Neural Theorem Provers Delineating Search Area Using RNN

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Abstract

Although traditional symbolic reasoning methods are highly interpretable, their application in knowledge graphs link prediction has been limited due to their computational inefficiency. A new RNNNTP method is proposed in this paper, using a generalized EM-based approach to continuously improve the computational efficiency of Neural Theorem Provers (NTPs). The RNNNTP is divided into relation generator and predictor. The relation generator is trained effectively and interpretably, so that the whole model can be carried out according to the development of the training, and the computational efficiency is also greatly improved. In all four data-sets, this method shows competitive performance on the link prediction task relative to traditional methods as well as one of the current strong competitive methods.

Keywords Knowledge Graph · Link Prediction · Neural Symbolic Reasoning · Deep Learning

1 Introduction

Knowledge graphs (Ehrlinger and Wöß [2016]) contains lots of real-world facts, which are useful in various applications. Each fact is typically specified as a triplet \((h, r, t)\) or another form \(r(h, t)\), meaning entity \(h\) has relation \(r\) with entity \(t\). For example, \(father(AnakinSkyWalker, LukeSkyWalker)\) can express a fact that Anakin is Luke’s father if we have known the famous movie Star Wars. As above, still the example of Star Wars, when Luke knew that another character Leia Organa Solo in this play is his sister? It is when Leia knew that her father is Anakin SkyWalker, too.
Even in the real world, people always can not know all the relations between things and things, people and people. As it is impossible to collect all facts, knowledge graphs are incomplete. Therefore, a fundamental problem on knowledge graphs is to complete Knowledge graphs by reasoning with existing ones, also known as knowledge graphs reasoning.

Prevailing knowledge graphs reasoning use neural models (Bordes et al. [2013], Lin et al. [2015], Sun et al. [2019], Nickel et al. [2011], Yang et al. [2014], Nickel et al. [2016], Trouillon et al. [2016], Dettmers et al. [2018]) and symbolic reasoning models (Galárraga et al. [2013, 2015], Omran et al. [2018], Ho et al. [2018], Niu et al. [2020],), which faced with kinds of problems including weak generalisation results on datasets, discrete results which is unstable and hard to train with lots of modern optimization methods, lacking of explanatory which will cause the model hard to improve its performance with the help of real-world experts.

Neuro-Symbolic Reasoning A promising direction for overcoming these issues consists in combining neural models and symbolic reasoning given their complementary strengths and weaknesses. Neuro-Symbolic (Neural Symbolic) Reasoning (Guo et al. [2016, 2018], Zhang et al. [2019], Richardson and Domingos [2006], Qu and Tang [2019], De Raedt et al. [2007], Das et al. [2017], Yang et al. [2017]) performs well because it contains explainable rules as well as it have continuous solution space. As experts can play roles on explainable rules and modern optimization methods can be used in continuous solution space, we focus on NTPs(Rocktäschel and Riedel [2017], Minervini et al. [2020a,b]), a family of neuro-symbolic reasoning models: NTPs are continuous relaxations of the backward-chaining reasoning algorithm that replace discrete symbols with their continuous embedding representations. NTPs have interesting properties: they can jointly learn representations and interpretable rules from data via back-propagation, and can potentially combine such rules in ways that may have not been observed during training. However, a major limitation in NTPs is that, during training, they need to consider all rules for explaining a given goal or sub-goal. This quickly renders them ineffective in settings requiring a large number of rules or reasoning steps.

As Knowledge Bases(KBs) increasing, NTPs will generate a large number of sub-goals, which exponential growth base on the searching deep and KB’s scale. It cause huge computational complexity and make NTPs can not solve problems with large datasets. Researcher make a lot of effort to make NTPs easier to use and reduce the amount of computation. GNTPs (Minervini et al. [2020a]) dynamically constructing the computation graph of NTPs and including only the most promising proof paths during inference, thus obtaining orders of magnitude more efficient models. CTPs(Minervini et al. [2020b]) learn an adaptive strategy for selecting subsets of rules to consider at each step of the reasoning process. This is achieved by a select module that, given a goal, produce the rules needed for proving it. Predicates and constants in the produced rules lie in a continuous embedding space. Hence, the select module is end-to-end differentiable, and can be trained jointly with the other modules via gradient-based optimisation. But their strategy to zoom out of the search space have the disadvantage that the select module is unexplained and hard to enhance with the help of experts. These methods improve the behavior of NTPs by adding neural network layer or parameter, which is lack of ability to enhance it using domain knowledge.

Our work focus on reducing the computational complexity of NTPs as well as making select module controllable and explainable. Rnnlogic (Qu et al. [2020]) provided an EM algorithm(Do and Batzoglou [2008]) based rule generator optimizer with explicit probability distribution representations. It use H values(a rule evaluation metric related to its predictor structure) to train rule generator. Together with the weight, it is cleared when the rule is assigned to the predictor. It is re-assigned in the e-step and passed into the generator later, which is equivalent to once the H value is
used for the rule generation once. Our approach combine with NTPs and use its feature that and module’s recursive searching ability may multiple access to one rule. So our approach make the score of a rule super-imposable and reduce the amount of calculation per iteration under the use of GRU (Chung et al. [2014]), a kind of RNN (Rumelhart et al. [1986]) network, which have fewer parameters and semantic memory ability. and module need the semantic memory ability to generate more appropriate rules. Super-imposable rules scores is used to make and module better score the rules based on the goal’s score.

2 Related Work

2.1 End To End Differentiable Provers

NTPs (Rocktäschel and Riedel [2017]) and its conditional proving strategies optimised version CTPs (Minervini et al. [2020b]) are continuous relaxation of the backward chaining algorithm: these algorithms works backward from the goal, chaining through rules to find known facts supporting the proof.

Given a query (or goal) G, backward chaining first attempts to unify it with the fact available in a given KB. If no matching fact is available, it considers all rules H: ¬B (We see facts as rules with no body and valuables), where H denotes the head and B the body, and H can be unified with the query G resulting in a substitution for the variables contained in H. Then, the backward chaining algorithm applies the substitution to the body B, and recursively attempts to prove until find the facts or catch the deep we have set.

Backward chaining can been seen as a type if and/or search: or means that any rule in the KB can be used to prove the goal, and and means that all the premise of a rule must be proven recursively.

Unification Module. In the backward chaining reasoning algorithm, unification matches two logic atoms, such as fatherOf(Anakin, Luke) and dadOf(X, Y). It is backward chining reasoning’s key operator, which play roles in discrete space. In discrete spaces, equality between two atoms (e.g. fatherOf ≠ dadOf) is evaluated by unification by examining the elements that compose them, and using substitution sets (e.g. X/Anakin, Y/Luke) binds variables to symbols. In NTP, to be able to match different symbols with similar semantics, unification uses a Gaussian kernel to compare the similarity of different representations in the embedding space.

In NTP, unifyθ(H, G, S) = S′ generate a neural network—a proof state S = (Sψ, Sρ) consisting of a set of substitutions Sψ and a proof score Sρ. For example, given a goal G = [fatherOf, Anakin, Luke] and a fact H = [dadOf, X, Y], the unify module uses Gaussian kernel k to compare the embedding representations of fatherOf and dadOf, updates the variable binding substitution set S′ψ = Sψ ∪ {X/Anakin, Y/Luke}, and calculates the new proof score S′ρ = min(Sρ, k(θfatherOf, θdadOf)) and proof state S′ = (S′ψ, S′ρ).

OR Module. The or module traverses a KB, computes the unification between goal and all facts and rule heads in it, and then recursively use the and module on the corresponding rule bodies. Given a goal G and each rule H : ¬B with the rule head H in a KB R, module orθR(G, d, S) unifies the goal G with the rule head H, and bodies B of each rule will be proved by using module and until reach the set deepest depth d or unify fail. or module is shown below:

\[
\text{or}_R^θ(G, d, S) = [S′|H : ¬B \in R, \\
S′ \in \text{and}_R^θ(B, d, \text{unify}_θ(h, g, s))]
\] (1)
For example, given a goal $G = [\text{grandpaOf}, Q, Luke]$ and a rule $H : \neg B$ with $H = [\text{grandfatherOf}, X, Y]$ and $B = [[\text{fatherOf}, X, Z], [\text{fatherOf}, Z, Y]]$, unify module compute the similarity of goal $G$ and the rule head $H$ to get a score, then and module prove the sub-goals generated by rule body $B$ to get sub-scores.

**AND Module.** After unification in or module, and module proves a list of sub-goals in a rule body $B$. $\text{and}_{\theta}(B : \mathbb{B}, d, S)$ module first substitute variables in the first sub-goal $B$ with constants using substitutions in $S$, then use or module to generate another sub-goals of $B$. $\mathbb{B}$ use the result state of above to prove the atoms by using the and module recursively:

$$\text{and}_{\theta}^0(B : \mathcal{B}, d, S) = |S'|d > 0,$$

$$S' \in \text{and}_{\theta}^0(B, d, S'),$$

$$S' \in \text{or}_{\theta}^d(\text{sub}(B, S_\theta), d - 1, S)$$

For example, we use and module to prove the rule body $B$ mentioned above. and module substitute variables with constants using substitutions in $S$ for the sub-goal $[\text{fatherOf}, X, Z]$, then use the or module to get a resulting state. and module will be used to prove $[\text{fatherOf}, Z, Y]$ using resulting state generated above.

**Proof Aggregation.** In a KB, we use modules above to generate a neural network, which evaluates all the possible proofs of a goal $G$. The largest proof score will be selected by NTPs:

$$\text{ntp}_\theta^d(G, d) = \max_{S \in \mathcal{S}} S_\rho$$

where $d \in \mathbb{N}$, and $\mathbb{N}$ is defined at the beginning. The initial proof state is set to $(\emptyset, 1)$ which express an empty substitution set and a proof score of 1.

**Training.** NTPs minimise a cross-entropy loss $L^\mathcal{R}(\theta)$ to learn embedding representations of atoms using the final proof score. Prover masking facts iteratively and try to prove them using other facts and rules.

### 2.2 Deficiencies and improvement goals

NTPs and its conditional proving strategies optimised version CTPs In the NTPs proving process, evaluating effect of rules is complex due to the recursively scoring process of or module and and module. CTPs reformulate goals by using extra neural network layers so that its training is end to end and easy to train. But we can’t know why a goal relation can be reformulated due to its ambiguous manifestations. We can’t add new knowledge to interpret its relationship selection and optimize it.

In Rnnlogic (Qu et al. [2020]), they provided a rule generator to generate rules, and use predictor to score rules by adding H values to each rule if it path arrive at the destination:

$$H(\text{rule}) = \{ \text{score}_\omega(t|\text{rule}) - \frac{1}{|\mathcal{A}|} \sum_{e \in \mathcal{A}} \text{score}_\omega(e|\text{rule}) \}$$

where $\mathcal{A}$ is the set of all candidate answers discovered by rules. It leak the ability to evaluate the importance of rules used by NTPs and module’s recursively working process. Relation’s contribution can’t be evaluate correctly because the $H(\text{rule})$ only consider the distinctions which rules are used. The hierarchical proving process need Generator knows
that not all relations used will get the same treatment the next time they are generated, the deeper the relations should be generated, the greater the number.

We propose a model that not only makes the relation selecte part interpretable, but also enables relation selectors to better function in the hierarchical proof process of NTPs. We will introduce it in the next chapter and demonstrate it experimentally in chapter four.

3 EM-like Optimization with Hierarchical Relation Generator

![Diagram](image)

Figure 1: We proposed a hierarchical relation storage structure as well as a hierarchical Knowledge storage structure. They can store some knowledge hierarchically in the process of UNIFY, and after a predictor training is completed, the stored knowledge can be converted into some relations through the Nearest Neighbor Search (NNS) algorithm, and those relations will be used in the training of the relation generator.

In this section, we introduce our approach which learns logic rules for knowledge graph reasoning. Considering NTPs have a recursively proving process, we provided a rule formulator with a super-imposable rule scoring structure. We use an EM-like algorithm with implicit probability. First, we use rule formulator to generate some rules. And in the e-step, we use these rules to train NTPs and recursively score the rules. In the m-step, we use the scores of rules to train rule formulator.

3.1 Relation Generator

Considering that the proof process of NTPs is from top to bottom, layer by layer deeper, there is a sequential relationship between the upper-level rule facts and the lower-level rule facts, so this paper uses RNN as the rule and fact selector for selection. In the proof process of the backward chain, if unify succeeds in the proof process, then the rules and facts traversed by the or operation are the same as the previously traversed rules and facts are related, and the related relationship is sequential. For example, grandpaOf ← fatherOf, parentOf, when we want to prove the goal with the relation grandpaOf, when we traverse to the above rule, we will expand grandpaOf into two subgoals, each with fatherOfThe relationship between and parentOf; and when we want to prove a goal with fatherOf, we
hardly ever use a rule like $fatherOf ← sonOf, grandparentOf$ to do a proof expansion. Therefore, the sequence relationship between our upper-level rule facts and lower-level rule facts is universal, and the use of RNN with sequence features for prediction can fully capture the implicit relationship. We also call the relation generator $RNN_θ$ below.

**Relation Selector:** We propose an RNN-based relation selector to generate relation sets according to the goals. First, relation selector has the generate structure $R ∗ B$, $R$ is goal’s relation(predicate) and $B$ is generated relation(predicate) consist of $r_1, r_2, \ldots, r_n$. We use a relation selector $RNN_θ$ to predict sequence relations. Given a goal sets $G$, we extract the relations $r$, Initialize $RNN_θ$:

$$h_0 = f(r),$$

The GRU gating unit is then used to make predictions on the rules at different locations:

$$h_t = GRU(h_{t-1}, g([r_{t-1}, r_t])),$$

$g$ is a linear transformation, $[r_{t-1}, r_t]$ is a connection between the previous relation and the current relation.

Perform a probability division on the generated rule set $R$ by $softmax(o(h_{t+1}))$ to get the next relation $r_{t+1}$. Each relation $r_i$ is added to a relation set $LogicPredicates$.

**Relation Storage:** Effectively training relation selectors is also a non-trivial task, so we propose a relational storage structure to better capture relational information from the predictor. Using a sets of coefficient of expansion $\{ep_1, ep_2, \ldots, ep_{maxDepth}\}$ related to the depth of the relations, we store relations like below:

$$RelStorage = \{r_1, \ldots, r_j, r_{j+1}, \ldots, r_k, r_{k+1}, \ldots, r_l, \ldots\}$$

(5)

After some processing, we use $RelStorage$ as the training set of Relation Selector, and the details are explained in the following training process.
3.2 Predictor base on NTPs

We remodeled some modules of NTPs to evaluate relations and accelerate computing.

Algorithm 1: Or Module

```
1 function or(G, d, S):
2    for H : \neg B \in SelectedKBs do
3       for S \in and(B, d, unify(H, G, S)) do
4          yield S
5    end
6 end
```

Algorithm 2: Unify Module

```
1 function unify(H, G, S = (S_\psi, S_\rho)):
2    S_\psi' = S_\rho \cup \bigcup_i T_i
3    with T_i = \begin{cases} 
                   \{H_i/G_i\} & \text{if } H_i \in \mathcal{V} \\
                   \{G_i/H_i\} & \text{if } G_i \in \mathcal{V}, H_i \notin \mathcal{V} \\
                   \emptyset & \text{otherwise}
               \end{cases}
4    if S_\rho < setedMinScore then
5       break
6    else
7       High-quality Knowledge add H
8    end
9    S_\rho' = \min\{S_\rho\} \cup_{H_i,G_i \notin \mathcal{V}} \{K(\theta_{H_i}, \theta_{G_i})
10   return (S_\psi', S_\rho')
```

**Or Module.** NTPs traverse all knowledge in KBs in the process of proof, which cause some computational issues. We reformulated it and make it only consider the knowledge we provide. As algorithm 1 shown, we only traverse the knowledge matched in the KBs by the relations generated by the generator. Other parts are consistent with NTPs.

**Unify Module.** In NTPs, unify module returns a new substitution set and a new goal’s score base on the similarity of relation and entity. As algorithm 2 shown, we set a threshold `setedMinScore` to control the unify module. If the similarity exceeds a threshold, we add this knowledge to our high-quality level for subsequent operations. And if not, terminate the proof branch.
3.3 Model Training

As figure 1 shows, a hierarchical relation storage structure and a hierarchical Knowledge storage structure are provided to prepare the training data for the generator. Generator and predictor are trained together by a EM-like algorithm.

**Algorithm 3:** Basic training process

**Input:** triple data set goals $[(h, r, t)]$, number of iterations $n$.

**Output:** Scores, trained generator $RNN_{θ}$, trained predictor $NTPs_{θ}$.

1. Initialize KB, $RNN_{θ}$, $NTPs_{θ}$;
2. for $i = 1$ to $n$ do
3.   $RNN_{θ}$ generate Logic Predicates;
4.   Selected KBs = Select(KBs, Logic Predicates);
5.   e-step: start train $NTPs_{θ}$:
6.     if unify(facts or rules ∈ SelectedKBs) not FAIL then
7.       High-quality Knowledge add (facts or rules);
8.     end
9.     while size(Relation Storage) < maxSize(Relation Storage) do
10.    High-quality Knowledge add NNS(KB);
11.    Relation Storage add predicates of High-quality Knowledge;
12. end
13. m-step: train Relation Selector with Relation Storage;
14. end

Algorithm 3 shows the basic process of training. We first initialize the generator $RNN_{θ}$ and predictor $NTPs_{θ}$. The relations of this batch of goals are input to the generator, and then the generator is used to generate a series of relations; The generated relations are matched in KBs to generate a knowledge domain. In the e-step, our predictor uses the knowledge in this domain to score this batch of goals, and put the useful knowledge into the High-quality knowledge. When the size of Relation Storage does not reach the set value, we need to use NNS to search for High-quality Knowledge in KB first, and add the predicate(relation) of High-quality Knowledge to Relation Storage. In the m-step, we connection the values in the Relation Storage with the goals’ predicates as training data to train the selector.

**KB initialization:** Read in the triplet data set, and create a tuple with the relationship or rule header as the key and the entity pair or rule body as the value for easy access.

**Generator initialization:** Establish an RNN network based on GRU gates, where the dimension of $h_t$ is consistent with the relation’s embedding size.

**Predictor initialization:** Because the embedding structure of the complex matches the unify operation in NTPs, we first use the complex to perform a pre-training on all KB data.
Generate knowledge set $\text{SelectedKBs}$: $\text{RNN}_\theta$ traverses each relation in the goal, generates a series of relation sets $\text{LogicPredicates}$, and performs each relationship in $\text{KB}$ for each relationship in $\text{LogicPredicates}$ matching, matching rules and facts generate a knowledge set $\text{SelectedKBs}$.

Training predictor $\text{NTPs}_\theta$: NTPs are the same as described above, but the OR module is modified, and the current facts or rules are added to High-quality Knowledge every time $\text{unify}$ succeeds. The other parts of the algorithm are basically the same as NTPs described above.

High-quality Knowledge completion: Use Nearest Neighbor Search (NNS) domain search algorithm to search the knowledge in High-quality Knowledge in $\text{KB}$, add the closest knowledge to Relation Storage until the set upper limit is reached.

4 Experiment

4.1 Experiment Settings

Datasets: Kinship, UMLS, Nations and Countries. In our experiment, we choose three benchmark datasets for evaluation, which are Alyawarra kinship (Kinship), Unified Medical Language System (UMLS), Nations. For the Kinship, UMLS and nations datasets. Nations contains 56 binary predicates, 111 unary predicates, 14 constants and 2565 true facts; kinship contains 26 predicates, 104 constants and 10686 true facts; UMLS contains 49 predicates, 135 constants and 6529 true facts real facts. Because our benchmark ComplEx cannot handle unary predicates, we remove unary atoms from Nations. For the Kinship, UMLS and nations datasets, there are no standard data splits. So we split each knowledge base into 30% training facts, 20% validation facts and 50% testing facts. For evaluation, we take a test fact and corrupt its first and second arguments in all possible ways such that the corrupted fact is not in the original KB. Subsequently, we predict each test fact and its corrupted rank to compute MRR and HITS@$m$. We also use the COUNTRIES dataset (Bouchard, Singh, and Trouillon 2015) to evaluate the scalability of our algorithm. The dataset contains 272 constants, 2 predicates, and 1158 ground truths, and is designed to explicitly test the logical rule induction and reasoning abilities of link prediction models. We compare (Rocktäschel and Riedel 2017), inference steps that require increasing length and difficulty (S1, S2, S3).

Evaluation Benchmark. In Kinship, UMLS, Nations and Countries, we predict each test fact and its corrupted rank to compute MRR and HITS@$m$($m=1,3,10$) after training. In country, we evaluate the area under Precision-Recall-curve (AUC-PR) with results comparable to previous methods. Average training time per iteration relativley (ATTP) is set to compare the computational performance. Knowledge Utilazition show the utilization of knowledge every time we use, it counting through the success of $\text{unify}$’s branch establishment and comparing the knowledge this batch’s goals use. ATTP and Knowledge Utilization can evaluate the expected performance on large datasets.

Modules Setting. In relation generator, we use embedding that comes with pytorch. And in predictor, we use ComplEx to pretrained the datasets because it fits the way $\text{unify}$ works. The scale proportion of $\text{SelectedKBs}$ is set to 30%. The number of $\text{RelationStorage}$ layers is the same as the number of recursive layers of NTPs, set to 3.
4.2 Results and Analysis.

Accuracy. Compared to other neuro-symbolic inference models, we get a good performance at HITS@10, especially in Kinship. It shows that we can easily narrow down the correct result to a small range. Because the calculation time and the amount of traversal knowledge are too small compared to NTP, NeuralLP, MINERVA, our final accuracy has dropped.

Table 1: Results compared to NTPs and previous methods

| Datasets | Metrics | Ours | CTP | NTP | NeuralLP | MINERVA |
|----------|---------|------|-----|-----|-----------|---------|
| Nations  | MRR     | 0.701| 0.709| 0.74| -          | -       |
|          | HITS@1  | 0.539| 0.562| 0.59| -          | -       |
|          | HITS@3  | 0.875| 0.813| 0.89| -          | -       |
|          | HITS@10 | 0.997| 0.995| 0.99| -          | -       |
| Kinship  | MRR     | 0.772| 0.764| 0.80| 0.619     | 0.720   |
|          | HITS@1  | 0.609| 0.646| 0.76| 0.475     | 0.605   |
|          | HITS@3  | 0.891| 0.859| 0.82| 0.707     | 0.812   |
|          | HITS@10 | 0.973| 0.958| 0.89| 0.912     | 0.924   |
| UMLS     | MRR     | 0.801| 0.852| 0.93| 0.778     | 0.825   |
|          | HITS@1  | 0.589| 0.752| 0.87| 0.643     | 0.728   |
|          | HITS@3  | 0.951| 0.947| 0.98| 0.869     | 0.900   |
|          | HITS@10 | 0.972| 0.984| 1.00| 0.962     | 0.968   |
| Countries| S1      | 100.0| 100.0| 100.0| 100.0     | 100.0   |
|          | S2      | 89.47| 91.81| 93.04| 75.1      | 92.36   |
|          | S3      | 95.21| 94.78| 77.26| 92.20     | 95.10   |

Figure 2: Knowledge utilization and average training time (relatively) per iteration compared to NTP and CTP. We can observe that our model has a performance advantage over previous models. (The knowledge utilization of CTP is hard to evaluate. Based on the fact that it improves performance by reformulating the goals, we cannot properly evaluate its performance by knowledge utilization.)
Computing Performance. As figure 2 shown, ATTP and Knowledge Utilization have a huge improvement over NTP and a relatively small improvement compared to CTP. Especially in Nations dataset, as figure 3 shown, which contains lots of rules with 2 body atoms. Our method is better than NTP in performance, because in multi-hop reasoning, NTP’s search method can cause serious performance bottlenecks, while our method makes the search domain learnable and the search range is smaller each time. Considering that the accuracy is not much different from CTP, the improvement in our computational performance is encouraging.

Compared with the most traditional symbolic reasoning methods, the accuracy has decreased, but our performance has increased by more than ten times, which is acceptable, and CTP has also set an example in this regard. Compared with CTP, our other advantage is that we can manually control the training of the generator by adjusting RelationStorage, which means that we can also use human strength to make the training results better.

For example, for a known specific task, such as related to the word grandfather, we can train in advance by adding words such as father and son to the sequence backbend of the warehouse to get a better acceleration effect. In the EM algorithm, this is equivalent to performing a fine-tuning of the implicit distribution of the intermediate variables in advance.

Figure 3: In Nations dataset, 2-hop and 1-hop reverse reasoning significant performance drain in NTPs. Our method limits the scope of knowledge search, and performance gains are relatively large in these tasks.

5 Conclusion and Future Work

Using neural symbolic reasoning method to reason in knowledge graph has the advantage of strong interpretability, and it is easy to optimize according to new knowledge. Our method corrects the shortcomings of low computational efficiency of traditional methods and the weak interpretability of some modules of CTP. NTP has good interpretability and can generate new rules. After our method improves its computational efficiency, it can be used more widely. Our method is more efficient, so that such method can be placed in more complex knowledge graphs in the future.

However, we also have some shortcomings. Although the hierarchical structure of the relationship corresponding to the backward chain reasoning is used to construct the RNN, its training effect is limited compared to the CTP. Finding a new and more efficient relational generator and a more efficient training structure for constructing the generator will be
my future focus in this model. This method based on the EM algorithm needs to combine the structure of the predictor and the generator, and can be used in more predictors in the future to improve their training efficiency and preferences.

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