRR and P@1 for the ranking tasks.

5.3 RQ3: Entity Representation

When considering identifying check-worthy sentences as a classification task, Table shows that all of the SVM(TF.IDF) and BERT-related language models are significantly improved when combined with entity embeddings, over the language models alone or with entity similarities. Meanwhile, we observe that using emb_concat only marginally outperforms emb_prod, without significant differences (row 3 vs. 4; row 7 vs. 8; row 11 vs. 12; row 15 vs. 16; row 19 vs. 20). Moreover, the ALBERT model with the emb_concat method using the Wikipedia2Vec KG embedding model (row 15) achieves the highest F1 score among all of the tested models shown in Table reftab:classification-RQ2. Thus, we conclude that using entity embeddings is more effective than using the entity similarity method suggested by Su et al. [10] on the classification task, which uses graph distance for estimating the similarity between entities.

Next, when considering the ranking task, Table shows that the BiLSTM+att, and BERT-related languages models all exhibit improved MRR and P@1 when combined with entity embeddings using the concatenation method, outperforming the entity similarity method (rows 3 & 4 vs. 2; 7 & 8 vs. 6; 11 & 12 vs. 10; rows 15 & 16 vs. 14; rows 19 & 20 vs. row 18). In terms of the entity representation methods for the embedded entities, emb_concat and emb_prod perform similarly for SVM and BiLST+att (rows 3 & 4, rows 7 & 8), however for the BERT models emb_concat exhibits an 84% increase over emb_prod (row 11 vs. 12). When combining the embedded entities with ALBERT and RoBERTa, we also observe that emb_concat consistently exhibits a performance increase over emb_prod (row 15 vs. 16; row 19 vs. 20). Thus, we can conclude that for the ranking task, the emb_concat model is more effective than emb-prob, and both embedding methods are more effective than the entity similarity baseline (rows 2, 6, 10, 14, 18).

Overall, in answer to RQ3, we conclude that using embedding entities obtained from KG embedding models, regardless of the representation method, improves all three BERT-based language representations better than the entity similarity information, with emb_concat exhibiting the highest effectiveness on both for the classification task (using the 2019 dataset) and the ranking task (using the 2019 & 2020 datasets).
Table 9: Classification performances on CheckThat! 2019 dataset, using emb_concat as entity representation combination method, while alternating language models $l_{rep}$ and entity embedding models $m_{ent}$. Bold indicate the best performance; Numbers in the Significance column indicate that the model is significantly better than the numbered model (McNemar’s Test, $p<0.01$).

| #  | $l_{rep}$          | $m_{ent}$          | P  | R  | F1  | Significance |
|----|-------------------|--------------------|----|----|-----|--------------|
| 1  | SVM(TF.IDF)       | Wikipedia2Vec      | 0.06| 0.05| 0.05|              |
| 2  | SVM(TF.IDF)       | TransE             | 0.06| 0.05| 0.05| -             |
| 3  | SVM(TF.IDF)       | TransR             | 0.06| 0.05| 0.05| -             |
| 4  | SVM(TF.IDF)       | RESCAL             | 0.06| 0.05| 0.05| -             |
| 5  | SVM(TF.IDF)       | DistMult           | 0.07| 0.05| 0.06| -             |
| 6  | SVM(TF.IDF)       | ComplEx            | 0.07| 0.05| 0.06| -             |
| 7  | BiLSTM+att        | Wikipedia2Vec      | 0.13| 0.10| 0.11| 1-6          |
| 8  | BiLSTM+att        | TransE             | 0.11| 0.08| 0.09| 1-6          |
| 9  | BiLSTM+att        | TransR             | 0.12| 0.08| 0.09| 1-6          |
| 10 | BiLSTM+att        | RESCAL             | 0.12| 0.08| 0.10| 1-6,8,9      |
| 11 | BiLSTM+att        | DistMult           | 0.13| 0.12| 0.12| 1-10         |
| 12 | BiLSTM+att        | ComplEx            | 0.14| 0.13| 0.13| 1-10         |
| 13 | BERT               | Wikipedia2Vec      | 0.19| 0.11| 0.14| 1-11         |
| 14 | BERT               | TransE             | 0.19| 0.10| 0.13| 1-11         |
| 15 | BERT               | TransR             | 0.19| 0.11| 0.14| 1-11         |
| 16 | BERT               | RESCAL             | 0.19| 0.11| 0.14| 1-11         |
| 17 | BERT               | DistMult           | 0.19| 0.12| 0.15| 1-16         |
| 18 | BERT               | ComplEx            | 0.20| 0.13| 0.15| 1-16         |
| 19 | ALBERT             | Wikipedia2Vec      | 0.22| 0.15| 0.18| 1-18         |
| 20 | ALBERT             | TransE             | 0.22| 0.14| 0.17| 1-18         |
| 21 | ALBERT             | TransR             | 0.23| 0.14| 0.18| 1-18         |
| 22 | ALBERT             | RESCAL             | 0.24| 0.15| 0.19| 1-21, 25-28  |
| 23 | ALBERT             | DistMult           | 0.24| 0.15| 0.19| 1-21, 25-28  |
| 24 | ALBERT             | ComplEx            | 0.25| 0.16| 0.20| 1-22, 25-30  |
| 25 | RoBERTa            | Wikipedia2Vec      | 0.21| 0.15| 0.17| 1-18         |
| 26 | RoBERTa            | TransE             | 0.21| 0.14| 0.16| 1-18         |
| 27 | RoBERTa            | TransR             | 0.21| 0.15| 0.17| 1-18         |
| 28 | RoBERTa            | RESCAL             | 0.20| 0.14| 0.16| 1-18         |
| 29 | RoBERTa            | DistMult           | 0.23| 0.15| 0.18| 1-18, 25-28  |
| 30 | RoBERTa            | ComplEx            | 0.24| 0.14| 0.18| 1-18, 25-28  |

5.4 RQ4: KG Embedding Model

Finally, we consider which KG embedding model is the most effective in providing entity embeddings for identifying the check-worthy sentences. Table 9 shows the results obtained by combining different KG entity embedding models with the various language representations for the classification task. We observe that ComplEx does not significantly outperform embedded Wikipedia2Vec when combined with SVM(TF.IDF) (row 6 vs. 1), but consistently and significantly outperforms Wikipedia2Vec, TransE, TransR and RESCAL (row 12 vs. rows 7-10; row 18 vs. 13-16; row 24 vs. 19-21; row 30 vs. 25-28) for all the neural language representation models we use. However, while ComplEx does not significantly outperform DistMult, across all language representation models, it does exhibit an average of 1% absolute improvement in F1 over the DistMul KG embeddings (see row 12 vs. 11, row 18 vs. 17, row 24 vs. 23, row 30 vs. 29). The results are expected, given previous reported results in the literature, since ComplEx and DistMult indeed outperform other KG embedding models on KG embedding link prediction task [13, 29].

For the ranking task, Table 10 shows that ALBERT + ComplEx achieves the best performance among our experiments, obtaining 0.1821, a tie with the best performing run in the official leader board, on the 2019 dataset. Moreover, it also shows that ALBERT + ComplEx obtains the highest MAP in the 2020 dataset among all the models we tested, as well as the models in the leader board. Under further investigation, we found that ALBERT + ComplEx successfully identified the single check-worthy sentence within one debate of the test set, and therefore obtained the highest improvement on MAP.

We further conducted a case study in order to understand why ComplEx can achieve the best performance consistently. Table 11 presents 2 cases where ComplEx model together with ALBERT language model successfully identified the check-worthy sentences, while other entity embedding models did not. Upon further investigation, we found that in these two cases, entity 1 and entity 2 are not related to each other closely, while Wikepedia did not mention entity 2 in
Table 10: Ranking performances on CheckThat! 2019 dataset, using emb_concat as entity representation combination method, while alternating language models lrep and entity embedding models ment. **Bold** indicate the best performance.

| # | lrep         | ment          | MAP  | MRR  | P@1  | P@5  | P@10 | P@20 | P@50 |
|---|--------------|---------------|------|------|------|------|------|------|------|
| 1 | SVM(TF.IDF)  | Wikipedia2Vec | 0.1332 | 0.3361 | 0.3254 | 0.2000 | 0.2000 | 0.1286 | 0.0915 |
| 2 | SVM(TF.IDF)  | TransE        | 0.1332 | 0.3361 | 0.3254 | 0.2000 | 0.2000 | 0.1286 | 0.0915 |
| 3 | SVM(TF.IDF)  | TransR        | 0.1263 | 0.5714 | 0.2857 | 0.1714 | 0.1429 | 0.0929 | 0.0929 |
| 4 | SVM(TF.IDF)  | RESCAL        | 0.1453 | 0.4176 | **0.3361** | 0.2857 | 0.2571 | 0.2000 | **0.2286** |
| 5 | SVM(TF.IDF)  | DISTMult      | 0.1453 | 0.3158 | 0.2857 | 0.2000 | 0.2000 | 0.2286 | 0.2000 |
| 6 | SVM(TF.IDF)  | ComplEx       | 0.1496 | 0.4187 | 0.3098 | 0.2857 | 0.2571 | 0.2000 | 0.1286 |
| 7 | BiLSTM+att   | Wikipedia2Vec | 0.0659 | 0.3361 | 0.2857 | 0.1429 | 0.1429 | 0.1429 | 0.1286 |
| 8 | BiLSTM+att   | TransE        | 0.0659 | 0.3158 | 0.2857 | 0.1429 | 0.1429 | 0.1429 | 0.1286 |
| 9 | BiLSTM+att   | TransR        | 0.0715 | 0.2257 | 0.1286 | 0.1429 | 0.1429 | 0.1429 | 0.1286 |
| 10| BiLSTM+att   | RESCAL        | 0.0659 | 0.3361 | 0.2857 | 0.1429 | 0.1429 | 0.1429 | 0.1286 |
| 11| BiLSTM+att   | DISTMult      | 0.0659 | 0.3158 | 0.2000 | 0.1429 | 0.1429 | 0.1429 | 0.1286 |
| 12| BiLSTM+att   | ComplEx       | 0.0715 | 0.2257 | 0.1286 | 0.1429 | 0.1429 | 0.1429 | 0.1286 |
| 13| BERT         | Wikipedia2Vec | 0.1011 | 0.6196 | 0.3361 | 0.1714 | 0.1429 | 0.0929 | 0.0686 |
| 14| BERT         | TransE        | 0.1011 | 0.6196 | 0.3098 | 0.2000 | 0.1714 | 0.1286 | 0.0929 |
| 15| BERT         | TransR        | 0.1011 | 0.6196 | 0.3098 | 0.1714 | 0.0929 | 0.0929 | 0.0929 |
| 16| BERT         | RESCAL        | 0.1263 | 0.5714 | 0.2857 | 0.1714 | 0.1429 | 0.0929 | 0.0929 |
| 17| BERT         | DISTMult      | 0.1263 | 0.6196 | 0.3098 | 0.2571 | 0.1429 | 0.0929 | 0.0929 |
| 18| BERT         | ComplEx       | 0.1453 | 0.6196 | 0.3361 | 0.2857 | 0.1714 | 0.1286 | 0.0929 |
| 19| ALBERT       | Wikipedia2Vec | 0.1580 | 0.6196 | 0.3098 | 0.2857 | 0.2571 | 0.2286 | **0.2286** |
| 20| ALBERT       | TransE        | 0.1332 | 0.4176 | 0.3361 | 0.1429 | 0.1429 | 0.1286 | 0.0929 |
| 21| ALBERT       | TransR        | 0.1263 | 0.3158 | 0.3098 | 0.2000 | 0.2286 | 0.1286 | 0.0929 |
| 22| ALBERT       | RESCAL        | 0.1332 | 0.5714 | 0.3098 | 0.2286 | 0.2000 | 0.1286 | 0.0929 |
| 23| ALBERT       | DISTMult      | 0.1580 | 0.4176 | 0.2857 | 0.2000 | 0.1429 | 0.1286 | 0.0929 |
| 24| ALBERT       | ComplEx       | 0.1821 | **0.6196** | **0.3361** | 0.3098 | **0.2857** | **0.2571** | **0.1286** |
| 25| RoBERTa      | Wikipedia2Vec | 0.1453 | 0.4176 | **0.3361** | 0.2857 | 0.2571 | 0.2000 | 0.2286 |
| 26| RoBERTa      | TransE        | 0.1332 | 0.4176 | 0.2857 | 0.2571 | 0.2000 | 0.2000 | 0.1286 |
| 27| RoBERTa      | TransR        | 0.1263 | 0.4176 | 0.2000 | 0.2857 | 0.2000 | 0.2286 | 0.2000 |
| 28| RoBERTa      | RESCAL        | 0.1453 | 0.3158 | 0.2857 | 0.2857 | 0.2000 | 0.2286 | 0.2000 |
| 29| RoBERTa      | DISTMult      | 0.1496 | 0.4187 | 0.3098 | 0.2857 | 0.2571 | 0.2000 | 0.1286 |
| 30| RoBERTa      | ComplEx       | 0.1660 | 0.5714 | **0.3361** | 0.3098 | 0.2000 | **0.2571** | **0.2286** |

Table 11: Two sentences that are correctly identified as check-worthy using ALBERT, ComplEx entity embedding model, and emb_concat model, but are otherwise not identified.

| Speaker     | Sentence                                                                 | Entity 1 | Entity 2 |
|-------------|---------------------------------------------------------------------------|----------|----------|
| Donald Trump| They want to take away your good health care, and essentially use socialism to turn America into Venezuela and Democrats want to totally open the borders. | Venezuela | Democrat |
| Donald Trump| And one state said – you know, it was interesting, one of the states we won, Wisconsin – I didn’t even realize this until fairly recently – that was the one state Ronald Reagan didn’t win when he ran the board his second time. | Wisconsin | Ronald Reagan |

the articles about entity 1. We therefore postulate that ComplEx is able to identify hidden relations between two weakly associated entities better than other entity embedding models.

Overall, we conclude that among all 6 KG embedding models we tested, ComplEx produces consistently the highest performance.

5.5 Failure Analysis

Due to the overall low performance of our models, we aim to identify the bottleneck of our framework, on the task of check-worthy sentences identification.

Table 14 shows that there are differences numbers of transcript and check-worthy sentences from different parties that participated in the debate. That is, check worthy sentences from interviews and speeches given by Trump alone makes up as much as 60% of the total number of check-worthy sentences. Moreover, there is a noticeable difference
Table 12: Classification performances on CheckThat! 2019 dataset. Bold indicate the best performance; Numbers in the column Significance indicate that the model is significantly better than the numbered model (McNemar’s Test, \( p < 0.01 \)).

| #  | \( l_{rep} \)       | \( m_{sent} \)    | \( e_{com} \)    | MAP  | MRR  | P@1  | P@5  | P@10 | P@20 | P@50 |
|----|---------------------|-------------------|------------------|------|------|------|------|------|------|------|
| 1  | Random Classifier   | -                  | -                | 0.01 | 0.01 | 0.01 | -    | -    | -    | -    |
| 2  | SVM(TF-IDF)         | -                  | -                | 0.01 | 0.01 | 0.01 | -    | -    | -    | -    |
| 3  | SVM(TF-IDF)         | Wikipedia2Vec      | emb_concat       | 0.06 | 0.05 | 0.05 | 1.2  | -    | -    | -    |
| 4  | SVM(TF-IDF)         | ComplEx            | emb_concat       | 0.07 | 0.05 | 0.06 | 1-2  | -    | -    | -    |
| 5  | BiLSTM+att          | -                  | -                | 0.12 | 0.07 | 0.09 | 1-4  | -    | -    | -    |
| 6  | BiLSTM+att          | Wikipedia2Vec      | emb_concat       | 0.13 | 0.10 | 0.11 | 1-5  | -    | -    | -    |
| 7  | BiLSTM+att          | ComplEx            | emb_concat       | 0.14 | 0.13 | 0.13 | 1-6  | -    | -    | -    |
| 8  | BERT                | -                  | -                | 0.12 | 0.09 | 0.10 | 1-5  | -    | -    | -    |
| 9  | BERT                | Wikipedia2Vec      | emb_concat       | 0.19 | 0.11 | 0.14 | 1-8  | -    | -    | -    |
| 10 | BERT                | ComplEx            | emb_concat       | 0.20 | 0.13 | 0.15 | 1-9  | -    | -    | -    |
| 11 | ALBERT              | -                  | -                | 0.14 | 0.11 | 0.12 | 1-6,8| -    | -    | -    |
| 12 | ALBERT              | Wikipedia2Vec      | emb_concat       | 0.22 | 0.15 | 0.18 | 1-10,13 | - | -    | -    |
| 13 | ALBERT              | ComplEx            | emb_concat       | 0.25 | 0.16 | 0.20 | 1-12,14-16 | - | -    | -    |
| 14 | RoBERTa             | -                  | -                | 0.14 | 0.11 | 0.11 | 1-6,8| -    | -    | -    |
| 15 | RoBERTa             | Wikipedia2Vec      | emb_concat       | 0.21 | 0.15 | 0.17 | 1-11,14 | - | -    | -    |
| 16 | RoBERTa             | ComplEx            | emb_concat       | 0.24 | 0.14 | 0.18 | 1-12,14,15 | - | -    | -    |

Table 13: Performances on the ranking metrics on both CLEF' 2019 & 2020 CheckThat! dataset. Bold denotes the best performance for a given measure in a given year.

| #  | \( l_{rep} \)     | \( m_{sent} \)    | \( e_{com} \)    | MAP  | MRR  | P@1  | P@5  | P@10 | P@20 | P@50 |
|----|-------------------|-------------------|------------------|------|------|------|------|------|------|------|
| 1  | SVM(TF-IDF)       | -                 | -                | 0.1193 | 0.3513 | 0.1429 | 0.2571 | 0.1571 | 0.1714 | 0.1086 |
| 2  | SVM(TF-IDF)       | Wikipedia2Vec     | emb_concat       | 0.1332 | 0.3361 | 0.3254 | 0.2000 | 0.2000 | 0.1286 | 0.0915 |
| 3  | SVM(TF-IDF)       | ComplEx           | emb_prod         | 0.1332 | 0.3158 | 0.3098 | 0.2000 | 0.2571 | 0.1429 | 0.0929 |
| 4  | BiLSTM+att        | -                 | -                | 0.1455 | 0.2432 | 0.1429 | 0.1429 | 0.1429 | 0.1857 | 0.1343 |
| 5  | BiLSTM+att        | Wikipedia2Vec     | emb_concat       | 0.0659 | 0.3361 | 0.2857 | 0.1429 | 0.1429 | 0.0714 | 0.0314 |
| 6  | BiLSTM+att        | ComplEx           | emb_concat       | 0.0715 | 0.2257 | 0.1286 | 0.1429 | 0.1429 | 0.1857 | 0.1343 |
| 7  | BERT              | -                 | -                | 0.1011 | 0.6196 | 0.3361 | 0.1714 | 0.1429 | 0.0929 | 0.0686 |
| 8  | BERT              | Wikipedia2Vec     | emb_concat       | 0.1011 | 0.6196 | 0.3361 | 0.2857 | 0.1714 | 0.1286 | 0.0929 |
| 9  | BERT              | ComplEx           | emb_concat       | 0.1332 | 0.4176 | 0.3098 | 0.2000 | 0.1714 | 0.1286 | 0.0929 |
| 10 | ALBERT            | -                 | -                | 0.1580 | 0.6196 | 0.3098 | 0.2857 | 0.2571 | 0.2286 | 0.2286 |
| 11 | ALBERT            | Wikipedia2Vec     | emb_concat       | 0.1821 | 0.6196 | 0.3361 | 0.3098 | 0.2857 | 0.2286 | 0.2286 |
| 12 | ALBERT            | ComplEx           | emb_concat       | 0.1660 | 0.5174 | 0.3361 | 0.3098 | 0.2857 | 0.2286 | 0.2286 |
| 13 | RoBERTa           | -                 | -                | 0.0424 | 0.1815 | 0.1000 | 0.6000 | 0.0400 | 0.1400 | 0.0200 |
| 14 | RoBERTa           | Wikipedia2Vec     | emb_concat       | 0.0424 | 0.1815 | 0.1000 | 0.6000 | 0.0400 | 0.1400 | 0.0200 |
| 15 | RoBERTa           | ComplEx           | emb_concat       | 0.0923 | 0.1814 | 0.1500 | 0.0700 | 0.0450 | 0.0225 | 0.0150 |

between transcript including Democrat candidates and Republic candidates. For example, check-worthy sentences from Democratic debates have a much higher number of entities detected per check-worth sentences, than those from Republican candidates. Further, we notice a strong correlation between the number of entities per check-worth sentences and the recall from the classification task, i.e., Democratic debates has an average number of entities per check-worthy sentences of 2.62, and has a recall of 0.31, compared to the republican debate that has 2 entities per check-worth sentences and only 0.15 recall, and transcripts considering Trump alone has an average number of entities as low as 1.16, with a recall of 0.11.
Table 14: Descriptive analysis of the test set of 2020 dataset. Note, this table consist of only check-worthy sentences (denoted as CW). The results we investigate here is obtained using ALBERT language model, ComplEx entity embedding method, and emb_concat method.

| debate type  | # of transcript | # of cw  | cw/transcript | # of entities/CW | Recall (classification) |
|--------------|-----------------|---------|---------------|------------------|------------------------|
| Democratic   | 4               | 26      | 6.5           | 2.62             | 0.31                   |
| Republican   | 1               | 7       | 7             | 2                | 0.15                   |
| Mixed        | 2               | 23      | 11.5          | 2.57             | 0.17                   |
| Trump alone  | 13              | 83      | 6.38          | 1.16             | 0.11                   |

Table 15: A selected cases of check-worthy sentences, the identified entities, and if ALBERT + ComplEx successfully identified it as check-worthy. **Bold** denotes the identified entities.

| Speaker | Sentence                                                                 | # of entities | Predicted correctly |
|---------|---------------------------------------------------------------------------|---------------|---------------------|
| Trump   | Trump was totally against the war in Iraq.                               | 2             | Y                   |
| Trump   | But when you make your car or when you make your air conditioner, and you think you’re going to fire all of our workers and open up a new place in another country, and you’re going to come through what will be a very strong border, which is already – you see what’s happened; 61 percent down now in terms of illegal people coming in. | 1             | N                   |
| Cruz    | Bernie helped write Obamacare.                                            | 2             | Y                   |
| Cruz    | There are many people in America struggling with exactly what you are, in the wreckage of Obamacare, with skyrocketing premiums, with deductibles that are unaffordable, and with really limited care. | 2             | N                   |
| Clinton | Trump’s on record extensively supporting intervention in Libya, when Gaddafi was threatening to massacre his population. | 3             | Y                   |
| Clinton | And I do think there is an agenda out there, supported by my opponent, to do just that. | 0             | N                   |

Moreover, Table 15 shows 6 sentences, with number of identified entities, and if the classifier correctly identified the sentence as check-worthy. We observe that in the three of false negative cases (row 2, 4, and 6), the number of entities are either less than or equals to 2.

We therefore postulate that the number of entities per sentence can indeed affect the performance of our proposed framework.

5.6 Recap of Main Findings

In this section, we recap on our main findings for RQs 1-4 and indicate the implications of our study, by use of Tables 12 & 13. For each language model, the summarising tables present results obtained using three conditions: language model only; with entity pair representation using Wikipedia2Vec KG embedding model and using emb_concat method; and with entity pair representation using ComplEx embedding and using emb_concat method. We do not include emb_prod method in our summarising tables, as our results for RQ3 showed that emb_concat consistently outperforms emb_prod across both 2019 & 2020 datasets and both classification and ranking tasks (see Section 5.3).

For the classification task (Table 12 on the 2019 dataset), we highlight our conclusion from RQ1 (see Section 5.1) that the ALBERT language model (rows 11 - 13) significantly outperforms all other language models. We also confirm our conclusion from RQ2 (see Section 5.2) that entity embeddings improve language models’ performance at identifying check-worthy sentences (row 3 & 4 vs. 2, rows 6 & 7 vs. 5, rows 9 & 10 vs. 8, rows 12 & 13 vs. 11, rows 15 & 16 vs. 14). Finally, we highlight our conclusion from RQ4 (see Section 5.4) that the ComplEx embedding method (rows 4, 7, 10, 13 & 16) – which uses the facts-alone KG embedding – significantly outperforms the semantic KG embedding method (i.e., Wikipedia2Vec, rows 3, 6, 9, 12 & 15).

For the ranking task (Table 13 on both the 2019 & 2020 datasets), we draw similar conclusions as for classification task: The ALBERT language model (rows 10 - 12 for the 2019 dataset, rows 22 & 23 for the 2020 dataset) consistently outperforms all other language models, while using the ComplEx embedding model (rows 3, 6, 9, 12, 15 for the 2019 dataset).
dataset, 17, 19, 21, 23, 25 for the 2020 dataset) consistently outperforms all other KG embedding models. Moreover, ALBERT + ComplEx + emb_concat (row 11 for the 2019 dataset, row 20 for the 2020 dataset) obtains the best performance among all tested models. Thus, we conclude that ALBERT, ComplEx, and emb_concat, can best identify and rank check-worthy sentences in a given speech or debate transcript.

In short, the findings of our study can thus be summarised as follows:

- Deep neural language models help identify the sentences that require further manual fact-checking;
- Embedded entities within sentence help identify the sentences that requires further manual fact-checking;
- The most effective way to combine entity pair representation with text representation is to concatenate two vectors together;
- The tested facts-alone KG embedding models perform better than tested semantic KG embedding method (i.e., Wikipedia2Vec). The best performing KG embedding model in our study is the ComplEx model.
- The performance of our framework is affected by the number of entities present in the sentence. Since Donald Trump prefer sentences with less entities, it’s difficult to identify his sentences as check-worthy than other candidates.

6 Conclusions

In this paper, we proposed a uniform framework for the task of check-worthy sentence identification, formulated as either a classification or a ranking task. We proposed to use BERT-related pre-trained language representations, and, in a novel manner, integrated entity embeddings obtained from knowledge graphs into the classifier and ranker. When considering the check-worthy sentence identification as a classification task, our experiments – conducted using the CLEF’2019 and 2020 CheckThat! datasets – showed that the ALBERT model outperforms the SVM(TF.IDF), BiLSTM+att, BERT, and RoBERTa text representation models. Moreover, the application of our proposed Entity-Assisted language models further improved the performance of the SVM(TF.IDF), BiLSTM+att, and all the BERT-related language models, over the models that combine language models with entity similarities and relatedness. When considered as a ranking task, we found that all types of entity embeddings improve all the language models in identifying the top ranked check-worthy sentences, but do not perform as well in the lower ranks. Furthermore, on both classification and ranking tasks, using ALBERT for text representation consistently performs the best among all the tested text representation models, with or without entity features. In addition, we found that use of the DistMult and ComplEx KG embedding models both improve all the language models the most, while ALBERT + ComplEx achieved the best F1 on classification task on the 2019 dataset, and the best MAP performance on both the 2019 (a tie with the best performing submission) and 2020 datasets. Thus, we conclude that our framework, which combines deep learning language models with embedded entity representations in a novel manner, can achieve the state-of-the-art performance in identifying check-worthy sentences. Moreover, we argue that given the flexibility of our framework, achieved by concatenating sentence and entities representations instead of jointly training them, it can be applied to a number of sentence classification tasks, using an appropriate language model and an appropriate KG embedding model. Our work also gives support to future workflows where journalists and representatives of other fact-checking organisations could benefit from accurate assistive classifiers, to focus their efforts only on a subset of suspicious claims that are worth checking thereby ensuring a faster and wider dissemination of news. Our future research plan regarding the check-worthiness task are 2-fold: first, we plan to enrich the information of the identified entities, (e.g., by adding the type of the entity, and the place and time of the entity, if applicable); second, we aim to research new approaches leveraging social media in check-worthy sentences classification and retrieval.

References

[1] Naeemul Hassan, Chengkai Li, and Mark Tremayne. Detecting check-worthy factual claims in presidential debates. In *Proceedings of CIKM*, pages 1835–1838, 2015.

[2] Pepa Atanasova, Preslav Nakov, Georgi Karadzhov, Mitra Mohtarami, and Giovanni Da San Martino. Overview of the CLEF-2019 CheckThat! Lab on automatic identification and verification of claims. task 1: Check-worthiness. In *Proceedings of CLEF in CEUR Workshop*, 2019.

[3] Giovanni Da San Martino, Maram Hasanain, Reem Suwaileh, Fatima Haouari, Nikolay Babulkov, Bayan Hamdan, Alex Nikolov, Shaden Shaar, and Zien Sheikh Ali. Overview of checkthat’ 2020: Automatic identification and verification of claims in social media. In *Proceedings of CLEF in CEUR*, 2020.
Entity-Assisted Language Models for Identifying Check-worthy Sentences

[4] Casper Hansen, Christian Hansen, J Simonsen, and Christina Lioma. Neural weakly supervised fact checkworthiness detection with contrastive sampling-based ranking loss. In Proceedings of CLEF in CEUR Workshop, 2019.

[5] Rudra Dhar, Subhabrata Dutta, and Dipankar Das. A hybrid model to rank sentences for checkworthiness. In Proceedings of CLEF in CEUR Workshop, 2019.

[6] Luca Favano, M Carman, and Jakob Grue Simonsen. TheEarthIsFlat’s submission to CLEF’19 CheckThat! challenge. In Proceedings of CLEF in CEUR Workshop, 2019.

[7] John Langshaw Austin. How to do things with words, volume 88. Oxford university press, 1975.

[8] Michael Saward. The representative claim. Contemporary political theory, 5(3):297–318, 2006.

[9] Isabelle Augenstein, Christina Lioma, Dongsheng Wang, Lucas Chaves Lima, Casper Hansen, Christian Hansen, and Jakob Grue Simonsen. MultiFC: A real-world multi-domain dataset for evidence-based fact checking of claims. In Proceedings of EMNLP-IJCNLP, pages 4685–4697, 2019.

[10] Ting Su, Craig Macdonald, and Iadh Ounis. Entity detection for check-worthiness prediction: Glasgow Terrier at CLEF CheckThat! 2019. In Proceedings of CLEF in CEUR Workshop, 2019.

[11] Ikuya Yamada, Hiroyuki Shindo, Hideaki Takeeda, and Yoshiyasu Takefuji. Joint learning of the embedding of words and entities for named entity disambiguation. In Proceedings of CoNLL, pages 250–259, 2016.

[12] Antoine Bordes, Nicolas Usunier, Alberto Garcia-Duran, Jason Weston, and Oksana Yakhnenko. Translating embeddings for modeling multi-relational data. In Proceedings of NeurIPS, pages 2787–2795, 2013.

[13] Théo Trouillon, Johannes Welbl, Sebastian Riedel, Éric Gaussier, and Guillaume Bouchard. Complex embeddings for simple link prediction. In Proceedings of ICML, pages 2071–2080, 2016.

[14] Zhengyan Zhang, Xu Han, Zhiyuan Liu, Xin Jiang, Maosong Sun, and Qun Liu. ERNIE: Enhanced language representation with informative entities. In Proceedings of ACL, pages 1441–1451, 2019.

[15] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of NAACL-HLT, page 4171–4186, 2019.

[16] Zhenzhong Lan, Mingda Chen, Sebastian Goodman, Kevin Gimpel, Piyush Sharma, and Radu Soricut. ALBERT: A lite BERT for self-supervised learning of language representations. In Proceedings of ICLR, 2019.

[17] Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. RoBERTa: A robustly optimized BERT pretraining approach. arXiv preprint arXiv:1907.11692, 2019.

[18] Karen Sparck Jones. A statistical interpretation of term specificity and its application in retrieval. Journal of documentation, 28:11–21, 1972.

[19] Eric Brill. A simple rule-based part of speech tagger. In Proceedings of ANLP, pages 152–155, 1992.

[20] Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. Efficient estimation of word representations in vector space. In Proceedings of ICLR, 2013.

[21] Chen Qu, Liu Yang, Minghui Qiu, W Bruce Croft, Yongfeng Zhang, and Mohit Iyyer. Bert with history answer embedding for conversational question answering. In Proceedings of SIGIR, pages 1133–1136, 2019.

[22] Zeynep Akkalyoncu Yilmaz, Shengjin Wang, Wei Yang, Haotian Zhang, and Jimmy Lin. Applying BERT to document retrieval with Birch. In Proceedings of EMNLP, pages 19–24, 2019.

[23] Peng Lin, Qi Song, and Yinghui Wu. Fact checking in knowledge graphs with ontological subgraph patterns. Data Science and Engineering, 3(4):341–358, 2018.

[24] Antoine Bordes, Xavier Glorot, Jason Weston, and Yoshua Bengio. A semantic matching energy function for learning with multi-relational data. Machine Learning, 94(2):233–259, 2014.

[25] Maximilian Nickel, Volker Tresp, and Hans-Peter Kriegel. A three-way model for collective learning on multi-relational data. In Proceedings of ICML, pages 809–816, 2011.

[26] Zhen Wang, Jianwen Zhang, Jianlin Feng, and Zheng Chen. Knowledge graph embedding by translating on hyperplanes. In Proceedings of AAAI, pages 1112–1119, 2014.

[27] Ines Chami, Adva Wolf, Da-Cheng Juan, Frederic Sala, Sujith Ravi, and Christopher Ré. Low-dimensional hyperbolic knowledge graph embeddings. In Proceedings of ACL, pages 6901–6914, 2020.

[28] Yankai Lin, Zhiyuan Liu, Maosong Sun, Y Liu, and X Zhu. Learning entity and relation embeddings for knowledge graph completion. In Proceedings of AAAI, pages 2181–2187, 2015.
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[29] Bishan Yang, Wen-tau Yih, Xiaodong He, Jianfeng Gao, and Li Deng. Embedding entities and relations for learning and inference in knowledge bases. In Proceedings of ICLR, 2015.

[30] Daifeng Li and Andrew Madden. Cascade embedding model for knowledge graph inference and retrieval. Information Processing & Management, 56(6):102093, 2019.

[31] Aditya Grover and Jure Leskovec. node2vec: Scalable feature learning for networks. In Proceedings of SIGKDD, pages 855–864, 2016.

[32] Zhiqing Sun, Zhi-Hong Deng, Jian-Yun Nie, and Jian Tang. Rotate: Knowledge graph embedding by relational rotation in complex space. In Proceedings of ICLR, pages 2071–2080, 2018.

[33] Shuai Zhang, Yi Tay, Lina Yao, and Qi Liu. Quaternion knowledge graph embeddings. In Proceedings of NeurIPS, pages 2735–2745, 2019.

[34] Luis A Pineda, Noé Hernández, Iván Torres, Gibrán Fuentes, and Nydia Pineda De Avila. Practical non-monotonic knowledge-base system for un-regimented domains: A case-study in digital humanities. Information Processing & Management, 57(3):102214, 2020.

[35] K Srinivasa and P Santhi Thilagam. Crime base: Towards building a knowledge base for crime entities and their relationships from online news papers. Information Processing & Management, 56(6):102059, 2019.

[36] Zhaochen Guo and Denilson Barbosa. Robust entity linking via random walks. In Proceedings of CIKM, pages 499–508, 2014.

[37] Zhengyan He, Shujie Liu, Mu Li, Ming Zhou, Longkai Zhang, and Houfeng Wang. Learning entity representation for entity disambiguation. In Proceedings of ACL, pages 30–34, 2013.

[38] Matthew E Peters, Mark Neumann, Robert L Logan IV, Roy Schwartz, Vidur Joshi, Sameer Singh, and Noah A Smith. Knowledge enhanced contextual word representations. In Proceedings of EMNLP-IJCNLP, pages 43–54, 2019.

[39] Antoine Bosselut, Hannah Rashkin, Maarten Sap, Chaitanya Malaviya, Aslı Çelikyılmaz, and Yejin Choi. COMET: Commonsense transformers for automatic knowledge graph construction. In Proceedings of ACL, pages 4762–4779, 2019.

[40] Pepa Gencheva, Preslav Nakov, Lluis Märquez, Alberto Barrón-Cedeño, and Ivan Koychev. A context-aware approach for detecting worth-checking claims in political debates. In Proceedings of RANLP, pages 267–276, 2017.

[41] Ayush Patwari, Dan Goldwasser, and Saurabh Bagchi. Tathya: A multi-classifier system for detecting check-worthy statements in political debates. In Proceedings of CIKM, pages 2259–2262, 2017.

[42] Israa Jaradat, Pepa Gencheva, Alberto Barrón-Cedeño, Lluis Märquez, and Preslav Nakov. Claimrank: Detecting check-worthy claims in arabic and english. In Proceedings of NAACL-HLT, pages 26–30, 2018.

[43] Slavena Vasileva, Pepa Atanasova, Lluis Márquez, Alberto Barrón-Cedeño, and Preslav Nakov. It takes nine to smell a rat: Neural multi-task learning for check-worthiness prediction. In Proceedings of RANLP, pages 1229–1239, 2019.

[44] Jakub Gasior and Piotr Przybyla. The IPIPAN team participation in the check-worthiness task of the CLEF2019 CheckThat! lab. In Proceedings of CLEF in CEUR Workshop, 2019.

[45] L Coca, Ciprian-Gabriel Cusmuliuc, and Adrian Iftene. CheckThat! 2019 UAICS. In Proceedings of CLEF in CEUR Workshop, 2019.

[46] J Martinez-Rico, Lourdes Araujo, and Juan Martinez-Romo. Nlp&ir@ uned at checkthat! 2020: A preliminary approach for check-worthiness and claim retrieval tasks using neural networks and graphs. In Proceedings of CLEF in CEUR Workshop, 2020.

[47] Ciprian-Gabriel Cusmuliuc, Lucia-Georgiana Coca, and Adrian Iftene. Uaics at checkthat! 2020: Fact-checking claim prioritization. In Proceedings of CLEF in CEUR Workshop, 2020.

[48] Yavuz Selim Kartal and Mucahid Kutlu. Tobb etu at checkthat! 2020: Prioritizing english and arabic claims based on check-worthiness. In Proceedings of CLEF in CEUR Workshop, 2020.

[49] Alberto Barrón-Cedeno, Tamer Elsayed, Preslav Nakov, Giovanni Da San Martino, Maram Hasanain, Reem Suwaileh, Fatima Haouari, Nikolay Babulkov, Bayan Hamdan, Alex Nikolov, et al. Overview of checkthat! 2020: Automatic identification and verification of claims in social media. In Proceedings of CLEF in CEUR Workshop, pages 215–236, 2020.

[50] Joachim Daiber, Max Jakob, Chris Hokamp, and Pablo N. Mendes. Improving efficiency and accuracy in multilingual entity extraction. In Proceedings of I-Semantics, pages 121–124, 2013.
[51] Kyunghyun Cho, Bart Van Merriënboer, Caglar Gulcehre, Dzmitry Bahdanau, Fethi Bougares, Holger Schwenk, and Yoshua Bengio. Learning phrase representations using RNN encoder-decoder for statistical machine translation. In *Proceedings of EMNLP*, pages 1724–1734, 2014.

[52] Giovanni Luca Ciampaglia, Prashant Shiralkar, Luis M Rocha, Johan Bollen, Filippo Menczer, and Alessandro Flammini. Computational fact checking from knowledge networks. *PLoS one*, 10(6):e0128193, 2015.

[53] Kenton Lee, Luheng He, and Luke Zettlemoyer. Higher-order coreference resolution with coarse-to-fine inference. In *Proceedings of NAACL-HLT*, pages 687–692, 2018.

[54] Ian H Witten and David N Milne. An effective, low-cost measure of semantic relatedness obtained from Wikipedia links. In *Proceedings of AAAI*, pages 25–30, 2008.

[55] Da Zheng, Xiang Song, Chao Ma, Zeyuan Tan, Zihao Ye, Jin Dong, Hao Xiong, Zheng Zhang, and George Karypis. DGL-KE: Training knowledge graph embeddings at scale. In *Proceedings of SIGIR*, page 739–748, 2020.

[56] Sean MacAvaney, Andrew Yates, Arman Cohan, and Nazli Goharian. CEDR: Contextualized embeddings for document ranking. In *Proceedings of SIGIR*, pages 1101–1104, 2019.

[57] Ting Su, Craig Macdonald, and Iadh Ounis. Ensembles of recurrent networks for classifying the relationship of fake news titles. In *Proceedings of SIGIR*, pages 893–896, 2019.

[58] Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, R’emi Louf, Morgan Funtowicz, and Jamie Brew. Huggingface’s transformers: State-of-the-art natural language processing. *arXiv preprint arXiv:1910.03771*, 2019.

[59] Ganggao Zhu and Carlos Angel Iglesias Fernandez. Sematch: Semantic entity search from knowledge graph. In *Proceedings of SumPre-HSWI*, 2015.