Inductive Relation Prediction by BERT

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Abstract

Relation prediction in knowledge graphs is dominated by embedding based methods which mainly focus on the transductive setting. Unfortunately, they are not able to handle inductive learning where unseen entities and relations are present and cannot take advantage of prior knowledge. Furthermore, their inference process is not easily explainable. In this work, we propose an all-in-one solution, called BERTRL (BERT-based Relational Learning), which leverages pre-trained language model and fine-tunes it by taking relation instances and their possible reasoning paths as training samples. BERTRL outperforms the SOTAs in 15 out of 18 cases in both inductive and transductive settings. Meanwhile, it demonstrates strong generalization capability in few-shot learning and is explainable.

1 Introduction

Knowledge graphs (KGs) are essential in a wide range of tasks such as question answering and recommendation systems (Ji et al., 2020). As many knowledge graphs are substantially incomplete in practice, knowledge graph completion (KGC) becomes a must in many applications (Nickel et al., 2016).

Embedding-based methods such as TransE (Bordes et al., 2013), Complex (Trouillon et al., 2017), ConvE (Dettmers et al., 2018), RotatE (Sun et al., 2019) and TuckER (Balažević et al., 2019), achieve the state-of-the-art performance on a few KGC benchmarks. However, the drawbacks of these approaches are obvious as they are limited to the transductive setting where entities and relations need to be seen at training time. In reality, new entities and relations emerge over time (inductive setting). The cost of retraining may be too high for dynamically populated knowledge graphs. In addition to the inductive setting, explainability, few-shot learning and transfer learning cannot be easily solved by these specialized embedding methods.

Logical induction methods partially meet the aforementioned need by seeking probabilistic subgraph patterns (GRAIL (Teru et al., 2020)), logical rules (AMIE (Galárraga et al., 2013), RuleN (Meilicke et al., 2018)) or their differentiable counterparts (NEURAL-LP (Yang et al., 2017), DRUM (Sadeghian et al., 2019)). The following shows a logical rule which is explainable, can be generalized, and can handle unseen entities,

$$(x, \text{president_of}, y) \land (z, \text{capital_of}, y) \rightarrow (x, \text{work_at}, z).$$ (1)

These logical rules introduce inductive ability for predicting missing links in KG. For example, once the rule in (1) is learned, the model can generalize to other president, capital and country.

Despite the compelling advantage of the existing logical induction methods, their inductive learning power is limited as it only exploits the structural information while ignoring the textual information associated with entities and relations, and furthermore, prior knowledge carried in these texts. This weakens the model’s usability when only small knowledge graphs are available – a typical few-shot setting. Moreover, none of them can handle unseen but relevant relations in KG completion.

In this work, we propose an all-in-one solution, called BERTRL (BERT-based Relational Learning), a model that combines rule-based reasoning with textual information and prior knowledge by leveraging pre-trained language model, BERT (Devlin et al., 2019). In BERTRL, we linearize the local subgraph around entities in a target relation $(h, r, t)$ into paths $p : (h, r_0, e_1), (e_1, r_1, e_2), \ldots, (e_n, r_n, t)$, input $(h, r, t) : p$ to BERT, and then fine-tune. BERTRL is different from KG-BERT (Yao et al., 2019)
Table 1: Comparison of BERTRL with other relation prediction algorithms on their capability of handling the transductive setting, unseen entities in the inductive setting, their potential of dealing with unseen relations, usage of prior knowledge, the explainability of their inference process, and whether they can reason with the context of entities in the knowledge graph explicitly. We take TuckER as a representative of embedding-based methods.

| Method          | Transductive Setting | Inductive Setting | Prior Knowledge | Explainable |
|-----------------|----------------------|-------------------|-----------------|-------------|
|                 | (Unseen Entities)    | (Unseen Relations) | Reasoning with context |               |
| TuckER          | ✓                    | ×                 | ✓               | ×           |
| RuleN           | ✓                    | ×                 | ✓               | ×           |
| GRAIL           | ✓                    | ✓                 | ×               | ✓           |
| KG-BERT         | ✓                    | ✓                 | ✓               | ✓           |
| BERTRL (ours)   | ✓                    | ✓                 | ✓               | ✓           |

where only relation instance \((h, r, t)\) is fed to BERT. While this difference looks small, it actually lets BERTRL reason explicitly via paths connecting two entities. KG-BERT’s prediction is mainly based on the representation of entities and relations: Knowledge graph is memorized inside BERT and reasoning is implicit. In BERTRL, knowledge is dynamically retrieved from the knowledge graph during inference: Reasoning is conducted explicitly, which enables BERTRL to achieve explainability and much higher accuracy. Table 1 illustrates the difference among these approaches.

Our approach naturally generalizes to unseen entities. It also has the potential to handle some unseen relations. Empirical experiments on inductive knowledge graph completion benchmarks demonstrate the superior performance of BERTRL in comparison with state-of-the-art baselines: It achieves an absolute increase of 6.3% and 6.5% in Hits@1 and MRR on average. In a few-shot learning scenario, it can even achieve a maximum of 32.7% and 27.8% absolute Hits@1 and MRR improvement.

In the transductive setting, BERTRL performs competitively with the state-of-the-art embedding methods and surpasses the inductive learning counterparts. In few-shot learning (partially transductive), BERTRL again introduces a larger margin over the baselines.

Finally, we analyze how BERTRL performs in unseen relation prediction, its explainability, its training and inference time, and conduct an ablation study on a few design choices.

2 Proposed Approach

Problem Formulation. Knowledge graph consists of a set of triples \( \{(h_{i}, r_{i}, t_{i})\} \) with head, tail entities \( h_{i}, t_{i} \in E \) (the set of entities) and relation \( r_{i} \in R \) (the set of relations). Given an incomplete knowledge graph \( G \), the relation prediction task is to score the probability that an unseen relational triple \((h, r, t)\) is true, where \( h \) and \( t \) denote head and tail entities and \( r \) refers to a relation. \((h, r, t)\) is also called target relational triple.

Our model scores a relational triple in two steps: (Step 1) Extracting and linearizing the knowledge \( G(h, t) \) surrounding entities \( h \) and \( t \) in \( G \); (Step 2) Scoring the triple with \( G(h, t) \) by fine-tuning the pre-trained language model BERTRL.

2.1 Model Details

Step 1: Knowledge Linearization. The knowledge \( G(h, t) \) surrounding entities \( h \) and \( t \) in a knowledge graph \( G \) provides important clues for predicting missing links between \( h \) and \( t \). \( G(h, t) \) could be exploited in various ways: It could be any subgraph around \( h \) and \( t \) and even not necessarily be connected. However, the different choices of \( G(h, t) \) will affect the model complexity and its explainability. RuleN (Meilicke et al., 2018) uses all the paths connecting \( h \) and \( t \) up to \( k \) length. Grail (Teru et al., 2020) uses a subgraph that merges all of these paths, aiming to leverage structural information. In order to use pre-trained language models like BERT, we need to linearize \( G(h, t) \) as \( \ell(G(h, t)) \) and concatenate it with \((h, r, t)\) as valid input to BERT,

\[
(h, r, t) : \ell(G(h, t)).
\] (2)

Our intuition is that BERT shall have the capability of learning signals in \( G(h, t) \) that could be correlated with \((h, r, t)\), and BERT shall be able to handle noisy and erroneous inputs.

Subgraph. One straightforward linearization of a subgraph would be concatenating text of its edges one by one separated by a delimiter such as a semicolon. This formalism has two major issues. First, local subgraphs could be very large: The size grows exponentially with respect to their diameters.
We call them reasoning paths presented in Section 3.6. The performance of different designs is KGC benchmarks. Performances can be achieved by one path in the existing training samples and likely most relation predictions can be picked up true ones. We suspect the BERT representation might generate many false associations as most of the paths are irrelevant to the target triple. Surprisingly, we found BERT is robust to those false associations taken in the training target triple. Each one individual path will form a training/inference instance.

### Step 2: BERT Scoring

In BERT, since we take individual paths as a linearization approach, each pair of triple and reasoning path is scored individually. For each target triple, one or a few reasoning paths would indicate the truth of the triple. This forms a multi-instance learning problem (Carbonneau et al., 2018), where predictions need to be aggregated for a bag of instances. We take a simplified realization - training individually and applying maximum aggregation of bag scoring at inference time.

BERT uses a linear layer on top of [CLS] to score the triple’s correctness, which can be regarded as a binary classification problem. It models the probability of label $y$ ($y \in \{0, 1\}$) given the text of triple $(h, r, t)$ and the text of reasoning path $h \rightarrow t$,

$$p(y|h, r, t, h \rightarrow t).$$  \hfill (3)

At inference time, the final score of a target triple $(h, r, t)$ is the maximum of the positive class scores over all of its reasoning paths:

$$score(h, r, t) = \max_{\rho} p(y = 1|h, r, t, h \mathrel{\rightarrow} t).$$  \hfill (4)

The path corresponding to the maximum score can be used to explain how the prediction is derived. We leave a more sophisticated aggregation function for future study.
2.2 Training Regime

In order to train BERTRL, both positive and negative examples are needed. We follow the standard practice to view existing triples in KG as positive. Then, for each positive triple, we do negative sampling to sample \( m \) triples corrupting its head or tail. Specifically, we randomly sample entities from common \( k \)-hop neighbors of head and tail entities, and make sure negative triples are not in KG. We do not include empty reasoning path examples in training, and always give a minimum confidence score for empty path in inference.

When constructing reasoning paths for a triple, we hide the triple in KG and find other paths to simulate missing link prediction. As the maximum length of the reasoning paths increases, the number of paths may grow exponentially. Many paths are spurious and not truly useful for inducing the triple. We do path sampling at training time to get at most \( n \) paths between target entities and take shorter paths first.

Finally we use cross entropy loss to train our model:

\[
\mathcal{L} = - \sum_{\tau} (y_{\tau} \log p_{\tau} + (1 - y_{\tau}) \log (1 - p_{\tau})),
\]

(5)

where \( y_{\tau} \in \{0, 1\} \) indicates negative or positive label, and \( \tau \in \mathbb{D}^+ \cup \mathbb{D}^- \). The negative triple set \( \mathbb{D}^- \) is generated by previously mentioned method that corrupts head \( h \) or tail entity \( t \) in a positive triple \( (h, r, t) \in \mathbb{D}^+ \) with a sampled entity \( h' \) or \( t' \), i.e.,

\[
\mathbb{D}^- = \{(h', r, t) \notin \mathbb{D}^+ \cup (h, r, t') \notin \mathbb{D}^+ \}. \quad (6)
\]

3 Experiments

We evaluate our method on three benchmark datasets: WN18RR (Dettmers et al., 2018), FB15k-237 (Toutanova et al., 2015), and NELL-995 (Xiong et al., 2017), using their inductive and transductive subsets introduced by (Teru et al., 2020). \(^2\) WN18RR is a subset of WordNet, a KG contains lexical relations between words. FB15k-237 is a subset of Freebase, a large KG of real-world facts. NELL-995 is a dataset constructed from high-confidence facts of NELL, a system constantly extracting facts from the web. The statistics of these datasets are given in Table 2; the details of the variants will be given later.

| split | #relations | #nodes | #links |
|-------|------------|--------|--------|
| train | 9          | 2,746  | 6,670  |
| ind-test | 8          | 922    | 1,991  |
| train-1000 | 9          | 1,362  | 1,001  |
| train-2000 | 9          | 1,970  | 2,002  |
| FB15k-237 | train     | 180    | 1,594  | 5,223  |
| ind-test | 142        | 1,093  | 2,404  |
| train-1000 | 180        | 923    | 1,027  |
| train-2000 | 180        | 1,280  | 2,008  |
| train-rel50 | 50        | 1,310  | 3,283  |
| train-rel100 | 100       | 1,499  | 3,895  |
| NELL-995 | train      | 88     | 2,564  | 10,063 |
| ind-test | 79         | 2,086  | 5,521  |
| train-1000 | 88         | 893    | 1,020  |
| train-2000 | 88         | 1,346  | 2,011  |

Through experiments, we would like to answer the following questions about BERTRL: (1) How does it generalize to relation prediction with unseen entities in the inductive setting? (2) How does it perform in the traditional transductive setting? (3) Does it work well in few-shot learning? (4) Does it have the potential to generalize to unseen relations? (5) How its reasoning path explains prediction? (6) What is the training and inference time? (7) How important is the knowledge linearization design?

Baselines and Implementation Details. We compare BERTRL with the state-of-the-art inductive relation prediction methods GRAIL (Teru et al., 2020) and RuleN (Meilicke et al., 2018). GRAIL uses graph neural network to reason over local subgraph structures. RuleN explicitly derives path-based rules and shows high precision. We use the public implementation provided by the authors and adopt the best hyper-parameter settings in their work. Differentiable logical rule learning methods like NeurLP (Yang et al., 2017) and DRUM (Sadeghian et al., 2019) are not included, as their performance is not as good as GRAIL and RuleN (Teru et al., 2020). For the transductive setting, we pick one of the state-of-the-art embedding methods, TuckER (Balažević et al., 2019) and path-based method MINERVA (Das et al., 2018), as representatives for evaluation. For TuckER, we use implementation in LibKGE (Broscheit et al., 2020) with the provided best configuration in the library. For MINERVA, we use the official implementation and best configuration provided by authors.

We also compare against a BERT-based KGC method KG-BERT (Yao et al., 2019), where only relation triple \((h, r, t)\) is fed to BERT. This is a
Table 3: Inductive results (Hits@1)

|               | WN18RR       | FB15k-237    | NELL-995     |
|---------------|--------------|--------------|--------------|
|               | 1,000 2,000 | 6,678 (full) | 1,000 2,000  | 1,000 2,000 | 10,063 (full) |
| RuleN         | 0.649        | 0.737        | 0.745        | 0.207       | 0.344        | 0.415        | 0.282       | 0.418        | 0.638       |
| GRAIL         | 0.516        | 0.769        | 0.769        | 0.273       | 0.351        | 0.390        | 0.295       | 0.298        | 0.554       |
| KG-BERT       | 0.364        | 0.404        | 0.436        | 0.288       | 0.317        | 0.341        | 0.236       | 0.236        | 0.244       |
| BERTRL        | 0.713        | 0.731        | 0.755        | 0.441       | 0.493        | 0.541        | 0.622       | 0.628        | 0.715       |

Table 4: Inductive results (MRR)

|               | WN18RR       | FB15k-237    | NELL-995     |
|---------------|--------------|--------------|--------------|
|               | 1,000 2,000 | 6,678 (full) | 1,000 2,000  | 1,000 2,000 | 10,063 (full) |
| RuleN         | 0.681        | 0.773        | 0.780        | 0.236       | 0.383        | 0.462        | 0.334       | 0.495        | 0.710       |
| GRAIL         | 0.652        | 0.799        | 0.799        | 0.380       | 0.432        | 0.469        | 0.458       | 0.462        | 0.675       |
| KG-BERT       | 0.471        | 0.525        | 0.547        | 0.431       | 0.460        | 0.500        | 0.406       | 0.406        | 0.419       |
| BERTRL        | 0.765        | 0.777        | 0.792        | 0.526       | 0.565        | 0.605        | 0.736       | 0.744        | 0.808       |

special case of BERTRL with an empty reasoning path. In our experiments, we do not feed additional description other than entity and relation names as (Yao et al., 2019) did. We aim to give all the methods the same input. In practice, both can be extended to accept additional information as this is what BERT is designed for.

Both BERT RL and KG-BERT were implemented in Pytorch using Huggingface Transformers library (Wolf et al., 2020). We employ BERT base model (cased) with 12 layers and 110M parameters and run experiments with a GTX 1080 Ti GPU with 12GB RAM. We use a batch size of 32 and fine-tune models for 2 epochs using the Adam optimizer. The best learning rate 5e-5 is set for BERT RL and 2e-5 for KG-BERT, selected from 2e-5 to 5e-5 based on validation set performance.

Evaluation Task. Following GRAIL (Teru et al., 2020), our default evaluation task is to rank each test triple among 50 other negative candidates. The negative triples are not in KG and generated by randomly replacing head (or tail) entity of each test triple. The sampling is going to speed up the evaluation process. The performance will be lower if the ranking is done among the full entity set.

Metrics. We evaluate the models on Hits@1 and Mean Reciprocal Rank (MRR). Hits@1 measures the percentage of cases in which positive triple appears as the top 1 ranked triple, while MRR takes the average of the reciprocal rank for positive triples.

3.1 Inductive Relation Prediction

We first evaluate the model’s ability to generalize to unseen entities. In a fully inductive setting, the entities seen in training and testing are completely disjoint. For all the methods, we extract paths from the target head entity to the tail entity with length up to 3 or the subgraph containing these paths.

Datasets. We conduct our experiment using the inductive subsets of WN18RR, FB15k-237, and NELL-995 introduced by (Teru et al., 2020). Each subset consists of a pair of graphs train-graph and ind-test-graph. The former is used for training, and the latter provides an incomplete graph for relation prediction. train-graph contains all the relations present in ind-test-graph. However, their entity sets do not overlap. In GRAIL, WN18RR, FB15k-237, and NELL-995 each induces four random inductive subsets (v1, v2, v3 and v4). We pick one subset for each (WN18RR v1, FB15k-237 v1 and NELL-995 v2). For each inductive dataset, we did stratified sampling on train-graph to create few-shot variants. The links are down-sampled to a number around 1,000 and 2,000, while keeping an unchanged proportion of triples for each relation. The few-shot training graph train-1000 and train-2000 contain all relations in its full setting, thus covering the relations in test-graph as well. The statistics of these variants are shown in Table 2.

Results. BERTRL significantly outperforms the baselines in most settings as shown in Tables 3 and 4, particularly by around 10 absolute Hits@1 and MRR points in FB15k-237 and NELL-995. These
two KGs have more relations and are associated with open-world knowledge (learned by BERT) compared with WN18RR. Methods like GRAIL and RuleN are not able to incorporate such prior knowledge.

In the few-shot setting, BERTRL stays robust and outperforms the baselines by an even larger margin. When more links are dropped in training graph, BERTRL achieves more performance gain over the baselines. BERTRL enjoys all sources of knowledge: structural (reasoning paths), textual (embedding), and prior knowledge (pre-trained language model). They all play an important role in knowledge graph completion.

In both settings, BERTRL performs better than KG-BERT, the version without reasoning paths inputted. It shows that incorporating paths allows pre-trained language models to gain explicit reasoning capability. On the other hand, with the triple information alone, KG-BERT is able to make a certain amount of correct inferences, suggesting that prior knowledge stored in pre-trained language models can be leveraged to do knowledge graph completion as manifested in (Yao et al., 2019). BERTRL combines explicit reasoning capability, prior knowledge, and language understanding all together in one model and has significant advantages.

### 3.2 Transductive Relation Prediction

BERTRL can also be applied in the transductive setting and be compared with the baselines.

### Datasets

To evaluate the transductive performance, we train these models on train-graph introduced in the inductive setting and test on links with the same set of entities. We use a list of test triples with 10% size of train-graph. In a few-shot setting, we reuse the few-shot train-graph used in the inductive setting and tested on the aforementioned test links. At testing time, full train-graph is used to collect knowledge around target entities (otherwise, the setting will be close to the inductive one). The few-shot setting makes datasets partially transductive, as some entities become unseen when links are dropped randomly. For TuckER and MINERVA, we assign a minimum score for both positive and negative triples containing unseen entities.

### Results

Tables 5 and 6 show that BERTRL outperforms the baselines in most of full and few-shot settings. It performs competitively with TuckER in the full setting and surpasses RuleN and GRAIL. It implies that BERTRL’s strong performance is not limited to inductive learning. In the few-shot setting, train-graph becomes sparse and unseen entities appear in testing. BERTRL again largely outperforms all the methods, which once more demonstrates the advantage of simultaneously exploiting all knowledge sources.

### 3.3 Unseen Relation Prediction

As BERTRL leverages a pre-trained language model, it has the potential to predict unseen relations in a zero-shot setting, which is not possi-
Table 7: Unseen relation prediction results (Hits@1)

|          | 50 relations | 100 relations |
|----------|--------------|---------------|
| KG-BERT  | 0.266        | 0.450         |
| BERTRL   | 0.485        | 0.500         |

Datasets. We create a down-sampled training dataset from full FB15k-237 train-graph, and test on ind-test-graph. The relations in FB15k-237 have a multi-level hierarchy, e.g., people/person/spouse_s. Words are shared across different relations, which makes unseen relation generalization possible. When down-sampling train-graph, we sample 50 and 100 relations without replacement weighted by their proportion in train-graph, written as train-rel50 and train-rel100.

Results. Table 7 shows Hits@1 results. It is observed that both KG-BERT and BERTRL make some correct predictions even without seeing the relations in training: The textual information shared among relation names benefits the reasoning of unseen relations. Certainly, both methods take advantage of the knowledge learned by BERT.

Table 8 shows the best and worst performed unseen relation prediction on train-rel50. For each unseen relation, we manually identify relevant relations showing in the training set. These examples show that the best performing relations have some close meaning counterparts seen in training. In contrast, the worst performing relations are usually distant from relations seen in training. This phenomenon indicates that in the zero-shot setting, BERTRL generalizes best to unseen but closely relevant relations. We suspect that knowledge captured by pre-trained language models also helps zero-shot learning.

3.4 Explainability

As stated in Section 1, rules like (1) are explainable to humans. BERTRL achieves certain explainability by leveraging reasoning paths and implicitly memorizes these rules through training. For a prediction task \((h, r, ?)\), BERTRL is going to generate many instances for different tail entity \(t\) by concatenating triple \((h, r, t)\) with each path \(h \rightarrow t\). Those with the highest scores are chosen as the answer. We can regard the path chain as the explanation of deriving \((h, r, t)\). We conduct manual case study using FB15k-237 dataset as an example. The texts are simplified.

The following KG completion query \((Chris, acts_in_film, \?)\) is to find what film the actor Chris acts in. The instance ranked highest by BERTRL consists of target triple \((Chris, acts_in_film, Jackie Brown), reasoning path \((Chris, nominated_for_same_award_with, Robert); \(Robert, acts_in_film, Jackie Brown);\) and an assigned score 0.95. It could be naturally explained as follows: Chris likely acts in film Jackie Brown, since Robert shares the same award nomination with Chris and also acts in Jackie Brown.

We then examined the percentage of the explanations that do make sense. We randomly sampled 100 test triples from FB15k-237 and ask human annotators to check their top-1 path chains highly scored by BERTRL. Human judges found that 84% of the path chains make sense, indicating strong explainability.

3.5 Training and Inference Time

We investigate training and inference time, using the transductive setting of FB15k-237 as an example. Figure 2 shows the running time of BERTRL compared with other methods using their default packages without further optimization. The running time is highly implementation and device dependent, however, the curves still show a trend and gives a rough scale of it. The training time of BERTRL gradually increases as the number of training triples grows. The inference time of BERTRL does not depend on the training data size and is slower than RuleN. Running time is one important factor in practice, and we leave how to speed up BERTRL to future work.

3.6 Ablation study

Table 9 shows the effect of different design choices in BERTRL, mainly knowledge linearization and...
Table 8: Examples of the best and worst preforming unseen relation prediction of BERT, trained on a 50 relations subset of FB15k-237.

| Unseen relation                                      | Hits@1     | Similar seen relation                                      |
|-------------------------------------------------------|------------|------------------------------------------------------------|
| /film/film_format                                     | 1.000      | /film/genre, /film/language                                 |
| /person/spouse_s./marriage/spouse                     | 1.000      | /person/spouse_s./marriage/type_of_union                   |
| /pro_athlete/teams./sports_team_roster/team           | 1.000      | /football_player/current_team./sports_team_roster/team     |
| /artist/origin                                        | 0.000      | -                                                          |
| /record_label/artist                                  | 0.100      | -                                                          |
| /ethnicity/languages_spoken                           | 0.250      | /person/languages                                          |

Table 9: Ablation study of BERTRL variants (Hits@1)

|                        | 1,000 | 2,000 | full  |
|------------------------|-------|-------|-------|
| Subgraph (edge list)   | 0.361 | 0.398 | 0.463 |
| Combined paths         | 0.351 | 0.461 | 0.505 |
| 5 sampled individual paths | 0.466 | 0.490 | 0.532 |
| 10 sampled individual paths | 0.449 | 0.505 | 0.500 |
| BERTRL (individual paths) | 0.441 | 0.493 | 0.541 |

path sampling. We use the FB15k-237 inductive dataset and its few-shot subset for evaluation.

**Combined Paths.** As discussed in Section 2.2, combined paths is one way linearizing structural knowledge. Although it includes more information in one input, it does not outperform individual paths. This indicates that BERT struggles to learn from complex input when training data is limited, which might be explained by Occam’s razor.

**Subgraph (Edge List).** Edge list is the worst performing linearization option. Linking entities in the input and then recognizing patterns could be more challenging for BERT than reasoning along paths where edges are ordered by their connection.

**Path Sampling.** We evaluate the performance of path sampling by randomly selecting $n$ paths between entities. Path sampling could speed up training as the training data becomes small. The performance is still good even when the number of sampled paths is very small, indicating BERTRL is robust to the size of the training set.

4 Related Work

**Transductive Models.** Most existing knowledge graph completion methods are embedding based, such as TransE (Bordes et al., 2013), Complex (Trouillon et al., 2017), ConvE (Dettmers et al., 2018), RotatE (Sun et al., 2019) and TuckER (Balazević et al., 2019). These methods learn embedding of entities and relations and construct scoring functions on top of the embedding. They are naturally transductive and can not be directly applied to or need re-training for the inductive setting where entities are not seen in the training.

Some methods, e.g., R-GCN (Schlichtkrull et al., 2018), DeepPath (Xiong et al., 2017), MINERVA (Das et al., 2018) and DIVA (Chen et al., 2018), learn to aggregate information from local subgraph and paths. However, they cannot be directly applied to the inductive setting as entity/node specific embeddings are needed.

**Inductive Models.** In contrast to the transductive setting, probabilistic rule learning AMIE (Galárraga et al., 2013) and RuleN (Meilicke et al., 2018) could apply learned rules to unseen entities. NeuralLP (Yang et al., 2017) and DRUM (Sadeghian et al., 2019) learns differentiable rules in an end-to-end manner. GRAIL (Teru et al., 2020) extracts subgraph connecting target entities and learns a general graph neural network to score a prediction. These methods are in nature inductive as they learn entity irrelevant rules or models and conduct reasoning with knowledge graph information only.

Besides these studies, there are methods learning to generate inductive embedding for unseen nodes. (Hamilton et al., 2017) and (Bojchevski and Günnemann, 2018) rely on the node features which may not be easily acquired in many KGs. (Wang et al., 2019) and (Hamaguchi et al., 2017) generate embedding for unseen nodes by learning to aggregate embedding from neighbors using GNNs. However, those two paradigms require a certain number of known entities and cannot be applied to entirely new graphs.

**Pre-trained Language Models.** Pre-trained language model is one of the most influential advances in natural language processing, e.g., BERT (Devlin et al., 2019), Roberta (Liu et al., 2019), and GPT (Radford et al., 2019; Brown et al., 2020). They are trained unsupervisedly on very large corpus and often achieve great performance after fine-tuning on
downstream tasks. Besides, (Petroni et al., 2019) introduces LAMA benchmark, and shows that pre-trained language models themselves already capture some factual knowledge even without fine-tuning.

KG-BERT (Yao et al., 2019) aims to leverage the power of pre-trained language model in knowledge graph completion, where it represents triples as text sequences and uses BERT to learn scoring function for relation prediction. Though it can be applied in the inductive setting, its prediction is mainly based on the pre-trained representation of entities and relations; it does not learn a general reasoning mechanism like GRAIL and BERT-RL.

5 Conclusion

We proposed BERT-RL, a pre-trained language model based approach for knowledge graph completion. By taking reasoning path and triple as input to a pre-trained language model, BERT-RL naturally handles unseen entities and gains the capability of relational reasoning. In few-shot learning, it outperforms competitive baselines by an even larger margin. It has the potential to generalize to unseen relations in a zero-shot setting. It not only achieves the state-of-the-art results in inductive learning, but also shown to be effective in transductive learning. Overall, this work opens a new direction of combining the power of pre-trained language model and logic reasoning.

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