

DEAP-FAKED: Knowledge Graph based Approach for Fake News Detection

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Abstract—Fake News on social media platforms has attracted a lot of attention in recent times, primarily for events related to politics (2016 US Presidential elections), healthcare (infodemic during COVID-19), to name a few. Various methods have been proposed for detecting Fake News. The approaches span from exploiting techniques related to network analysis, Natural Language Processing (NLP), and the usage of Graph Neural Networks (GNNs). In this work, we propose DEAP-FAKED, a knowleDgE grAPh FAKE nEws Detection framework for identifying Fake News. Our approach is a combination of the NLP - where we encode the news content, and the GNN technique - where we encode the Knowledge Graph (KG). A variety of these encodings provides a complementary advantage to our detector. We evaluate our framework using two publicly available datasets containing articles from domains such as politics, business, technology, and healthcare. As part of dataset pre-processing, we also remove the bias, such as the source of the articles, which could impact the performance of the models. DEAP-FAKED obtains an F1-score of 88% and 78% for the two datasets, which is an improvement of $\sim 21\%$, and $\sim 3\%$ respectively, which shows the effectiveness of the approach.

Index Terms—Online Social Media, Knowledge Graphs, Machine Learning, Fake News.

I. INTRODUCTION

Online social media platforms such as Twitter, Facebook have become a de facto news sources for the public in general [1]. However, not every piece of information escalated on these platforms is genuine. These platforms often cater to the spread of misinformation (such as Fake News, hoaxes, and rumors) [2], which is intended to deliberately deceive the readers for personal advantage. As evident by the impact of misinformation on various events, for instance, a widely circulated piece of Fake News about the 2016 US presidential election [3] worried the world, demonstrating that Fake News may have a global impact. Furthermore, the covid19 pandemic [4] has become a significant source of misinformation these days. It is imperative that misinformation can be found in practically every sphere, including health [5], [6], politics [7], [8], and finance [9], [10]. This clearly reflects the utmost concern about proposing mechanisms for detecting misinformation.

Previously, researchers have looked into various aspects of misinformation, such as examining user profiles involved in rumors [11], determining the veracity of the rumor on social media platforms [12]. Several techniques have been employed in this domain, for instance, NLP [13], network-

based approaches ranging from simple network analysis [14] to recent advancements of GNNs [15], and multi-modal approach as well [16]. Recently, heterogeneous graphs have been examined, such as exploiting social context information [17], news articles, and its metadata to build heterogeneous information networks [18].

In this work, we exploit a KG-based framework for detecting Fake News articles, a specific category of misinformation. KGs are the integrated graph-structured knowledge base that has been compiled from diverse sources¹. Specifically, one fact is represented using *head, relation, tail* triplets (h, r, t) where h, t are the nodes representing entities and r represents the relation between the two nodes (entities). In addition to storing the extracted knowledge, KGs are widely employed in machine learning for predicting tasks, as the usage of KGs has been shown in the literature to aid in the development of better models [19].

In this work, we have proposed DEAP-FAKED, a two-part KG-based framework for Fake News detection, where each part is independent, and they deal with different techniques. In the first part, we employ an NLP-based technique to encode the news content. In our case, we use the news title. For this purpose, we use biLSTM based neural networks, which are the de facto for sequence data encoding. In the second part, we first identify and extract named entities from the news text and then map them to a KG. Next, we employ GNN-based technique to encode the entities in the KG. These two parts are then concatenated together in order to detect Fake News.

In comparison to previous works, our work is different in the following ways. First, we show that by utilizing only titles of the news articles in our framework, we are able to achieve better results. Second, we have also handled the biasedness², which has largely been ignored in previous works. To evaluate our methodology, we used two publicly available datasets containing $\sim 15k$ number of articles in total. In comparison to the baseline methodologies we employed, we show that our framework produces better results consistently. Our framework is able to achieve F1-score of 88% and 78% for the two datasets, which is an improvement of 21% and 3%, respectively.

¹<https://blog.google/products/search/introducing-knowledge-graph-things-not/>

²<https://hbr.org/2019/10/what-do-we-do-about-the-biases-in-ai>

The rest of the paper is organized as follows. Section II covers Related Work, Section III covers Proposed Methodology, Section IV covers Dataset Description and Experimental Setup, Section V covers Evaluation Results, and Section VI covers Conclusions and Future Work.

II. RELATED WORK

This section first discusses literature with respect to misinformation covering both Fake News and rumors. Next, we also discuss the role of KGs in misinformation detection.

Presently, misinformation has attracted a lot of attention from the research community, and it has been examined from a variety of angles, in particular, utilizing user profiles to identify users who are involved in rumors [11], determining the veracity of rumors on social media platforms [12], and analyzing the network structure to detect Fake News [14]. Apart from utilizing text, researchers have also looked into a multi-modal approach [16].

Researchers have used techniques such as NLP [13], network-based approaches to predict misinformation, ranging from simple network analysis [14] to exploiting current breakthroughs in GNNs such as utilizing Graph Convolutional Network [15], gated GNN [20]. In addition, other works looked into Generative-Adversarial Network (GAN) [21], LSTM-based architecture [22], deep Convolutional Neural Network [23], event Adversarial Network [16], hybrid Convolutional Neural Network [24].

Recently, heterogeneous graphs are also being explored, which is a promising direction in misinformation detection, especially in Fake News. In [17], authors detect Fake News leveraging social context information into a heterogeneous graph. News articles and their metadata are being used to build heterogeneous information networks [18]. Heterogeneous Graph Neural Networks such as Adversarial active learning [25] and Graph-aware co-attention networks [26] have also been explored for detecting Fake News. As part of the heterogeneous graphs, KGs-based approaches have also been investigated in Fake News detection. For example, a Knowledge-driven Multi-modal Graph Convolutional Network (KMGCN) has been used in [27]. In [28], by harvesting data from popular fact-checking websites and exploring additional information from DBpedia, authors introduced a KG of fact-checked claims. While some works have proposed general Fake News detection by exploring content [29], [30], others have focused on specific domains of Fake News such as politics [31], healthcare [32], to name a few. In addition, researchers have also used KGs for presenting explainable Fake News detection methods [33].

In this work, we identify whether a particular news article is Fake or not, using KG approach. Specifically, we show that by utilizing only titles of the news articles in our framework, we are able to achieve good evaluation scores. In addition, we have also handled the bias in the dataset, which has been ignored in the previous studies.

III. METHODOLOGY

Our proposed framework DEAP-FAKED consists of three individual components, which is shown in Fig. 1. These components are,

- 1) **News encoder:** this component performs the contextual encoding of the news title.
- 2) **Entity encoder:** this component identifies the named entities present in the news title and encodes the individual entities using KG.
- 3) **Classification Layer:** this component consolidates the news encoder's and entity encoder's representations to perform the final downstream Fake News classification learning.

We will now discuss each of these components in more detail.

A. News encoder

Efficient representation of sequential data is a long-standing research problem in the NLP domain [34]. The intention is to represent the text data, which is inherently sequential in nature, into a continuous vector representation. On the individual token level, such representation has been shown to encode semantic, associative, and even analogical similarities [35]. Further aggregation of the token representation has also been applied to transfer such similarities to a higher sentence level [36]. This makes it imperative to encode the news title into a vector representation in such a way that it becomes easier to compare multiple news based on their semantic similarities rather than their syntactic similarities.

While conventional work has focused on the sequential representation of textual data, which is unidirectional in nature, recent work [37] proposed a more efficient contextual representation, which is bidirectional. This approach makes sure that the individual token attends to both the prior and later tokens for their local representation, which in turn implies that the final sentence representation is more holistic and contextual in nature. We tried a variety of stacking, unidirectional and bidirectional sequence encoders. Finally, we select a 2-layer stacked biLSTM as the main subcomponent of our news encoder, as shown in the right block of the Fig. 1.

B. Entity encoder

The recent trend in Fake News detection research leverage complementary information, apart from the news title, to further improve the detection performance. The additional information includes, but is not limited to, the news content [38], the social interaction [39], the news propagation [40], and even the feedback on the news [41]. While these approaches have made sufficient progress, access to such wide and diverse of data is a bottleneck for several industrial applications and academic research. We try to handle this shortcoming by leveraging an inherent information present within the news text - *Named Entities*. For example, a news title with text - "*US Officials See No Link Between Trump and Russia*", contains two entities - "*Trump*" of person type and "*Russia*" of geolocation type. These entities bring an interesting paradigm

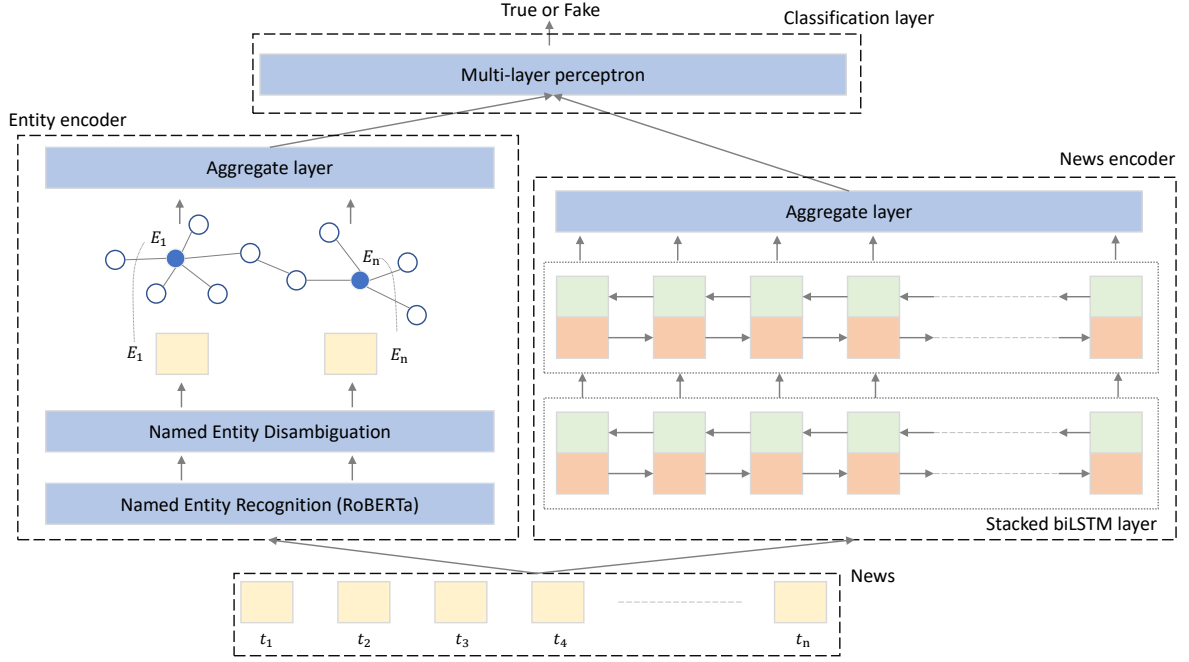


Fig. 1: Illustration of the proposed DEAP-FAKED framework. The left sub-figure shows the entity encoder module. The right sub-figure shows the news encoder module. The top sub-figure is the Fake News classifier module. The bottom shows the tokenized news as the input to the entity encoder and news encoder.

to the research, as now, for Fake News detection we consider not only the news content but also the association of multiple entities present in the news. This way, our framework complements the original news content, and on the other hand, it does not create a bottleneck requirement of hard-to-get data sources.

To consider entities, our framework includes an entity encoder component (left block in Fig. 1), which first identifies the relevant entities in the news and then encodes them. We use Wikidata³, an open-source KG, as the source to match the entities and ComplEx KG embedding technique [42] to embed the entities. Following our news example, “Trump” from the news can be mapped to the respective KG entity instance, which in turn is connected to other entities in the form of triplets. A triplet is a collection of three elements which is represented in the (h, r, t) fashion. Here, h and t represent entities and r represent the connection between them. Example of connected triplet for entity “Trump” could be $(Trump, birthCountry, USA)$ and $(Trump, gender, Male)$. We consider KG as the base of our entity encoder for the following reasons, (1) recent advances in KG embedding has shown efficient propagation of information within the graph, which makes an entity’s representation a consolidation of itself and also its neighbors’ information, (2) several large scale KGs

like Wikidata and DBpedia are open-source projects and hence readily available. The entity encoder component includes the following sub modules,

1) *Named entity recognition (NER)*: this sub module is a classification layer that assigns labels to the input news content. The final result includes a set of tokens that have been assigned to a set of predefined classes. While the assignment represents entity identification, the classes represent the entity types and could include *Persons, Objects, Places, Locations*, etc. We use Spacy⁴ based RoBERTa model, which has shown comparative results with the state-of-the-art entity recognizer. The result is further passed to the disambiguation part.

2) *Named entity disambiguation (NED)*: while the NER sub modules identify the entity and its type, to leverage the KG, we include a disambiguation step, which connects the entity identified by NER with the most similar entity present in the KG. As we consider Wikidata KG as our knowledge base, we use disambiguation services⁵ exposed by Wikidata for this step. The result is the mapping of each entity from the last step with the corresponding Wikidata entity URI.

3) *KG embedding*: we perform KG embedding using the ComplEx embedding algorithm [42], which represents entities and relations of the KG in complex space. Of this embedding, we discard the imaginary part and keep the real part as the

³<https://www.wikidata.org/>

⁴<https://spacy.io/>

⁵<https://www.wikidata.org/w/api.php?action=help>

final representation of the entities. ComplEx embedding is favored as it can capture anti-symmetric relations better than the operations in the Euclidean space. The disambiguated entities from the last step are filtered from the pre-trained KG representation matrix.

4) *Entity encoder aggregation layer*: the final sub module performs a permutation invariant aggregation of the entities' representation extracted after the KG embedding step. This is an essential distinction, as while a news article could contain multiple entities, the order in which the entities appear is irrelevant if we segregate the news content representation. This can be easily shown by transforming news from its active to passive style, which highlights that the association matters and not the order.

C. Fake News classifier

Fake News classifier consolidated the representation output of the entity and news encoder sub modules, as shown in the top block of the Fig. 1. In our framework, the two representations are concatenated to create a super representation of the news content and entities. This representation is then passed to further non-linear activated layers with decreasing layer dimensionality. The final layer consolidated the information into a single dimension which is activated by a sigmoid layer, where the final output represents the probability of the news as either true or fake. A binary cross-entropy loss is applied to this layer's output which is used for calculating the gradient during backpropagation.

IV. DATASET DESCRIPTION AND EXPERIMENTAL SETUP

In this section, we present the dataset, the baseline methods and the experiment details. In entirety, we want to answer the following questions,

- 1) Is the DEAP-FAKED framework able to improve the Fake News detection performance by considering open-source KG?
- 2) What is the change in performance observed after considering entity information along with news content?
- 3) How does the other open-source knowledge bases of textual nature, like Wikipedia, compare with KG for the Fake News detection?

A. Dataset

1) *Fake News dataset*: For a holistic analysis of our proposed framework, we considered news items belonging to diverse domains. The first dataset is the **Kaggle Fake News** dataset⁶, which consists of 20,387 news items, having a near equal combination of true and Fake News. The news covers several domains such as Politics, Business, and Technology. While the dataset provides several additional pieces of information, we ignore news content and author information and only consider the news title for our analysis. This decision further complicates the Fake News detection problem as the available resource for classification is quite limiting in terms

of textual length. However, it is in accordance with previous studies observation that a majority of Fake News is propagated on social media platforms like Twitter, which has strict short text limits^{7 8}. Furthermore, the initial analysis of the dataset exposed the presence of bias terms in the dataset, which are majorly associated with one of the classes - true or Fake News. One such example is the publication house name, where most of the news items from famous publications like "New York Times" are true news. These biases are usually introduced in the dataset during the data collection phase. To handle such cases, we removed any mention of the bias terms from the dataset. The news items are then processed by removing stopwords and special characters. Finally, only the news items whose entities can be mapped to the KG using NER and NED steps are kept. The complete pre-processing step brought down the news item count to $\sim 14k$ with a distribution of 60% - 40% of true and Fake News classes, respectively. We denote this dataset as **KFN-UB**.

The second dataset is **CoAID** [43], which contains diverse COVID-19 healthcare misinformation, including Fake News from websites and social platforms. CoAID includes 4,251 news items. In accordance with the first dataset, we identified and removed bias terms from the CoAID dataset and then performed the text cleaning and entity mapping steps. This brought down the total news item count to 632. We denote this cleaned unbiased dataset as **CoAID-UB**. A complete distribution detail of both the datasets is provided in Table I.

| stats | KFN-UB | CoAID-UB |
|------------|--------------------------------|------------|
| Domain(s) | Politics, Business, Technology | Healthcare |
| Total News | 14,187 | 632 |
| True News | 9,129 | 359 |
| Fake News | 5,058 | 273 |

TABLE I: Comparative distribution of news items after pre processing the Kaggle Fake News and CoAID dataset, denoted as KFN-UB and CoAID-UB respectively.

2) *Knowledge Graph*: For the KG, we use Wikidata5M [44], which is a subset of the Wikidata KG. It is created by only considering the "valid" facts, where the validity is confirmed if all entities and relations in the fact have a Wikipedia article and long description (at least five words long). A complete statistics of the dataset is provided in Table II. This dataset is chosen as (1) it consists of the most relevant entities and hence could provide a good coverage for the news articles, and (2) it is a good trade-off from the complete Wikidata KG, which contains $\sim 18M$ entities and $\sim 748M$ facts, hence mitigate big data issue and reduces extensive computation requirement for KG embedding. As suggested in the previous section, the ComplEx algorithm is used to generate embedding for each entity in the Wikidata5M KG,

⁷<https://news.mit.edu/2018/study-twitter-false-news-travels-faster-true-stories-0308>

⁸<https://www.marketwatch.com/story/fake-news-spreads-more-quickly-on-twitter-than-real-news-2018-03-08>

⁶<https://www.kaggle.com/c/fake-news/overview>

which is later used in the entity encoder to filter out respective entities within the news.

| stats | Wikidata5M | Wikidata |
|-----------|------------|-------------|
| entities | 4,594,485 | 18,697,897 |
| relations | 822 | 1,874 |
| triplets | 20,624,575 | 748,530,833 |

TABLE II: **Comparative distribution of entities, relations and triplets in Wikidata5M and wikidata**

B. Baselines

We compare DEAP-FAKED with the following models:

- 1) **ExtraTreeClassifier**: ExtraTreeClassifier is a decision tree-based classification algorithm that fits randomized decision trees on various sub-samples of the dataset. It further improves upon the predictive accuracy and controls the over-fitting problem by averaging over the multiple fitted trees. In our case, we first extract the count vectorization-based feature matrix from the tokenized news items and then pass it to ExtraTreeClassifier.
- 2) **LSTM**: Long-Short Term Memory is a gated variant of Recurrent Neural Networks. It mitigates the exploding gradient problem of the classical sequence-based neural networks. LSTM is able to attend to long-term memory and hence is considered the de facto baseline for many text-related downstream tasks. In our case, we pass the title of the tokenized news items to the LSTM layer and connect the last hidden state of the LSTM with a sigmoid activated MLP layer to perform the Fake News classification.
- 3) **SentRoBERTa** [45]: SentRoBERTa is a modification of the pre-trained RoBERTa network that uses siamese and triplet network structures to derive semantically meaningful sentence embeddings. In our case, we use SentRoBERTa to generate sentence level embedding for news titles that are connected with the sigmoid activated MLP layer to perform the Fake News classification.
- 4) **StackedBiLSTM**: StackedBiLSTM is a two layer stacking of the conventional bidirectional LSTM layer. Being bidirectional, it is able to consider past as well as future token when processing a particular token. This property is generalized at the sentence level as well. A stack of 2 such bidirectional layers provides StackedBiLSTM additional relevant parameters to create efficient embeddings. In our case, we pass the tokenized news title to the StackedBiLSTM layer and connect the last hidden state with sigmoid activated MLP layers to perform the Fake News classification.
- 5) **EntWiki-StackedBiLSTM**: This model incorporates the entities along with the news title. For each news item, the news title is encoded using the StackedBiLSTM, as discussed before. Apart from this, we leverage the entity encoder component of our framework with one major difference - instead of using KG, we use Wikipedia article material for entity encoding. For this purpose, we

extract the Wikipedia description of the entity identified in the news item and encode that description using SentRoBERTa. The news title and entity encoding are then concatenated and passed to the sigmoid activated MLP layer to perform the Fake News classification.

Note that the selected baseline models are diverse in terms of complexity as well as the information considered for prediction. ExtraTreeClassifier is a relatively simpler Machine learning model working on bag of words based features. It completely ignores the entity information by only considering the news title. LSTM, SentRoBERTa, and StackedBiLSTM are neural network-based models which add another layer of complexity by factoring sequential order of the text and not a simple bag of words. They also only consider the news title information. Finally, EntWiki-StackedBiLSTM is the most complex of the baselines, as it considers the entities along with the news title. It compares well with our framework as the only difference between the two models is that while DEAP-FAKED considers KG in entity encoder, EntWiki-StackedBiLSTM uses Wikipedia articles.

C. Experiment Setup

1) **Metric**: For the evaluation of the Fake News detection, we consider Accuracy and F1 macro score as the preferred metrics of comparison. While accuracy is the de facto metric for the classification task, it lacks comparative prowess when the dataset is imbalanced. To handle such a case, we also consider the F1-score, which is a harmonic mean of the recall and precision metric. Further considering macro averaging of F1 score, we assign a weighted score to each class's score, which is based on the proportion of data item counts of each class. This provides a more holistic metric for our use case, where the datasets are imbalanced.

2) **Implementation details**: Each model is developed and tested in Keras. For the performance calculation, each dataset has been split into 80% - 20% ratio for train and test set, respectively, and in a stratified fashion. For the KFN-UB dataset, the batch size is set to 32, whereas for the CoAID-UB dataset, it is 8. The hidden state's dimension is fixed to 256 for all of the models, along with early stop loss patience step size of 2, and max epochs of 100. For the bag of words model, max feature size is set to 10k and for the LSTM based models, max vocabulary is set to 10k as well. Finally, each model is trained on the datasets for three trials with different seed values. The average performance metric is recorded for the best performing model on the test dataset.

V. EVALUATION

To answer the questions asked in Section IV, we present the consolidated performance score in Table III.

Q1 raises concerns about the use of DEAP-FAKED for improving the performance for Fake News detection. As evident by the results, DEAP-FAKED reports the highest score on both of the datasets. Observing scores for the KFN-UB dataset, the improvement is quite impressive as the difference

| Model vs Dataset | KFN-UB | | | | CoAID-UB | | | |
|------------------------------|---------------|---------|---------------|----------|---------------|---------|---------------|----------|
| | F1 avg. | F1 std. | Acc avg. | Acc std. | F1 avg. | F1 std. | Acc avg. | Acc std. |
| <i>ExtraTreeClassifier</i> | 0.7663 | 0.002 | 0.7831 | 0.002 | 0.7526 | 0.009 | 0.7638 | 0.008 |
| <i>LSTM</i> | 0.7810 | 0.009 | 0.8109 | 0.008 | 0.7255 | 0.021 | 0.7402 | 0.008 |
| <i>SentRoBERTa</i> | 0.6476 | 0.054 | 0.6879 | 0.040 | 0.7292 | 0.130 | 0.7375 | 0.116 |
| <i>StackedBiLSTM</i> | 0.7878 | 0.005 | 0.8137 | 0.002 | 0.7476 | 0.046 | 0.7585 | 0.030 |
| <i>EntWiki-StackedBiLSTM</i> | 0.8809 | 0.006 | 0.8898 | 0.008 | 0.7436 | 0.031 | 0.7454 | 0.032 |
| <i>DEAP-FAKED</i> | 0.8866 | 0.007 | 0.8955 | 0.007 | 0.7813 | 0.032 | 0.7822 | 0.033 |

TABLE III: Performance score of the models detailed in the paper is presented here. For each of the dataset, we report F1 macro and Accuracy metric values. We present average and standard deviation of the performance observed after performing 3 trials with different starting seed. For both the datasets, DEAP-FAKED reports the best performance value.

is $\sim 24\%$ in terms of average F1-score and $\sim 21\%$ in terms of average accuracy score. One additional point to highlight is the low standard deviation in the reported scores of DEAP-FAKED, which is 0.007 for both, F1-score and Accuracy score. These reports showcase the superiority and also the stability of the model, even on performing multiple trials with different starting random seeds. One interesting observation is the low performance of the SentRoBERTa model. Its low score is attributed to the drastic difference between the dataset used for pretraining the model and the KFN-UB, which covers a wide variety of domains. Using the pre-trained model only for news embedding generation left the baseline with a small number of tunable parameters present in the classification layer, which could have been another reason for the low score. This observation is proved right if we consider the tunable LSTM based models, which report higher scores. Observing the scores for the CoAID-UB dataset, DEAP-FAKED reports improvements of $\sim 3\%$ in terms of average F1 and Accuracy score. The standard deviation is also minimal, especially when comparing to the other neural network based models. The low improvement score is expected as the CoAID-UB dataset belongs to the medical domain, but Wikidata5M KG covers a wider set of domains with an unequal distribution. We attribute the difference in improvements to the higher popularity of certain domains over others, especially in the case of entities present in the Wikidata5M KG. One interesting observation is the high performance of the ExtraTreeClassifier model, which in spite of being a bag of words based model, performs better than complex recurrent layer based models. On further analysis, we found that the reason for this behavior is the smaller news title size in the CoAID-UB dataset. A decrease in the text size directly affects the capability of pure sequential text-based models which use recurrent layers, as they fail to get enough tokens per text to create meaningful representation. Because of this, a simple bag of words based model may report a higher performance score unless we complement the text data with additional information like entities - as done by DEAP-FAKED.

Q2 raises concerns over the requirement of entity information for the Fake News detection problem. To answer this question, we performed a comparative analysis of the models which contain the entity encoder module against the models which doesn't. The result of this analysis is presented in Table

| | KFN-UB | | CoAID-UB | |
|----------------------------------|---------------|---------------|---------------|---------------|
| | F1 avg. | Acc avg. | F1 avg. | Acc avg. |
| <i>Models w/o entity encoder</i> | 0.7537 | 0.7805 | 0.7477 | 0.7585 |
| <i>Models w. entity encoder</i> | 0.8838 | 0.8926 | 0.7624 | 0.7638 |

TABLE IV: Comparative score of models with and without the entity encoder sub module. We report the average F1 and Accuracy score for KFN-UB and CoAID-UB datasets.

IV. As evident from the table, models with the entity module have, on average higher performance scores for both datasets. To be exact, the average improvement is $\sim 13\%$ F1-score for KFN-UB and $\sim 1.5\%$ F1-score for CoAID-UB.

Q3 raises concerns about the preference of KG-based entity encoder in DEAP-FAKED against text-based entity encoder. To answer this question, we can reflect back to the result of EntWiki-StackedBiLSTM and DEAP-FAKED from the Table III. As evident in both the cases, the KG-based model performs better than the text-based model. This is due to the concentrated information present in the KG-based embeddings, where encoding is propagated from multiple hops to the root entity node. This aggregation of relevant information lets the root node capture information which is far away in the KG. On the other hand, textual descriptions are the uncompressed and unstructured form of information. Hence, a large amount of textual information is required to consolidate the same amount of information when compared to KG. This point is further endorsed by the fact that we observed similar performance between the two models in KFN-UB dataset, where news title are long and hence contains lots of entities. On the other hand, a larger difference in score is observed in the CoAID-UB dataset, where news titles are smaller in size and hence relatively with a lesser number of entities. The reduction in entities is further complemented with "infamous" entities in CoAID-UB, which inherently have smaller descriptions, which in overall contributed to the mentioned observation.

VI. CONCLUSIONS AND FUTURE WORK

Considering the recent surge in the number of Fake News, especially on online social media platforms, the topic related to Fake News detection has gained attention from the vast research community. In this work, we proposed DEAP-FAKED, a knowledge graph-based framework for the detection of Fake News. The approach uses minimum text, that is, only the title

of the news articles, which requires less computational time and simulates the low-text Fake News propagation observed in the social media platform. We compliment the low-text news title by identifying named entities and mapping these entities to an open-source KG. Embeddings are trained for entities in the KG by following an unsupervised KG embedding procedure, and the representation of the relevant entities is later filtered out for Fake News classification. On the dataset side, we consider a wide variety of datasets belonging to different domains. We carefully remove the bias from the datasets before feeding the data to the models. Comparing the proposed framework with other baseline approaches, we answer questions on the selection, performance, and preference of the proposed framework. Overall, DEAP-FAKED scores are better than the state-of-the-art results on both the datasets.

We have multiple plans to improve this work -

- 1) Experimenting with a combination of KG-based and Wikipedia textbase entity encoders could lead to an enhanced framework.
- 2) Handling of literal nodes in the knowledge graph, like numbers, dates, strings, descriptions, etc. The current KG embedding technique used (ComplEx) does not consider these types of nodes in KG.
- 3) Facts and information changes over time. So, each relation should have a time associated with it, such that more importance is given to *new* triplets and less to *old* triplets
- 4) Use of techniques, for instance, attention networks for explaining the outcomes of the models.

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