Human-oriented fuzzy-based assessments of knowledge graph embeddings for fake news detection

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Abstract. In the era of information overload, distinguishing between real and fake news is a critical challenge, particularly in public social networking domains. For this purpose, an approach based on the synergy accomplished by a Neurosymbolic AI system, powered with Fuzzy Logic techniques, is introduced to achieve understandable fact-checking classification results. The work proposes a fact-checking approach based on Knowledge Graph Embedding (KGE) techniques. It extracts the involved entities from textual data in the form of triples that, projected in a vector space, form graphs that effectively highlight contextual information. The classification results are interpreted by exploiting fuzzy set modelling, which aims to improve the presentation of the final results. Specifically, we use the Hits@N metric to design fuzzy variables whose linguistic terms reflect news distribution. Then, by exploiting fuzzy rule design, human-like classification performance evaluation is provided. Through experimental evaluation of the benchmark dataset, our approach shows its effectiveness in discriminating between real and fake news, enhanced by straightforward explanations driven by the fuzzy rule design.

Keywords: Fuzzy logic · Knowledge graph embeddings · NeuroSymbolic AI · Fake news detection · Human-oriented approach

1 Introduction

In recent years, the proliferation of fake news through different media, such as social media platforms, online news websites, and messaging apps, has emerged as a significant challenge in digital communication. Fake news, simulated or deceitful information presented as real news, can potentially mislead and control individuals, affect public opinion, and even impact political processes [26]. As a result, detecting fake news has become critical for ensuring the trustworthiness and integrity of information published through online platforms.

The primary challenges in detecting fake news, as identified by [23, 17], encompass difficulties in obtaining precise statistical ratings for news, the necessity of auxiliary information like user social engagements on social media, and the complexities presented by large, incomplete, unstructured, and noisy data. These challenges are mainly caused by the nature of fake news, primarily written in natural language and formulated to mislead readers. To mitigate these hindrances, various methodologies have been proposed, including the utilisation of Natural Language Processing (NLP) [27], supervised techniques [7], unsupervised techniques [5], deep learning-based approaches [17], and fuzzy-based approaches [32, 19].

The most common techniques for detecting fake news are supervised methods, specifically machine learning-based methods. These methods aim to improve the accuracy of fake news detection. Nevertheless, these works overlook aspects such as dealing with vague and noisy data and improving the explanation of the results. The aforementioned aspects can be addressed through NeuroSymbolic AI powering fuzzy logic and graph-based techniques.

The ability of fuzzy logic to deal with imprecise and uncertain information offers a robust framework for modelling the uncertainty present in textual statements and supporting the explainability of outcomes that often are just machine-interpretable.

In light of this consideration, our approach exploits the effectiveness of NeuroSymbolic AI (NeSy AI), leveraging knowledge graph techniques to build knowledge graphs based on semantic relationships extracted from unstructured textual data. The generated graphs are then employed to train a knowledge graph embedding model for fact-checking. Combining fuzzy logic with knowledge graph-related techniques enables determining the authenticity of different sentence parts with a degree of certainty, thereby improving fake news detection and their classification through a human-oriented approach. To the best of our knowledge, this is the first proposal that integrates fuzzy logic with KGE techniques for fake news detection.

The contributions of this paper are manifolds as:

1) A knowledge graph extracted from natural language text is leveraged to train a KGE model. Specifically, two knowledge graphs and their respective KGE models are created for fact-checking, one from fake news and the other from real news. This way, the KGE models are specialised to represent text describing real and fake news. The final system can evaluate the veracity of the news, discriminating accurately between fake and real news.

2) Fuzzy sets are defined to support the human-oriented interpretation of the fakeness/veracity of computed results. Two fuzzy variables are designed to describe the result of the KGE model evaluation of fake and real news, and one fuzzy variable provides a final outcome about the fakeness of the input news.

3) In a nutshell, it's a comprehensive news evaluation approach that interprets the truthfulness of news stories in a human-like manner., exploiting fuzzy sets to translate the KGE metrics, such as Hits@N, for news classification evaluation and to provide a final classification interpretation of the news.

The remainder of the paper is organised as follows: Section 2 outlines the main contributions developed in this research area. Section 3 depicts the tools, techniques and methods used for creating knowledge graphs and training knowledge graphs embedding models, as well as the main details of the proposed fuzzy layer. Section 4 presents and discusses the results of the proposed system. Finally, Section 5 presents the conclusions derived from the study.

2 Related works

Various approaches have been proposed to address fake news detection. These methods encompass machine learning, NLP, knowledge graph-related techniques, and fuzzy logic.

One of the most used approaches is the application of machine learning techniques. In [22] and [20] both utilised various machine learning algorithms, such as K-Nearest Neighbour, Support Vector Machine, Decision Tree, Naïve Bayes, and Logistic regression, to detect fake news with high accuracy. In [13], the authors present a simple approach for detecting fake news on social media using the K-Nearest Neighbour classifier with a classification accuracy of approximately 79% on a Facebook news posts dataset. An approach based on transformer architecture, specifically an extension of the Bidirectional Encoder Representations from Transformers (BERT) architecture, called joint BERT, is proposed in [28]. The proposal outperforms baseline methods on specific Arabic fake news datasets, showing higher accuracy and F1 score.

Another technique widely used for fake news detection is NLP. That is the case in [10], where two methods are developed for analysing tweets about COVID-19 and 5G conspiracy theories. For the first dataset, the authors used well-known techniques such as Bag of Words (BoW) and BERT and for the former one, a Graph Neural Networks-based approach (GNNs). In [34], a novel method that adopts fact-checking in conjunction with linguistic characteristics analysis to differentiate fake news from real news is presented. For that, a crowd-sourced knowledge graph is suggested as an initial solution for gathering up-to-date factual information regarding news events.

Collectively, these studies highlight the potential of different approaches in effectively identifying and combating fake news from an accuracy point of view. Knowledge graph-based techniques are also widely used in fake news detection. Unlike the above approaches, knowledge graph-based techniques enhance fake news detection systems by providing a structured representation of information, enabling semantic understanding and explanations.

Gong et al. [9] comprehensively reviewed graph-based fake news detection methods, categorising them into knowledge-driven, propagation-based, and heterogeneous social context-based methods. Graph-based methods are effective resources for unsupervised fake news detection since they help to investigate inter-user behaviour [8]. A heterogeneous document graph for incorporating topics and entities from news is created for learning the topic-enriched and contextual entity representations for fake news classification [11]. In [15], a framework named DEAP-FAKED for identifying fake news is presented. The authors combine natural language processing and tensor decomposition models to encode news content and embed Knowledge Graph entities. The framework was evaluated in two datasets containing articles from domains, achieving an F1-score of 88% and 78% for the two datasets.

Several approaches in the literature exploit fuzzy logic to address fake news detection. In particular, the synergy between Convolutional Recurrent Neural Networks (CRNN) and Fuzzy Logic has been used for fake news classification, outperforming existing methods and achieving high accuracy on multiple datasets [6]. In order to improve the prediction of Arabic fake news, fuzzy logic is employed to enhance the prediction of a modified random forest model focusing on text, user features, and text features [31]. In [32], the authors propose an innovative fuzzy logic-based deep hybrid model to improve fake news detection by leveraging news articles and textual and numerical context information, achieving state-of-the-art results on a fact-checking benchmark dataset. Another work integrating the fuzzy paradigm with neural networks and using sentiment analysis to improve fake news detection is presented in [16].

Like machine learning approaches, the above proposals, based on graph methods and fuzzy logic, aim to improve fake news detection mostly from an accuracy point of view. Conversely, in this work, we propose a human-oriented approach to improve end-users understanding by integrating the fuzzy paradigm with KGE techniques.

3 Method

The proposal aims to create a feasible framework for detecting fake and real news and increase robustness and end-user explanations. Figure 1 depicts the data flow of the pipeline describing the proposed framework. The input news collection is arranged for the *KGE model training* component and divided into training and validation data. Then, the data is further split into fake news and real news. At this point, data are processed by the *Knowledge graph building* to yield two knowledge graphs, one for the fake news and the other for the real news. The graphs feed the *KGE model training* component that is trained on that input graphs. Once the KGE models are trained, they can be used to evaluate unseen news; the Hits@N measure is used to estimate the relevance of the input news for the input news collection, so, for each unseen news, two Hits@N values are yielded for fake and real news. The *Fuzzy layer* is in charge of providing a more straightforward and human-oriented interpretation of those measures values that, leveraging proper fuzzy variables design, provide a linguistic interpretation about the *Fakeness* of the input news. In the upcoming sections, additional details are provided for each introduced component.

3.1 Knowledge graph construction

As stated, our approach relies on representing unstructured data through a Knowledge Graph (KG). KG is a structured representation of knowledge, typically in the form of entities (nodes) and their relationships (edges) between entity pairs. It allows the organisation of information in a graph format for efficient storage, retrieval, and finding complex relationships. In our approach, two KGs

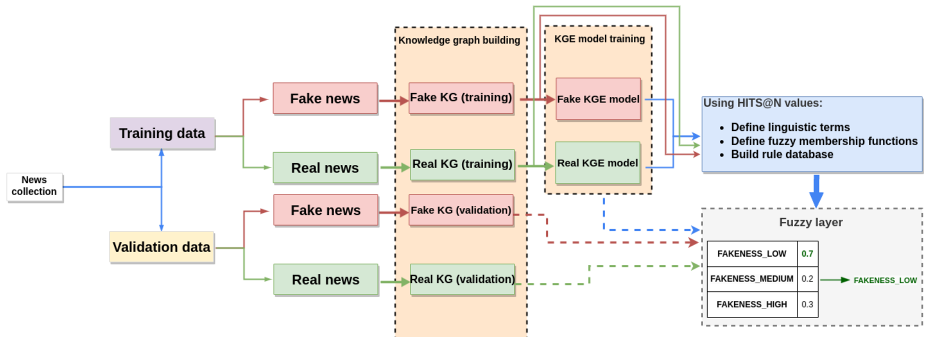


Fig. 1: Pipeline describing the proposed approach.

are constructed, one from fake news and another from real news. The KGs encode entities and relationships in the form of triples (h,r,t) to be later projected in vector space representations (see Section 3.2).

To extract the triples from natural language text, we utilise REBEL [12], a pre-trained language model, which is a seq2seq model built on BART [14]. REBEL performs end-to-end relation extraction by translating natural language sentences into triples for various relation types. These triples are then used to construct the knowledge graph. The so-computed KGs, jointly with their respective models, serve as a foundation for capturing the semantic relationships relevant to fake and real news, which can then be used for fact-checking.

3.2 Knowledge graph embedding model training

KGEs are typically used for downstream tasks [24] like link prediction and entity recognition. However, recent research on NeuroSymbolic AI [2] shows embeddings as an additional step into the Knowledge Representation (KR) validation rather than a traditional downstream task.

Among the several KGE models in the literature, the translational space embedding model, also known as TransE [1], allows representation of the relationship between two entities by a translation operation in the embedding space. It provides a simple but powerful framework for capturing semantic associations between entities and relationships in a KG, in contrast to more advanced models such as DistMult [33] and ComplEx [30], which use high-dimensional spaces; HolE [18] which uses circular correlation in tensor spaces; RotatE [29] employs complex-valued rotation matrices or the convolutional approach of ConvE [4].

In this paper, we use TransE to train both KGE models. TransE is created with the perception that the head entity h is close to the tail entity t embeddings through the relationship l. TransE exploits the hierarchical relationship concept, meaning the distance between two connected entities through a relationship is small since they share similar attributes. The loss function (Eq. 1) for the TransE model [1] is described as follows:

$$\mathcal{L} = \sum_{(h,l,t)\in S} \sum_{(h',l',t')\in S'_{(h,l,t)}} [\gamma + d(h+l,t) - d(h'+l,t')]_+ \tag{1}$$

$$S'_{(h,l,t)} = \{(h', l, t)|h \in \mathcal{E}\} \cup \{(h, l, t')|t' \in \mathcal{E}\}. \tag{2}$$

where S is the set of the input triples, $\gamma > 0$ is a margin hyper-parameter, S' is the model-corrupted triples, defined in Eq. 2 shadowing *head* or *tail* and $d(h + l, t)$ is the distance measure between the entities.

Knowledge Validation: The KGE-based validation framework [25] takes the principle of the embedding evaluation where the rank-based scores of new triples also called *unseen* triples T_u confronted with a given model, trained over a specific knowledge base KB should be high if the new triple is placed in the dimensional space close to the entities in the KB; this means that if the unseen triple belongs to the knowledge base, its ranking should be close or equal to 1. In practical terms, if the rank-based score, namely, $MRR(T_u) \simeq 1$, the unseen triple belongs to that knowledge base.

Considering a controlled scenario, where for a domain $D1$, two unseen sets of triples UT_{True} and UT_{False} are given to the KGE model trained on the KB. The rank-based score evaluation results close or equal to 1 and 0, respectively, for UT_{True} and UT_{False}, entails that it is reasonable to state the triples close to 1 belongs to the domain D1, otherwise do not belong the domain. So for each triple r, let $vec(r)$ be the vector-based representation of the triple r in KGE of KB, the following assertions hold:

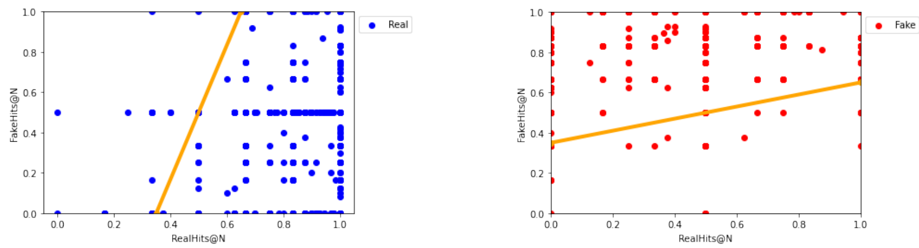
$$\begin{aligned} \forall r \in UT_{True}, vec(r) \in KGE \iff MRR(r) \simeq 1 \\ \forall r \in UT_{False}, vec(r) \in KGE \iff MRR(r) \simeq 0 \end{aligned} \tag{3}$$

3.3 Fuzzy layer for fake news detection

The proposed approach introduces fuzzy logic to deal with imprecise data and improves the comprehension of the whole system. In the pipeline overview shown in Figure 1, the fuzzy logic modelling is represented by the light blue box on the right. Additional details about each component in the pipeline are provided in the following sections.

Definition of fuzzy variables and fuzzy linguistic terms Two fuzzy variables (input variables) are created to represent the results of the KGE model evaluation, one for fake KG and the other for real KG. Specifically, we use Hits@N metrics, *RealHits@N* and *FakeHits@N*, representing the membership degree of news to real or fake, respectively, from a fuzzy perspective. Also, an output variable, *Fakeness*, which measures the level of the fakeness of news, is defined. For each fuzzy variable, three fuzzy linguistic terms *low*, *medium*, and *high* are defined. The number of fuzzy linguistic labels for each variable is odd, as suggested in the literature [3] and also considering the intrinsic nature of the language, where news can be considered neutral.

Fuzzy membership functions definition Considering that Hits@N values range from [0, 1], we have defined the universe of *RealHits@N* and *FakeHits@N* in the same range. We have also defined the same range as the universe for the output variable, *Fakeness*, where 0 means not fake and 1 is completely fake. For



(a) Real news.

(b) Fake news.

Fig. 2: *RealHits@N* and *FakeHits@N* scores distribution for real and fake news.

all the fuzzy variables in our approach, we have divided the range into three splits representing each fuzzy linguistic label. The term *low* is represented by the sub-range [0, 0.35], *medium* by [0.35, 0.65], and finally, *high* by [0.65, 1]. These values have been selected considering the distribution of *RealHits@N* and *FakeHits@N* scores for real and fake news (Figures 2 (a) and (b), respectively) in the training set. Figure 3 depicts fuzzy sets and membership functions for *RealHits@N* variable. Notice that the same design of fuzzy sets works for *FakeHits@N* and *Fakeness*.

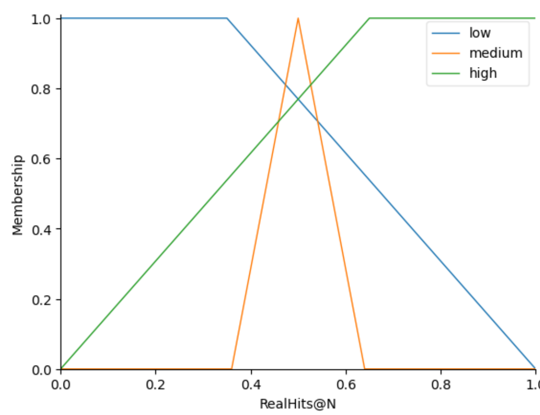


Fig. 3: Fuzzy sets describing the fuzzy linguistic terms *low*, *medium* and *high* of *RealHits@N* variable using trapezoidal and triangular membership functions.

Definition of fuzzy rules Seven fuzzy logic rules have been defined for the control system, each carefully designed to ensure coherent decision-making. As for membership functions, they are defined considering the distribution of *RealHits@N* and *FakeHits@N* scores (see Figure 2). Table 1 shows the fuzzy rules defined. For instance, Rule 3 states that if the fuzzy variable *RealHit@N* is *low* and the fuzzy variable *FakeHit@N* is *high*, then the fuzzy variable *Fakeness* is *high*. The criteria for formulating the rules is to establish clear, concise, and void of conflicts rules.

Table 1: Defined fuzzy rules.

	Rule1	**Rule2**	**Rule3**	**Rule4**	**Rule5**	**Rule6**	**Rule7**
$Hits@N_{Real}$	low	medium	low	medium	high	high	high
$Hits@N_{Fake}$	low	medium	high	high	low	medium	high
Fakeness	medium	medium	high	high	low	low	low

4 Experimental study

Several experiments were conducted to evaluate the viability of our proposal. The dataset utilized is CONSTRAINT[4] [21], renowned for its application in fake news detection. It consists of fake and real news regarding COVID-19 on social media platforms. The dataset includes 10700 posts with full text and the label corresponding to the classification.

4.1 Experiment setup

To demonstrate the feasibility of our proposal, the approach has been analysed from two perspectives: 1) classification and 2) explanations. The following steps describe the action line:

1. The dataset is split into training and testing sets (80% and 20%).
2. The training set is divided considering the class (real and fake news).
3. Two KGs are created using REBEL, one for real and another for fake news.
4. Two KGE models are trained for each KG using the TransE model.
5. Using both models, the metrics *RealHits@N* and *FakeHits@N* are evaluated for each news on the training set. where **HITS@N** $= \frac{|q \in Q : q < n|}{|Q|} \in [0, 1]$
6. Then, the fuzzy model is defined, encompassing fuzzy linguistic terms, membership functions, and fuzzy rules, all tailored in consideration of the discussed measures.
7. Finally, utilising the testing set, the incoming news is classified.

Notice that the steps can be used on any dataset. The value of *RealHits@N* and *FakeHits@N* in this experimentation are computed, setting N=5.

4.2 Results

Evaluation of our fuzzy approach from classification perspective Table 2 showcases the results achieved by our fuzzy-based approach from the classification point of view. The classification has been performed using three different approaches. In all cases, we use the membership degree of the *Fakeness* variable to its fuzzy linguistic terms (*low*, *medium* and *high*). Firstly, we classify the news just considering the membership degree of the *Fakeness* output variable to the fuzzy linguistic terms *low* and *high* regardless of membership degree value for *medium* term. Thus, news with a higher degree to *low* label is classified as real

[4] https://github.com/parthpatwa/covid19-fake-news-detection

and fake news otherwise. The second approach classifies the news considering the same fuzzy linguistic terms used in the previous approach, but this time, we consider only the news where the membership value for the *medium* label is not the highest. This means we exclude all news classified as *"neutral"* by the system, making it closer to a real-world problem. Lastly, we part from the former approach, but we also discard the news with membership degree for *low* term higher than 0.35 or membership degree for *high* term lower than 0.65 (subranges used for defining membership functions).

Table 2: Classification measures using three different approaches.

	Approach-1	**Approach-2**	**Approach-3**
Accuracy	0.67	**0.71**	0.65
Precision	0.62	0.65	**0.66**
Recall	0.76	0.54	**0.88**
F1-score	0.68	0.59	**0.75**

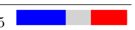
Generally, **Approach-3** produces the best results (highlighted in bold). This is mainly because, in this case, news classified as "Neutral" is discarded, and using the lower and upper thresholds allows for better discrimination. Notice that we can not compare with state-of-the-art solutions because it would not be a faithful comparison, as our method classifies in real (*Fakeness-low*), neutral (*Fakeness-medium*) and fake (*Fakeness-high*).

Let us remark on two crucial things: first, our fuzzy-based approach is mainly devoted to improving the presentation of the classification process achieved with the KGE model, and then the recall performance is good, emphasising that the model captures most of the relevant news (real or fake).

Evaluation of our fuzzy approach from explanations perspective Table 3 depicts some selected news to demonstrate how the proposed human-oriented approach enhances the understandability of the system. The table shows the ground truth from the dataset, the fuzzy variables, and the fuzzy linguistic terms of the *Fakeness* variable.

Through these examples, it is easy for an end-user without technical knowledge to understand and interpret the results. The table also includes a final column to showcase the system output graphically (blue colour stands for *Fakeness-low*, grey for *Fakeness-medium* and red for *Fakeness-high*. By means of the chart in the last column, we can understand that even when a piece of news is classified as fake news (the ground-truth classification), it can contain some real facts (see example 2). In the same way, news considered real apriori (see example 5) might be composed of real and fake facts due to the inherent nature of natural language. In those cases, it is completely difficult to determine whether a piece of news is real or not. However, the proposed fuzzy-based approach allows classifying as "Neutral", which means not fake or real.

Table 3: News examples for demonstrating the human-oriented capability of the proposal.

	Ground-truth	RealHits@N	FakeHits@N	Fakeness	Low	Medium	High	Visualisation
Low vitamin D was an independent predictor of worse prognosis in patients with COVID-19.	real	0.5	0	0.39	**0.94**	0.21	0.6	
A photo shows a 19-year-old vaccine for canine coronavirus that could be used to prevent the new coronavirus causing COVID-19.	fake	0	0.5	0.61	0.6	0.21	**0.94**	
Resources have a section for communicating with people ages 15-21.	real	0.67	0.5	0.42	**0.89**	0.45	0.65	
Coronavirus crisis in Italy leads Donald Trump to close all US Pizzerias	fake	0.1	0.9	0.72	0.51	0.08	**0.97**	
More than half of pregnant women recently admitted to a UK hospital with covid-19 infection were from black or other ethnic.	real	0.52	0.44	0.48	0.8	**0.87**	0.73	

5 Conclusion

The paper introduces a novel human-oriented approach that accomplishes a fuzzy-based assessment of knowledge graph embeddings for fake news detection. This method employs fuzzy rule-based modelling to explain the outcomes of knowledge graph embeddings in a human-oriented manner. Fuzzy variables such as *RealHits@N* and *FakeHits@N* represent, indeed, some KGE metrics, and an output fuzzy variable *Fakeness* provide a synthetic evaluation about the fakeness or not of an incoming news. Through experimental evaluation, we demonstrated the effectiveness of our fuzzy-based approach in detecting fake news. Moreover, the synergy between the KGE and fuzzy modelling provides a robust framework for enhancing the presentation of the final results in the detection process. In future work, we intend to use other data sets to evaluate the generalisability of our fuzzy-based approach in different contexts and data sources. Furthermore, we will investigate the integration of large language models (LLMs) in conjunction with fuzzy logic to develop hybrid systems capable of improving explanations capabilities.

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