Fact-checking via Path Embedding and Aggregation

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ABSTRACT

Knowledge graphs (KGs) are a useful source of background knowledge to (dis)prove facts of the form (s, p, o). Finding paths between s and o is the cornerstone of many fact-checking approaches. While paths are useful to (visually) explain why a given fact is true or false, it is not completely clear how to identify paths that are most relevant to a fact, encode them and weight their importance. The goal of this paper is to present the Fact checking via path Embedding and Aggregation (FEA) system. FEA starts by carefully collecting the paths between s and o that are most semantically related to the domain of p. However, instead of directly working with this subset of all paths, it learns vectorized path representations, aggregates them according to different strategies, and use them to finally (dis)prove a fact. We conducted a large set of experiments on a variety of KGs and found that our hybrid solution brings some benefits in terms of performance.

KEYWORDS

Fact-checking, Embeddings, Path Embedding, Path Aggregation

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1 INTRODUCTION

We live in a digital era, where both false and true rumors spread at an unprecedented speed. In this context, having a way to assess the reliability of individual facts is of utmost importance. How could fact-checkers or even simple citizens quickly verify the reliability of statements like (Dune, directed, D. Lynch)?

One way would be to employ time-consuming techniques requiring to both manually collect and check (digital) evidence; for instance, one could look up sources like encyclopedias, newspapers and even gain further evidence by asking friends. Another way is to devise automatic fact-checking systems1 [25, 27]. Existing approaches, can roughly been categorized in three main categories. First, text-based approaches based on a variety of learning models; these can use probability and logics (e.g., [2]), deep-learning (e.g., [14]), and also include multi-modal (e.g., text and video) information (e.g., [3]). While these approaches can rely on large amounts of text and/or multimedia sources like audio and video, there are difficulties in automatically understanding such pieces of information to (dis)prove a fact. This makes it difficult to give precise semantics to the fact being checked and contextualize it. One on hand, giving semantics boils down to understanding the fact itself rather than relying on statistical indicators like the popularity of a tweet about the fact. For instance, to (dis)prove the fact (Dune, director, D. Lynch), it is crucial to understand that the predicate director relates a Film and a Director and that Director is a subclass of Person. On the other hand, contextualizing facts and gaining insights from (chains of) related facts can represent a valuable source of knowledge [28]. As an example, the fact (Jaguar, owner, Tata Motors) provides more insights when understanding that it is about the car brand instead of the animal; the additional fact (Tata Motors, type, Company) can help in shedding light on this aspect.

Second, approaches that leverage structured knowledge (e.g., knowledge graphs) instead of unstructured text (e.g., [7, 18, 20, 22]). In this case, structured background knowledge allows for more precise forms of reasoning for fact-checking. For instance, it has been shown that the paths between the subject and object of a targeted fact, that include other entities and predicates, form a valuable body of semantic evidence (see e.g., [7, 19]). These approaches offer advantages in terms of semantic interpretation and contextualization of a statement. For instance, the statement (Dune, director, D. Lynch) can be given both a semantic characterization and put into context by looking at the excerpt of KG in Fig. 2 (a) taken from DBpedia. Here, we see that the domain of the fact is that of movies and that there are frequently occurring semantic relations between D. Lynch and actors (e.g., K. Mclaughlin) that also acted in Dune. Moreover, the usage of paths or entire portions of a KG of interest for the target statement can provide (visual) evidence about why the fact is true or false. By looking at the evidence depicted in Fig. 2 (a), it becomes plausible to consider the statement (Dune, director, D. Lynch) as true. Nevertheless, KG-based approaches lack mechanisms to automatically differentiate the importance of the collected paths. Third, a more recent strand of research has considered the usage of entity and predicate embeddings for fact-checking (e.g., [4, 21]). The idea of these approaches is to treat fact-checking as a link prediction problem. While these approaches have the advantage of working with vectorized representations of entities and predicates to automatically identify and extract salient features, they are sub-optimal as they do not directly tackle the problem of vectorizing entire facts, paths, and their aggregation.

1.1 Overview

The goal of this paper is to present the Fact checking via path Embedding and Aggregation (FEA) system. FEA carefully collects paths from a KG between the subject and object of a fact to be checked that are most semantically relevant to it. However, instead
of directly working with this subset of all paths, it learns vectorized path representations, aggregates them according to different strategies, and use them to finally (dis)prove a fact. To the best of our knowledge, this is the first work combining triple and path embedding and aggregation for fact checking.

To outline the rationale of FEA, we consider again the statement (Dune, director, D. Lynch) and the excerpt of the DBpedia KG along with its schema shown in Fig. 2. As previously mentioned, the (visual) semantic evidence in Fig. 2 (a) helps in understanding that the fact is true; we can see, for instance, that D. Lynch directed other movies where the same actors as Dune were acting. Besides, we also note that some patterns like \( \text{director} \rightarrow \text{cinematography} \rightarrow \text{director} \) or \( \text{cinematography} \rightarrow \text{director} \rightarrow \text{director} \) emerge. While this analysis is easy from a visual perspective, automatizing it sets two main challenges. The first is about how to extract such patterns and the corresponding paths to find semantic evidence. The second is about how to inject it into an automatic fact-checking mechanism. FEA tackles these challenges in three steps:

1. **Evidence Collection from the Schema**: given the predicate \( p \) in a target fact \((s, p, o)\), FEA constructs fact templates from the KG schema. Fig. 1 (a) shows two of the available templates for the predicate director obtained from the schema in Fig. 2 (b). Then, it finds schema-level patterns from the subject (Film) to the object (Person) of the fact template that only include the top-\( k \) most related to the input predicate \( p \). As an example, for director, patterns including starring, cinematography, and editing will be preferred to those including less related predicates as birthYear or college.

2. **Evidence Collection from the Data**: FEA finds data-level paths complying with schema-level patterns found in (1). When using the pair (Dune, D. Lynch) to replace the endpoints of the patterns in Fig. 1 (b), FEA finds the data-level paths \[ \text{Dune} \rightarrow \text{J. Nance} \rightarrow \text{Eraserhead} \rightarrow \text{D. Lynch} \] and \[ \text{Dune} \rightarrow \text{cinematography} \rightarrow \text{F. Francis} \rightarrow \text{The E. Man} \rightarrow \text{D. Lynch} \], among the others.

3. **Learning**: FEA represents each fact \( t=(s_i, p_j, o_k) \) in a path as a vector \( f_E=\text{Emb}f(t) \), where \( \text{Emb}f(\cdot) \) is a fact embedding function. Then, a path is represented as a sequence of such vectors. FEA learns an aggregate representation of all paths \( P_V \) according to different strategies (detailed in Section 4), ranging from simple ones that average the contribution of each path (AvgPooling) to more sophisticated ones able to also capture dependencies between facts in a path (LSTM-MaxPool). A final verdict about a targeted fact is provided by giving as input to a classifier the aggregate representation of all paths \( P_V \) (Section 3.4).

### 1.2 Contributions

In this paper, we contribute a fact-checking approach that given a fact of the form \((s, p, o)\) assigns a truth score. We make the following main contributions:

1. A schema-driven algorithm for extracting paths from KGs that can provide evidence to (dis)prove a fact;
2. An approach to vectorize paths based on the embeddings of facts in a path.
3. Different path aggregation strategies to assemble semantic evidence from paths useful for fact-checking.
4. An extensive evaluation on a variety of datasets and a comparison with related work.

Our approach delivers better performance (in terms of number of facts correctly evaluated) than the state-of-the-art (e.g., [7, 22]), while at the same time giving more flexibility in terms of strategies to collect semantic evidence in the form of paths, distillate and feed such evidence to a learning model.

### 2 PRELIMINARIES

A Knowledge Graph (KG) contains facts (aka statements) that can be divided into an ABox and a TBox. We see the ABox as a node and edge-labeled directed multi-graph \( G=(V, E) \) where \( V \) is a set of uniquely identified vertices representing entities (e.g., D. Lynch), \( E \) a set of predicates or properties (e.g., director) and \( T \) a set of facts of the form \((s, p, o)\), where \( s, o \in V \) and \( p \in E \). The TBox is another multi-graph defined as \( T=(C, P, L, T) \), where \( C \) is the set of all class names, \( P \) is the set of all property names, \( L \) is a set of properties defined in some ontological language, and \( T \) is a set of triples of the form \((u, p, v)\) where \( u, v \in C \cup P \) and \( p \in L \). Fig. 2 (a) shows an excerpt of the DBpedia TBox used to structure knowledge of the ABox in Fig. 2 (a). Here, we can see that director has as domain Film or that Artist is a subclass of Person. In this paper, we consider \( L \) to be the subset of the RDFS ontological language defined as follows: \( L=[\text{rdfs:subClassOf}, \text{rdfs:subPropertyOf}, \text{rdfs:domain}, \text{rdfs:range}] \). We consider RDFS as it is widely available and allows new facts about the TBox to be efficiently derived by applying (a subset of) the RDFS inference rules [17]. In what follows, we use the notation \( \text{domain}(p) \) (resp., \( \text{range}(p) \)) to indicate the domains (resp., ranges) of a property. After applying the RDFS inference on the TBox \( T \), we consider an alternative graph representation, which facilitates the extraction of schema-level patterns. We call this representation TBox Graph (Fig. 2 (b)).

**Definition 2.1. (TBox Graph).** Given a TBox \( T=(C, P, L, T) \), its TBox graph is defined as \( G_T=(V_T, E_T, T) \), where each \( v_i \in V_T \) is a class name belonging to \( C \), \( p_i \in P_T \cup \{\text{rdfs:subClassOf}\} \), and \((v_s, p_i, v_t) \in T_T \) is a triple such that \( \text{domain}(p_i)=v_s \) and \( \text{range}(p_i)=v_t \).
Schema availability and completeness. Our approach assumes the KG to be endowed with a minimal schema definition. This assumption is realistic in practice; popular KGs like DBpedia, Yago, and Wikidata feature even richer schema definitions. Another aspect concerns the completeness of the schema as it can be the case that some classes and properties are under-specified (e.g., missing domain and range). Our experiments on different datasets covering a broad number of domains, show that when the available schema specifications miss domains and ranges, considering the general concept Thing in lieu of them is enough. In general, one can manually refine/complete the portion of the schema that touches a particular domain of interest or use approaches that surface/refine a KG schema from the data or rely on other schema definitions like schema.org or WordNet to complete under-specified aspects in the schema of the KG of interest.

3 THE FEA FRAMEWORK
FEA is an end-to-end framework combining knowledge graph exploration and deep learning techniques for fact-checking. The cornerstone of FEA to (dis)prove a fact is the ability to both contextualize the fact, collect semantic evidence in the form of paths and use it into a deep-learning model. The problem that we can solve can be formulated as follows: given a fact \((s, p, o)\), and a set of paths \(P(s, p, o) = \{\pi_1, \pi_2, \ldots, \pi_k\}\) connecting s and o and related to the domain expressed by \(p\), the overall goal is to estimate the truthfulness of the fact by:

\[
\Phi_{(s,p,o)} = m_\Theta((s, p, o), P((s, p, o)))
\]

where \(m\) is the model having parameters \(\Theta\) and \(\Phi \in [0, 1]\) is the truthfulness score. The FEA framework consists of four main modules: path extractor, path embedder, path aggregator, and fact checker. Fig. 3 provides an overview of the framework. The end-to-end learning objective of FEA is guided by the input fact to be checked \((s, p, o)\) and a set of (domain-specific) paths extracted from a knowledge graph. The output of the model \(\Phi_{(s,p,o)}\) represents the truthfulness of the fact. Note that the set of input paths can provide evidence useful to understand why a given fact is true or false, for instance by displaying paths, similarly to what it has been done in Fig. 2 (a).

We now describe each module of the framework.

3.1 Path Extractor
This module is responsible for the exploration of the KG to gather information in the form of paths, which will be used by the other modules. The Path Extractor does not blindly explore the whole path search space, which can be huge, but focuses on finding paths that are relevant to the input fact via a two step process. First, it explores the KG’s schema conditioned on an input predicate to learn schema-level patterns. Second, it explores the KG’s data conditioned on the schema-level patterns and input fact to generate the data-level paths.

3.1.1 Schema-level patterns. The Path Extractor leverages the TBox graph to find schema-level patterns for a specific input predicate \(p\). It assembles paths up to a length \(l\) between the domain(s) and range(s) of \(p\) treating the input graph as undirected. To reduce the search space, this module only extracts the schema-level patterns most relevant to \(p\), where relevance is defined in terms of the extent to which the path is semantically related to \(p\). As an example, for the predicate director, paths including predicates like director, starring producer are intuitively more relevant than paths including birthDate or college. To quantify the relevance between a predicate and a schema-level pattern, the Path Extractor relies on a predicate relatedness measure, which given a pair of predicates \((p_1, p_2)\) computes their relatedness as:

\[
\text{Rel}(p_1, p_2) = \text{Cosine}(\text{Emb}(p_1), \text{Emb}(p_2))
\]

where \(\text{Emb}(\cdot)\) is an embedding function (e.g., RotatE [23]) and \(\text{Cosine}\) is the cosine operation between the vector embeddings of \(p_1\) and \(p_2\). Finally, the relatedness between a path and a predicate \(p\) is computed as the average relatedness between \(p\) and all predicates in the path. The relatedness-driven algorithm to extract schema-level patterns is sketched in Algorithm 1. At line 2 the algorithm extracts...
We want to point out that schema-level patterns with the domain and range of univers al step of the graph ensures the compliance with \( \pi \). This is done by relying on an algorithm based on a variant of Depth-First-Search (DFS), which starts from \( s \) and at each traversal step of the graph ensures the compliance with \( \pi \) in terms of predicate traversed and entity types toward reaching the entity \( o \). Consider the fact (Dune, director, D. Lynch), the schema-level-path \( \pi = \text{Work} \rightarrow \text{starring} \rightarrow \text{director} \rightarrow \text{Person} \) and the KG in Fig. 2 (a). The algorithm starts from the node Dune and traverses the edge starring (as per \( \pi \)) reaching the nodes J. Nance, K. Mclaughlin, and E. McGill. From each of these nodes, it traverses edges labeled as starring in reverse direction (again as per \( \pi \)) and reaches the nodes Eraserhead, Twin Peaks and Twin Peaks Fire Walks with Me. Finally, according to the last step of \( \pi \), the algorithm traverses edges labeled as director thus closing the paths between the subject Dune and the object D. Lynch of the input fact. Note that when considering the pattern \( \pi = \text{Film} \rightarrow \text{director} \rightarrow \text{Film} \), it is not possible to find any path between Dune and D. Lynch complying with \( \pi \) in the ABox. If no path complying with any schema-level pattern can be found, FEA performs an unconstrained DFS.

### 3.2 Path Embedder

To be processed by the learning model at the core of FEA, paths found by the Path Extractor are given a numerical representation. This is done by vectorizing each fact (triple) in a path, which can be done in different ways. One way is to encode paths (e.g., [1]) using embeddings or fact vectors [29] to first learn entity and predicate embeddings via a generic function \( \text{Emb}() \), which given an entity or a predicate, returns its corresponding vector embedding. Hence, to compute the embedding of a fact \( t=(s, p, o) \), one can perform some operation on its constituents vectors, that is, \( \text{Emb}(t)=\text{op}(\text{Emb}(s), \text{Emb}(p), \text{Emb}(o)) \). Note that we do not consider one-hot encodings since these techniques do not take into account the structure of the KG. Another way to learn fact embeddings is to rely on approaches like triple2vec [8], which instead of learning embeddings for entities and predicates separately directly learns fact embeddings. We will report on the performance of FEA when considering both approaches in Section 5.3. For the time being, given a fact \( t=(s, p, o) \), we define its embedding as \( t\text{e}=\text{embf}(t) \). Building upon the embedding of facts, a path \( \pi=[t_1, t_2, \ldots, t_l] \) of length \( l \) including \( l \) facts is encoded as a sequence \( \pi\text{e}=[\pi_{1}\text{e}, \ldots, \pi_{l}\text{e}] \). We observe that previous attempts to encode paths (e.g., [1]) focused on single label graphs only intending to tackle the link prediction problem in terms of predicting whether a link, *no matter the specific predicate*, exists between a pair of nodes. Our goal in this paper is to consider KGs including different entity and predicate types. Different approaches to do so is possible to explicitly incorporate the semantics of predicates into path representations, which paves the way to applications like fact-checking, where the goal is to establish whether a specific relation expressed, via a predicate, exists between a pair of nodes.

### 3.3 Path Aggregator

Paths converted into their vector form by the Path Embedder are then passed to the Path Aggregator. The Aggregator implements a variety of aggregation strategies (detailed Section 4). At this stage, we can see the aggregator as another learning module, which takes the paths from the Path Embedder and provides an overall vector representation for them. As the Path Extractor groups paths according to their different lengths, the Path Aggregator processes each
length-specific set of paths separately. Finally, the path representations for each length are concatenated together to give the final length-specific path representation \( P^V \) (see Fig. 3).

### 3.4 Fact Checker

The last step of the FEA framework consists in providing the final truthfulness score about the input fact. This is done by the Fact Checker, which takes as input the output of the Path Aggregator (i.e., the vector representation \( P^V \)) and feeds it into a classifier. We treat the fact-checking problem as a binary classification problem, where a true fact and a false fact are assigned 1 and 0 as target values, respectively. The final goal is to optimize the negative log-likelihood objective function, which defined as follows:

\[
L = - \sum_{f^+ \in F^+} \log \hat{y}_{f^+} + \sum_{f^- \in F^-} \log(1 - \hat{y}_{f^-})
\]

where \( F^+ = \{f^+ \mid y_{f^+} = 1\} \) and \( F^- = \{f^- \mid y_{f^-} = 0\} \) are the true and false facts, respectively.

### 4 AGGREGATORS

In the previous sections, we have outlined the FEA architecture. In particular, we have discussed how FEA from a set of paths interlinking \( s \) and \( o \) (obtained by the Path Extractor) obtains an overall vector representation via the Path Aggregator. The idea of aggregating graph information has been previously used (e.g., GraphSage [12], LEAP [1]) mainly for node classification and link prediction, where the goal is to predict whether a link exists between a pair of nodes no matter the label. However, these pieces of related work have only considered nodes in a graph disregarding edges, edge labels, and the KG schema.

Our goal is to aggregate path information involving both nodes and labeled edges that are crucial for fact-checking using KGs, where the goal is to establish whether a specific semantic relation between a pairs of nodes holds. In particular, we are concerned with aggregating sequences of paths of the form \([s_1, p_1, o_1], (o_1, p_2, o_2), \ldots (o_n, p_n, o_{n+1})\) instead of paths intended as sequences of nodes \([s_1, o_1, o_3, \ldots o_n, o_{n+1}]\). Another crucial difference between FEA and related approaches (e.g., LEAP [1]) is the fact that the Path Extractor module only considers paths relevant to the specific domain of the fact to be checked (expressed as fact predicate), while these related work extract all paths for link prediction. The intuition is that to (dis)prove a fact, a subset of domain-related paths can provide the necessary pieces of semantic evidence. In general, we can see an instance of Aggregator as a neural network that takes as input the paths (along with the batch size, fact embeddings, number of paths, path length) and gives a final vector representation. Inspired by previous work [1], we considered three main aggregation strategies.

#### 4.1 Average Pool

This kind of aggregator is the simplest we consider. It combines the different representations of paths by concatenating the vector representations of the facts in a path. Then on the set of paths obtained, the aggregator performs a 1D average pooling operation. The final combined path representation is a single vector obtained by averaging the paths between \( s \) and \( o \). The whole operation can be summarized as follows:

\[
P^V = \text{AvgPool}(\{\otimes(o^1_i), \forall i \in \mathcal{P}\})
\]

where \( \text{AvgPool} \) is the one-dimensional average pooling operation, and \( \otimes(\cdot) \) is the vector concatenation operation. This representation relies on the embeddings of the facts in each path.

#### 4.2 Max Pool

This kind of aggregator shares with the AvgPool the fact representation obtained, even in this case, by concatenating the vectors of both the nodes and the predicate in a fact. What changes is the final vector of the path; instead of being the average, it is now computed by using a dense neural network layer. The resulting activations are then passed through a max-pooling operation which helps to derive a single vector representation for the paths of length \( l \). The whole operation can be summarized as follows:

\[
P^V = \text{MaxPool}(\{\sigma(W_l \cdot \otimes(o^1_i) + b_l), \forall i \in \mathcal{P}\})
\]

where \( \text{MaxPool} \) is the one-dimension max pool operation (which selects bitwise the maximum value from multiple vectors to derive a single final vector), \( W_l \) are the weights to be learned, \( b_l \) the bias, and \( \sigma \) the activation function.

#### 4.3 LSTM Max Pool

We now outline the most sophisticated aggregator we considered. The idea is to treat a (vectorized) path as a sequence an employ an LSTM network to cater for sequential dependencies between facts in a path. With this reasoning, each fact in a path represents a point of a sequence. At each step \( l = 1 \), the LSTM layer outputs a hidden state vector \( h_{l-1} \), consuming subsequence of embedded facts \([f_1, ..., f_{l-1}]\). In other words, \( x_{l-1} = h_{l-1} \). The input \( x_{l-1} \) and the hidden state \( h_{l-1} \) are used to learn the hidden state of the next path step \( l \). As our final goal is to leverage the representations of all paths, after processing all of them via the LSTM, the aggregator employs another LSTM followed by a max pool operation to produce the combined path representation \( P^V \).

### 5 EVALUATION

We designed FEA with a modular architecture, which makes it easy to consider different strategies for embedding facts and different aggregation mechanisms. We tested the ability of our approach to check facts considering both existing and not existing facts in a given KG on synthetic (Section 5.3) and existing benchmarks (Section 5.4). Details about the experimental setting, the datasets, and the implementation are available in the Appendix.

#### 5.1 Evaluation Methodology

To evaluate the performance of FEA and competitors, we use the Area Under the Receiver Operating Characteristic curve (AUC). We identify AUC as the primary quality indicator because is a generic measure (independent of the threshold values) and has been extensively used in previous work (e.g., [7, 22]). All experiments have been carried out on a machine with a 4 core 2.7 GHz CPU and 16 GB RAM.
5.2 Embedding and Relatedness Computation

We considered three different approaches to pre-compute fact embeddings. DistMult [29] and ComplEx [26] give embeddings for entities and predicates separately; in this case, the embedding of a fact is obtained as the concatenation of the embeddings of its constituent parts. The third approach, triple2vec [8] directly computes fact embeddings by leveraging the notion of line graph of a KG. In particular, the triples of a KG become the nodes of the line graph. The approach then uses random walks and the word2vec approach to find the embeddings of each node of the line graph, which gives the embeddings of the triples of the original graph.

Predicate embeddings were used to obtain a predicate relatedness matrix, where the relatedness of each pair of predicates is computed as per equation (2) for all datasets but DBpedia. In this case, we obtained the predicate relatedness matrix from KStream\(^2\). This was necessary since neither DistMult nor ComplEx could run on this dataset on our machine.

5.3 Large scale evaluation

We conducted a large scale fact-checking experiment on all KGs by generating synthetic benchmarks. In this experiment, the goal was to test the impact of model parameters like the approach to compute fact embeddings, train and test size and, most important, aggregation strategy. Facts for training and testing were extracted to cover all the different predicates proportionally (i.e., the more popular a predicate the larger the number of triples for fact-checking). It is important to observe that positive facts used in these experiments were removed from the KG during the evaluation. The generation of train and test instances is discussed in the Appendix.

5.3.1 Impact of fact embedding. We evaluated the impact of the fact embedding approach used by the Path Embedder when considering the three aggregation strategies. The number of positive and negative examples considered are shown close to the dataset name in Fig. 4. Note that the number of false facts considered is double than that of true facts. This is to take into account the fact that there are many more possible false statements than there are true statements in the synthetic generated datasets. Moreover, we considered 50% of these examples (both positive and negative) for training and the remaining for testing. We observe that in almost all datasets triple2vec provides better performance. This is especially true as the size of the KG increases. For instance, in the smallest dataset Countries, we observe that triple2vec coupled with the LSTM Aggregator gives the best performance, even if DistMult and ComplEx performed almost equally good when considering this aggregator. For DBpedia, we only report results for triple2vec as DistMult and ComplEx raised an out-of-memory error. In general, we observe that with the AvgPool and MaxPool aggregators the impact of the embedding strategy is less significant.

We hypothesize that the better performance of triple2vec is because it computes embeddings for every fact while for the other two
5.3.2 Impact of Train/Test Split. In this experiment, we report results only when considering \texttt{triple2vec} as a fact embedding approach. We also tested the other two fact embedding approaches but they gave an inferior performance on all datasets. We set the hyper-parameter $k=10$, which controls the number of predicates for the generation of schema-level patterns (see Section 3.1.1).

Fig. 5 reports results on all datasets. We observe that the performance improves as more training data are used. Nevertheless, already with only 50% of training data, the AUC score is consistently above 0.5 in all datasets when considering the \texttt{LSTMMaxPool} aggregator. Observe that this kind of aggregator gave the best performance for all different train/test splits. Nevertheless, in smaller datasets like UMLS and Countries, the \texttt{AvgPool} aggregator also gave good results. We also experimented with other values of $k$ (results are not reported for lack of space) and observed that: (i) for broad-domain KGs (e.g., DBpedia, YAGO, NELL) a value higher than 10 does not bring any improvement as actually it worsens the performance. This is due to the fact that paths collected include predicates that do not contribute to a precise contextualization of the fact; (ii) for more specific KGs like UMLS and Countries, larger values of $k$ offer better performance; even if when considering more than 30% of all available predicates, the performance starts to decrease. Overall, we observed that a value of $k$ between 7 and 10 offers the best trade-off between the time required to find schema and data-level paths and AUC score. Results on more specific datasets like UMLS and Countries are better in general. This can be explained by the fact that the paths used as evidence to (dis)prove a fact offer a clearer support for the learning model; in other words, while in more general KGs there can be paths that can lead the model astray in terms of fact contextualization, in more specific datasets this is less probable. It is interesting to observe that thanks to the hyper-parameter $k$, FEA can control how much it can be led astray from the domain expressed by $p$. This offers greater flexibility than previous work where it is not possible to contextualize targeted facts in terms of paths generated.

5.4 Comparison with related work

Building upon the analysis conducted in Section 5.3, we now report on the comparison of FEA with related work on existing benchmarks. We considered: (i) \textsc{Cheep} [7], an approach, which leverages paths to come up with a truthfulness score for an input fact; (ii) \textsc{PredPath} [19], which exploits frequent anchored predicate paths between pair of entities in the KG; (iii) Path Ranking Algorithm
KLinker

LEAP worst-performing system is which reduces the fact-checking problem to the problem of max-

ation problem in unlabeled graphs. We included it since it also designed to work on labeled graphs as it aims to solve the link not able to capture all needed semantic evidence. As expected, the only consider one path perform worse; perhaps a single path is aggregator. We note that approaches like second-best performing system, when considering the LSTMMax-

pered. In particular, it brings some improvement wrt FEARED. In particular, it brings some improvement wrt

homogeneity, and functionality properties of the facts to cover a broader variety of scenarios than previous benchmarks.

We observed that TransE, which also tackles the link prediction problem, but on knowledge graphs, performs better than LEAP; although worse than the other systems. This could be because it does not consider paths. Results are more interesting in the second benchmark (Table 2), which has carefully been designed to test the behavior of fact-checking systems on (non)popular (NP) and random entities (R). On this benchmark, we ran experiments for FEA, LEAP, and CHEEP while for TransE, KLinker, and PredPath we report results from [13]. Here we observe that FEA performs particularly well on non-popular entities with both LSTMMaxPool and Avg aggregators. This may be explained by the fact that even when the number of paths is smaller than between popular entities, the Path Aggregator can correctly capture the necessary evidence, which passed to the other modules of the FEA framework (after embedding) captures the truthfulness of facts eventually. FEA leverages deep-learning techniques for the embedding of paths providing a strategy that can capture dependencies between the facts in a path and aggregate them. Moreover, we remark the importance of considering the semantics of paths for fact-checking but, most importantly, the need to correctly relate the semantics of such paths with the fact to be checked in order to only consider the most relevant ones. Indeed, even if LEAP uses node embedding and path aggregation strategies, it is the worst performing system. We noted that the system fails to especially recognize false facts since even if the existence of a link is correctly predicted, this is not enough as for fact-checking it is necessary to establish the existence of a specific link.

5.4.2 Evaluation Results. We observe that on the first benchmark (Table 1), FEA performs quite well for all predicates considered. In particular, it brings some improvement wrt CHEEP, the second-best performing system, when considering the LSTMMaxPool aggregator. We note that approaches like PredPath, which only consider one path perform worse; perhaps a single path is not able to capture all needed semantic evidence. As expected, the worst-performing system is LEAP, which, however, has not been designed to work on labeled graphs as it aims to solve the link prediction problem in unlabeled graphs. We included it since it also features path aggregation strategies that were a source of inspiration in designing FEA. However, the semantics of predicates and paths seems to play a crucial role in fact-checking.

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Fea

| Approach       | birthPlace (273/1092) | deathPlace (126/504) | almaMater (1546/6184) | nationality (50/200) | profession (110/440) |
|----------------|----------------------|----------------------|----------------------|----------------------|---------------------|
| FEA-LSTMAggr   | 0.93                 | 0.91                 | 0.81                 | 0.89                 | 0.99                |
| FEA-MaxAggr    | 0.90                 | 0.87                 | 0.80                 | 0.86                 | 0.97                |
| FEA-AvgAggr    | 0.91                 | 0.86                 | 0.81                 | 0.87                 | 0.99                |
| CHEEP          | 0.91                 | 0.87                 | 0.77                 | 0.85                 | 0.98                |
| KStream        | 0.82                 | 0.84                 | 0.75                 | 0.93                 | 0.93                |
| KLinker        | 0.91                 | 0.87                 | 0.78                 | 0.86                 | 0.93                |
| PredPath       | 0.86                 | 0.76                 | 0.83                 | 0.95                 | 0.92                |
| FEA            | 0.81                 | 0.74                 | 0.80                 | 0.91                 | 0.88                |
| TransE         | 0.54                 | 0.56                 | 0.66                 | 0.77                 | 0.82                |

Table 1: Performance (average AUC) on both real-world (left) and synthetic (right) datasets (average of 4 runs).

References:

1. https://github.com/shiralkarprashant/knowledgestream/
2. https://github.com/huynhbp/RUCKLE-Fact_checking/
3. It includes 5 real-world datasets derived from Google Relation Extraction Corpora and WSDM Cup Triple Scoring challenge and 5 synthetic datasets mix a-priori true and false facts. As the benchmarks are defined on DBpedia entities, we considered this KG as a source of background knowledge in this experiment. The number of true/false facts for each benchmark is reported below the predicate name in Table 1. The second benchmark released by Huynh and Papotti [13] takes into account popularity, transparency, homogeneity, and functionality properties of the facts to cover a broader variety of scenarios than previous benchmarks.

6 RELATED WORK

Several approaches have been proposed to leverage structured information from knowledge graphs to (dis)prove facts of the form \((s, p, o)\). The common approach is to consider the set of paths interlinking \(s\) and \(o\) as a form of evidence. CHEEP [7] leverages the schema to generate evidence patterns that are then used to generate data-level paths whose "support" is then used to provide a final truthfulness score. Although we share the usage of the schema, our approach can automatically learn and weight the importance of the different paths, including the sequence of facts in a path, thanks to an end-to-end modular framework. KStream [22] casts the fact-checking problem into that
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Table 2: AUC results on the benchmarks in [13] for popular (P), non popular (NP), and random (R) entity pairs. Train and test pairs has been provided by the authors of [13].

| Approach       | Predicate       | P  | NP | R   |
|----------------|-----------------|----|----|-----|
| FEA-LSTMAggr   | nearestCity     | .97| .78| .78 |
|                | foundedBy       | .92| .76| .86 |
|                | manufacturer    | .91| .88| .94 |
|                | employer        | .79| .67| .77 |
| FEA-MaxAggr    | nearestCity     | .79| .61| .72 |
|                | foundedBy       | .77| .63| .79 |
|                | manufacturer    | .88| .79| .86 |
|                | employer        | .66| .54| .62 |
| FEA-AvgAggr    | nearestCity     | .85| .64| .78 |
|                | foundedBy       | .79| .63| .80 |
|                | manufacturer    | .89| .88| .91 |
|                | employer        | .68| .59| .67 |
| CHEEP          | nearestCity     | .86| .61| .72 |
|                | foundedBy       | .81| .62| .79 |
|                | manufacturer    | .78| .86| .81 |
|                | employer        | .67| .85| .64 |
| PredPath       | nearestCity     | .84| .56| .69 |
|                | foundedBy       | .80| .63| .81 |
|                | manufacturer    | .55| .31| .53 |
|                | employer        | .58| .38| .50 |
| KLInker        | nearestCity     | .87| .66| .76 |
|                | foundedBy       | .82| .67| .80 |
|                | manufacturer    | .80| .85| .92 |
|                | employer        | .59| .43| .66 |
| LEAP           | nearestCity     | .81| .40| .41 |
|                | foundedBy       | .69| .58| .71 |
|                | manufacturer    | .68| .57| .64 |
|                | employer        | .58| .64| .63 |
| TransE         | nearestCity     | .89| .80| .80 |
|                | foundedBy       | .75| .60| .75 |
|                | manufacturer    | .72| .47| .70 |
|                | employer        | .62| .46| .48 |

of computing the maximum flow between s and o. Although we share the usage of predicate relatedness, KStream does not use it to prune the path search space as we do. Moreover, KStream does not consider the KG schema and thus the computation of the flow can include a large portion of the KG. Finally, our approach can automatically learn and aggregate path representations thanks to the usage of embedding and deep learning techniques. PredPath [19] focuses on finding a single path that can shed light on the truthfulness of a fact. As resulted from our evaluation, a single path may be unable to correctly single out the necessary body of semantic evidence. LEAP [1] uses path aggregation strategies and node embeddings to predict the existence of a link between a pair of input nodes. Although we took inspiration from LEAP to define the path aggregation strategies, our approach differs in several respects. First, LEAP focuses on shorter paths while we focus on paths that are semantically relevant to the input fact. Second, LEAP works on unlabeled graphs while we considered labeled multi-graphs. As such, LEAP is unable to predict whether a specific link exists between a pair of nodes, which is the goal of fact-checking systems. Indeed, checking the fact (Dune, director, D. Lynch) is different from checking the existence of a link between Dune and D. Lynch. Our approach to generate schema-level patterns shares some commonalities with rule learning systems (e.g., [9]) although our goal is to only consider patterns that are relevant to the input fact. Moreover, our work fed data-level paths to a deep-learning pipeline for embedding and aggregation. Our work also differs from logic-based approaches (e.g., [16]) aiming at representing/querying facts to capture incompleteness/uncertainty.

There are a variety of link prediction systems, including those based on embeddings (e.g., [21, 26, 29]), that can be applied to the task of fact-checking. Our approach differs in several respects. First, our model goes beyond embedding-based approaches that only leverage entity embeddings. FEA’s learning model is based on triple (fact) and path embeddings, and their aggregation, including a mechanism (based on LSTM) to capture sequential dependencies between facts in a path, and a weighted pooling mechanism that weights their relative importance toward the final verdict. Moreover, FEA can provide evidence for a fact thanks to the set of paths input to the learning model that can be visualized. In a way this allows to combine the benefits of pure path-based approaches (e.g., [7, 22]) with those of deep-learning models. Other systems leverage text (e.g., [6, 24]) and are out of the scope of this analysis, which is focused on how to embed and carefully aggregate paths from KGs for fact checking.

7 CONCLUSIONS AND FUTURE WORK

Knowledge Graphs can provide useful support, in terms of structured background knowledge, for fact-checking. Our proposal aims at bridging the gap between two existing strands of approaches, that is, path-based approaches and embedding based approaches each with its relative merits. FEA achieves this goal thanks to the interplay between a schema-based algorithm, which carefully focuses on the subset of paths most relevant to an input fact, and a path embedding/aggregation mechanism able to distillate this body of semantic evidence. Our experiments showed that the fact embedding mechanism plays an important role: the one-size-fits-all entity/predicate embedding approach (e.g., TransE [4], DistMult [29]) is sub-optimal as compared to approaches that directly embed each fact (i.e., triple2vec [8]) in a path. It also emerged that capturing the dependencies between facts (via the LSTMMaxPool aggregator) can improve the performance. Overall, fact-checking cannot be solved by looking at the fact alone; it is necessary to understand its semantics, contextualize it by considering related (chains of) facts, and distillate semantic evidence from paths. Investigating other aggregation strategies, the usage of adversarial learning techniques [11], and temporal information [6] is in our research agenda.

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APPENDIX

7.1 Hyperparameters

We considered the hyperparameter l={1,2, 3, 4} (path lengths) and considered the top-50 schema level paths (stored in the priority queue as per Algorithm 1 line 1). For each such schema-level pattern, we used up to 150 data-level paths for each length randomly selected. We used the Adam [15] optimizer with learning rate set to 0.001 and trained the model for 100 epochs with early stopping enabled.

7.2 Knowledge graphs and datasets

We performed experiments using several KGs as a source of background knowledge for fact-checking. Details about the datasets are available in Table 3. The datasets are taken from a variety of real-world KGs, some of which model broad knowledge (e.g., DBpedia, Yago) while others are more domain-specific (e.g., UMLS, Countries). We considered a subset of Wikidata sampling from the 100 predicates that have the most number of facts. We considered the version of DBpedia in [22] but discarded typing information. We also considered a subset of it (DBpedia1M). For Countries and UMLS that do not have a schema, FEA extracted data-level paths by performing a constrained DFS, which only retrieves paths involving the top-k most related input predicates to a targeted predicate.

| Dataset       | #Entities | #Relations | #Facts |
|---------------|-----------|------------|--------|
| Countries⁵    | ~250      | 2          | ~1K    |
| UMLS⁷         | ~130      | 49         | ~5K    |
| NELL-995⁷     | ~75K      | 200        | ~155K  |
| FB15K-237⁷    | ~14.5K    | 237        | ~272K  |
| Yago⁹         | ~3.5K     | 37         | ~355K  |
| Wikidata⁷     | ~100K     | 100        | ~698K  |
| DBpedia⁸      | ~4M       | 661        | ~8M    |
| DBpedia1M     | ~276K     | 2284       | 1M     |

Table 3: Knowledge graphs considered.

7.3 Training and test instances generation

Existing fact-checking benchmarks (e.g., [13, 22]) have been defined on DBpedia. In order to evaluate FEA on a larger variety of KGs, we generated synthetic benchmarks including positive and negative (s, o) pairs for each predicate p in a KG. Note that we treat KGs as trusted sources of knowledge (i.e., facts are assumed to be correct) but incomplete because of the open-world assumption, which states that a fact not in the KG can either be false or missing. Let \( T_\mathcal{G}^- \) be the set of pairs linked by p existing in a knowledge graph G and let \( T_s^- \) be the set of pairs that are not linked by p in G. Given a predicate p, to collect positive train instances, a subset of pairs \( T_s^+ \subset T^- \) is used. In particular, for each schema-level pattern obtained for p, each pair (s, o) \( \in T_s^- \) replaces the schema-level pattern’s endpoints and allows to find a set of data-level paths. The remaining set of pairs \( \mathcal{T}_s^+ = T^+ \setminus T_s^+ \) represent the positive test pairs. To collect negative pairs, we adopt the Local Closed World Assumption (LCWA), which states that if a KG contains one or more object (resp. subject) values for a given subject (resp. object) and predicate, then it contains all possible occurrences for the two entities involved for that predicate [9, 13]. Moreover, to ensure high accuracy for the generated negative pairs, the types of the entities are required to be the same in a new negative pair. For example, if the fact D. Lynch director Dune, it implies that the KG contains all information about the director of Dune. Therefore, for any other director (e.g., S. Kubrick) in the KG, its combination with Dune is a false fact (i.e., (S. Kubrick, director, Dune) is a false fact). Note that to generate more precise negative examples the type of the entity that we replace needs to be the same (i.e., a director). We also divide the negative train (\( T_{tr}^- \subset T^- \)) and test (\( T_{ts}^- = T^- \setminus T_{tr}^- \)) pairs.

7.4 Reproducibility

FEA⁹ has been implemented in Python using the GraphTool library¹⁰ to deal with graph data and pathfinding, pykg2vec¹¹ to compute entity and predicate embeddings, and KERAS/Tensorflow¹² for the implementation of the aggregators, the training and testing of the whole system.

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¹https://github.com/shehzaadzd/MINERVA
²https://github.com/yago-naga/
³https://www.wikidata.org
⁴http://carl.cs.indiana.edu/data/
⁵The system and the datasets are available upon request
⁶https://graph-tool.skewed.de/
⁷https://pypi.org/project/pykg2vec/
⁸https://keras.io