HyTE: Hyperplane-based Temporally aware Knowledge Graph Embedding

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Abstract

Knowledge Graph (KG) embedding has emerged as an active area of research resulting in the development of several techniques (Bordes et al., 2013; Nickel et al., 2016b; Yang et al., 2014; Lin et al., 2015; Trouillon et al., 2016; Dettmers et al., 2018; Guo et al., 2018). These methods learn high-dimensional vectorial representations for nodes and relations in the KG, while preserving various graph and knowledge constraints.

We note that KG beliefs are not universally true, as they tend to be valid only in a specific time period. For example, (Bill Clinton, presidentOf, USA) was true only from 1993 to 2001. KG beliefs with such temporal validity marked are called as temporally scoped. These temporal scopes are increasingly available on several large KGs, e.g., YAGO (Suchanek et al., 2007), Wikidata (Erxleben et al., 2014). The mainstream KG embedding methods ignore the availability or importance of such temporal scopes while learning embeddings of nodes and relations in the KGs. These methods treat the KG as a static graph with the assumption that the beliefs contained in them are universally true. This is clearly inadequate and it is quite conceivable that incorporating temporal scopes during representation learning is likely to yield better KG embeddings. In spite of its importance, temporally aware KG embeddings is a relatively unexplored area. Recently, a KG embedding method which utilizes temporal scopes was proposed in (Jiang et al., 2016). However, instead of directly incorporating time in the learned embeddings, the method proposed in (Jiang et al., 2016) first learns temporal order among relations (e.g., wasBornIn → wonPrize → diedIn). These relation orders are then incorporated as constraints during the KG embedding stage. Thus, the embedding learned by (Jiang et al., 2016) is not explicitly temporally aware.

In order to overcome this challenge, in this paper, we propose Hyperplane-based Temporally aware KG Embedding (HyTE), a novel KG em-

1 Introduction

Knowledge Graphs (KGs) are large multi-relational graphs where nodes correspond to entities, and typed edges represent relationships among them. KGs encode factual beliefs in the form of triple (entity, relation, entity), e.g., (Brussels, isCapitalOf, Belgium). Examples of a few KGs include NELL (Mitchell et al., 2018), YAGO (Suchanek et al., 2007), and Freebase (Bollacker et al., 2008). KGs have been found to be useful for a variety of tasks, viz., Information Retrieval (Kotov and Zhai, 2012; Xiong and Callan, 2015), Question Answering (Dong et al., 2015; Bordes et al., 2015; Yao and Durme, 2014), among others.

KG embedding has emerged as a very active area of research over the last few years, resulting in the development of several techniques (Bordes et al., 2013; Nickel et al., 2016b; Yang et al., 2014; Lin et al., 2015; Trouillon et al., 2016; Dettmers et al., 2018; Guo et al., 2018).
bedding technique which directly incorporates temporal information in the learned embeddings. HyTE fragments a temporally-scoped input KG into multiple static subgraphs with each subgraph corresponding to a timestamp. HyTE then projects the entities and the relations of each subgraph onto timestamp specific hyperplanes. We learn the hyperplane (normal) vectors and the representation of the KG elements distributed over time jointly. Our contributions are as follows.

• We draw attention to the important but relatively unexplored problem of temporally aware Knowledge Graph (KG) embedding. In particular, we propose HyTE, a temporally aware method for learning Knowledge Graph (KG) embedding.

• In contrast to previous time-sensitive KG embedding methods, HyTE encodes temporal information directly in the learned embeddings. This enables us to predict temporal scopes for previously unscoped KG beliefs.

• Through extensive experiments on multiple real-world datasets, we demonstrate HyTE’s effectiveness.

We have made HyTE’s source code and datasets used in the paper available at https://github.com/malllabiisc/HyTE

2 Related Work

Temporal fact and event extraction: Time, apart from being an information, also introduces a separate dimension to knowledge. Thus temporal scoping of relational facts is an imperative part of automatic knowledge graph construction and completion. T-YAGO (Wang et al., 2010) extracts temporal facts from semi-structured data like Wikipedia Infoboxes, and categories using only regular expressions. On the other hand, systems like PRAVDA harvests temporal information from free text sources using label propagation. CoTS (Talukdar et al., 2012b) uses integer linear program based approach to model temporal constraints and proposes joint inference framework with few seed examples.

A method for discovering temporal ordering among factual relations was proposed in (Talukdar et al., 2012a). The task of extracting temporally rich events and time expressions and ordering between them is introduced in TempEval challenge (UzZaman et al., 2013; Verhagen et al., 2010). Various approaches (McDowell et al., 2017; Mirza and Tonelli, 2016) made for solving the task proved to be effective in other temporal reasoning tasks. Although we try to attend to a similar problem, the method proposed in this paper is more related to relational embedding learning paradigm than scoping temporal facts from the web.

Relational embedding learning methods: An enormous amount of research has been done in this field, especially for KG completion or link prediction task (Bordes et al., 2013). (Nickel et al., 2016a) provides a detailed review of the recent KG embedding learning methods. These can be broadly categorized into two different paradigms. TransE(Bordes et al., 2013), TransH(Wang et al., 2014), TransR (Lin et al., 2015), TransD (Ji et al., 2015) are the translational distance-based models. Here the main theme is to minimize the distance between two entity vectors where one of them is translated by a relation vector. The realm of matrix factorization based methods includes bilinear model RESCAL (Nickel et al., 2011), DistMult (Yang et al., 2014), HoIE (Nickel et al., 2016b). Some of the other notable models are Neural Tensor Networks(NTN) (Socher et al., 2013). We also provide some background on the traditional methods in section 3. However, the temporal dimension remains silent in all of these inference methods.

Link prediction through embeddings of the graph nodes and edges, are not only useful for inference over KG but also important for predicting incomplete pieces of the KG itself. Learning temporally steered embeddings is an important but proportionately less explored problem. Only some handful of methods have been proposed for this purpose. t-TransE (Jiang et al., 2016) learns time aware embedding by learning relation ordering jointly with TransE. They try to inflict temporal order on time-sensitive relations e.g. wasBornIn → wonPrize→ diedIn. t-TransE does not use the time information directly, whereas we incorporate time directly in our learning algorithm. Another approach Know-Evolve (Trivedi et al., 2017) models the non-linear temporal evolution of KG elements using bilinear embedding learning method. They deploy recurrent neural network to capture non-linear dynamical characteristics of the embeddings. However, they restrict their domain to event-based interac-
Figure 1: In the figure, the vectors $e_h$, $e_r$, and $e_t$ correspond to the triple $(h,r,t)$ that is valid at time $\tau_1$ and $\tau_2$. $e_h(\tau_1)$, $e_r(\tau_1)$, and $e_t(\tau_1)$ are the projections of this triple on the hyperplane corresponding to time $\tau_1$ (similarly for time $\tau_2$). Our method HyTE minimizes the translational distance, $\sum \|e_t(\tau_i) + e_r(\tau_i) - e_t(\tau_i)\|_1$, in order to learn the temporally aware representations of entities and relations in this triple.

3 Background: KG Embedding

In this section, we provide an overview of the existing methods for knowledge graph representation learning (Bordes et al., 2013), (Wang et al., 2014). Consider a KG $G$ with a set of entities $E$. The set of directed edges, $D^+$ consists of triples $(h,r,t)$, where the edge direction is from $h$ to $t$ and the edge label (also popularly known as relation) is $r$.

3.1 TransE and TransH

TransE (Bordes et al., 2013) is a simple and efficient translational distance model. It interprets the relation as a translation vector between head and tail entity vectors. Given two entity vectors $e_h$, $e_t \in \mathbb{R}^n$, it tries to map the relation as a translation vector $e_r \in \mathbb{R}^n$, i.e., $e_h + e_r \approx e_t$ for observed triple $(h,r,t)$. So the distance based scoring function used for plausible triples is hereby, 

$$f(h, r, t) = \|e_h + e_r - e_t\|_{l_1/l_2},$$

where $\| \cdot \|_{l_1/l_2}$ is the $l_1$ or $l_2$-norm of the difference vector. $f(h, r, t)$ will be minimized for observed or correct triples. In order to differentiate between correct and incorrect triples, their TransE score difference is minimized using margin based pairwise ranking loss. More formally, we optimize 

$$\sum_{x \in D^+} \sum_{y \in D^-} \max(0, f(x) - f(y) + \gamma),$$

with respect to the entity and relation vectors. $\gamma$ is a margin separating correct and incorrect triples. $D^+$ is the set of all positive triples, i.e., observed triples in KG. The negative samples are drawn randomly from the set -

$$D^- = \{(h', r, t) | h' \in E, (h', r, t) \notin D^+\} \cup \{(h, r, t') | t' \in E, (h, r, t') \notin D^+\}.$$  

TransE fails to model the many-to-one, one-to-many, many-to-many type of relations as it does not learn a distributed representation of entities when it is involved with many relations. In order
to tackle these situations, TransH was proposed. TransH (Wang et al., 2014) models a relation \( r \) as a vector on a relation specific hyperplane and project entities associated with it on that particular hyperplane in order to learn distributed representation of the entities.

We notice that not only the role of the entities changes with time, but also the relationship between them changes. In this paper, we intend to capture this temporal behavior of the entities and relations and try to learn their embeddings accordingly. As discussed above, TransH (Wang et al., 2014) uses relation specific hyperplanes in order to prevent an entity from exhibiting identical characteristic when it is involved with different relations. Taking inspiration from the objective of TransH, we propose a hyperplane based method for learning KG representation distributed in time.

4 Proposed Method: HyTE

In this section, we present a detailed description of HyTE (Figure 1) which not only exploits the relational properties among entities but also uses the temporal meta-data associated with them.

4.1 Temporal Knowledge Graph

Usually knowledge graphs are treated as a static graph consisting of triples in form of \((h, r, t)\). Adding a separate time dimension to the triple makes the KG dynamic. Consider the quadruple \((h, r, t, [\tau_s, \tau_e])\), where \(\tau_s\) and \(\tau_e\) denote the start and end time during which the triple \((h, r, t)\) is valid. Unlike (Jiang et al., 2016), we incorporate this time meta-fact directly into our learning algorithm to learn temporal embeddings of the KG elements. Given the timestamps, the graph can be dismantled into several static graphs consisting of triples that are valid in the respective time steps, e.g., knowledge graph \( G \) can be expressed as \( G = \bigcup_{\tau_i} G_{\tau_i} \bigcup \cdots \bigcup G_{\tau_T} \), where \(\tau_i\), \(i = 1, 2, \cdots , T\) are the discrete time points.

We constructed this temporal component graphs \((G_{\tau})\) from the quadruples by considering \((h, r, t)\) to be a positive triple at each time point between \(\tau_s\) and \(\tau_e\). Now, given a quadruple \((h, r, t, [\tau_s, \tau_e])\), we consider it to be a positive triple for each time point between \(\tau_s\) and \(\tau_e\). So, we include \((h, r, t)\) in each \(G_{\tau}\), where \(\tau_s \leq \tau \leq \tau_e\). The set of positive triple corresponding to time \(\tau\) is denoted as \(D^\tau_+\).

4.2 Projected-Time Translation

TransE considers entity and relation vectors in the same semantic space for a static graph. We observe that time is the main source of different many-to-one, one-to-many or many-to-many relations, e.g., \((h, r)\) pair can be associated with different tail entity \(t\) at different points of time. Thus traditional methods fail to disambiguate them directly. In our time guided model, we want the entity to have a distributed representation associated with different time points.

We represent time as a hyperplane i.e., for \( T \) number of time steps in the KG, we will have \( T \) different hyperplanes represented by normal vectors \(w_{t_1}, w_{t_2}, \cdots, w_{t_T}\). Thus, we try to segregate the space into different time zones with the help of the hyperplanes. Now, triples valid at time \(\tau\) (i.e., the sub graph \(G_{\tau}\)) are projected onto time specific hyperplane \(w_{\tau}\), where their translational distance (TransE Section 3 our case) is minimized. To illustrate, in Figure 1, the triple \((h, r, t)\) is valid for both time frame \(\tau_1\) and \(\tau_2\). Hence they are projected on hyperplanes corresponding to those times.

Now we compute the projected representation on \(w_{\tau}\) as,

\[
P_{\tau}(e_h) = e_h - (w^\tau_{\tau} e_h)w_{\tau},
\]

\[
P_{\tau}(e_t) = e_t - (w^\tau_{\tau} e_t)w_{\tau},
\]

\[
P_{\tau}(r) = e_r - (w^\tau_{\tau} e_r)w_{\tau},
\]

where we restrict \(\|w_{\tau}\|_2 = 1\).

We expect that a positive triple, valid at time \(\tau\), will have the mapping as \(P_{\tau}(e_h) + P_{\tau}(r) \approx P_{\tau}(e_t)\). Thus, we use the following scoring function.

\[
f_{\tau}(h, r, t) = \|P_{\tau}(e_h) + P_{\tau}(r) - P_{\tau}(e_t)\|_{l_1/l_2}.
\]

We learn \(\{w_{\tau}\}^T_{\tau=1}\) for each time stamp \(\tau\), along with the entity and relation embeddings. So, by projecting the triple into its time hyperplane, we incorporate temporal knowledge into the relation and entity embeddings, i.e., the same distributed representation will have a different role in different points in time.

Optimization : As mentioned in section 3.1, we minimize the margin-based ranking loss.

\[
\mathcal{L} = \sum_{\tau \in [T]} \sum_{x \in D^\tau_+} \sum_{y \in D^\tau_-} \max(0, f_{\tau}(x) - f_{\tau}(y) + \gamma),
\]
where, $\mathcal{D}^+_\tau$ is the set of valid triples with timestamp $\tau$. The negative samples are drawn from the set of all negative samples, $\mathcal{D}^-$. We explored two different types of negative sampling:

- **Time agnostic negative sampling (TANS)** considers the set of all the triples that do not belong to the KG, irrespective of timestamps. More formally, for time step $\tau$ the negative samples are drawn from the set,

$$\mathcal{D}^-_\tau = \{(h', r, t, \tau) | h' \in \mathcal{E}, (h', r, t) \notin \mathcal{D}^+ \} \cup \{(h, r, t', \tau) | t' \in \mathcal{E}, (h, r, t') \notin \mathcal{D}^+_\tau \}. \quad (1)$$

- **Time dependent negative sampling (TDNS)** emphasizes on time. Along with the time agnostic negative sample, we add extra negative samples which are present in the KG but do not exist in the subgraph for a particular time stamp. Thus we draw negative samples from the set,

$$\mathcal{D}^-_\tau = \{(h', r, t, \tau) | h' \in \mathcal{E}, (h', r, t) \notin \mathcal{D}^+ \} \cup \{(h, r, t', \tau) | t' \in \mathcal{E}, (h, r, t') \in \mathcal{D}^+_\tau \}, \quad (2)$$

The above mentioned loss $\mathcal{L}$ is minimized subjected to the constraints.

$$\|e_p\|_2 \leq 1, \forall \ p \in \mathcal{E}, \quad \|w_\tau\|_2 = 1, \forall \ \tau \in [T]$$

We enforce the first one by adding $l_2$- regularization of entity vectors with $\mathcal{L}$. We take care of the second constraint by normalizing the time embeddings viz., the hyperplane normal vectors after each update of stochastic gradient descent.

We perform link prediction as well as temporal scoping in order to show the effectiveness of HyTE. For link prediction, we train the model using the optimization procedure as described with time agnostic negative sampling (TANS, Equation 1). The temporal scoping task (Section 5.5) requires the time hyperplanes to be well structured in the embedding space. The time-dependent negative sampling (TDNS Equation 2) is more suitable in case of the temporal scoping problem.

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**Table 1:** Details of datasets used. Please see Section 5.1 for details.

| Datasets       | #Entity | #Relations | Train/Valid/Test |
|----------------|---------|------------|-----------------|
| Wikidata12K    | 12,554  | 24         | 32.5k/4k/4k     |
| YAGO11K        | 10,623  | 10         | 16.4k/2k/2k     |

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1. [https://staff.aist.go.jp/julien.leblay/datasets/]
5.2 Method Compared

For evaluating the performance of our algorithm, we compare against the following methods:

- **t-TransE** (Jiang et al., 2016): This method uses a temporal ordering of relations to model knowledge evolution in the temporal dimension. They regularize the traditional embedding score function with observed relation ordering with respect to head entities.

- **HolE** (Nickel et al., 2016b): We consider this method as a representative of the state-of-the-art in non-temporal KG representation learning.

- **TransE** (Bordes et al., 2013): This is a simple but effective translation based model. We build HyTE on top of TransE and demonstrate the gains over this method.

- **TransH** (Wang et al., 2014): This method models each relation as different hyperplanes on which the translation operations are carried out. Our proposed method, HyTE also modifies TransE in a similar fashion by treating the timestamps as hyperplanes.

- **HyTE**: Our proposed method. Please see Section 4 for more details.

5.3 Entity Prediction

The task here is to predict the missing entity, given an incomplete relational fact with its time. We experimented with both YAGO11K and Wikidata12k dataset. Training is done in perspective of both head and tail prediction. More formally, for generation of negative sample from a correct triple \( (h, r, t, \tau) \), we split them in two parts - \( (h, r, ?, \tau) \) (for tail entity prediction) and \( (?, r, t, \tau) \) (for head entity prediction). In this task, we follow the TANS (Equation 1) procedure for generating negative samples, i.e., for each of tail and head query terms we randomly replace an entity such that the newly generated triple is not observed in the graph, for eg, we sample \( t' \in \mathcal{G} \setminus \{t\} \) such that \( (h, r, t', \tau) \notin D_+^{\tau} \).

**Ranking Protocol**: For a test triple \( (h, r, t, \tau) \), we generate corrupted triples by replacing tail entity (for tail prediction) or head entity (for head prediction) with all possible entities. Filtered protocol, proposed by (Bordes et al., 2013), says that the corrupted triples must not be a part of the graph itself. To illustrate, given a test triple \( (h, r, t) \) for tail prediction task, we compute scores for the candidate set \( C(h, r) = \{(h, r, t' : \forall t' \in \mathcal{G}) \setminus (\text{Train} \cup \text{Test} \cup \text{Valid}) \cup (h, r, t)\} \). We rank all the triples in \( C(h, r) \) in the increasing order of their score and find the rank of the actual triple \( (h, r, t) \). We report the mean rank over all the test queries (MR) and proportion of correct entities in top 10 rank (Hits@10).

5.4 Relation Prediction

The aim of this task is to predict the relation between two entities, i.e, for a given time-stamped triple with missing relation \( (h, ?, t, \tau) \), we predict the relation \( r \). For evaluation, we corrupt the triples with all possible relations and report the rank of the actual relation. We report Hits@1 for this task as the number of relations are quite less in numbers for both the datasets, 10 and 24 for YAGO11k and Wikidata12k respectively. Please note that we do not train our model separately for this task, rather we report the values obtained by the exact same model used for head and tail entity prediction.

The main motivation for this task is to deal with the relational conflict between two entities at a particular time-scope. For example, given the year 1992, a person 'X' and a city 'Y', one would like to know if he/she was bornIn or diedIn that city in that year. Through the explicit use of temporal information during training, we find that our method HyTE outperforms the baseline methods in both the datasets (as shown in 6.1)

5.5 Temporal Scope Prediction

Given the scarcity of time annotations of the KG facts, predicting time for atemporal part of the KG is an important problem. Unlike the previous baseline methods, our model can predict the time scope for a given triple. In order to perform better in this task, we want the hyperplanes to be well separated even after maintaining consistency with the positive triples. To incorporate this nature during training, we use the time-dependent negative sampling technique (TDNS Equation 2). Rest of the training procedure remains the same as the link prediction task. The model is trained on the same train split used for link prediction. In this task, we predict the time interval or the time instance \( \tau \) for a given test triple \( (h, r, t, ?) \). We project the relation and the entities of the triple on all the time hyperplanes and check the plausibility of that test triple on each
### Results

**Implementation details**: For all the methods, we have kept batch size $b = 50k$ on both the datasets. The dimensions of the embeddings ($d$) are varied in the range $\{64, 128, 256\}$. The margins ($\eta$) for all the methods are chosen from the set $\{1, 2, 5, 10\}$. Learning rate used for SGD, $lr \in \{0.01, 0.001, 0.0001\}$.

The best configuration is chosen by corresponding lowest MR on the validation set. For both YAGO11k and Wikidata12k, we obtained $d = 128$, $\eta = 10$, $lr = 0.0001$ using $l_1$-norm in the scoring function.

Both YAGO11k and Wikidata12k contain time annotations to the granularity of days. For the temporal scoping task, we only deal with year level granularity by dropping the month and date information. Timestamps are then treated as 61 and 78 different intervals for YAGO11k and Wiki-data12k respectively. The results depict the effectiveness of TDNS. Please see Section 6.2 of them. For evaluation, we order the time frames in increasing order of their plausibility score for that particular triple. Now, we select the rank of the time ($\tau$) associated with the test triple. If the associated time is an interval, we consider the lowest rank among the times in between the interval.

6.1 Performance analysis & comparison

The obtained results for different tasks are based on the above mentioned hyperparameters.

**Link Prediction**: The results reported in Table 2 demonstrate the efficacy of HyTE. We observe that our model outperforms the traditional state-of-the-art link prediction model HolE (Nickel et al., 2016b) by a significant margin in both the datasets. We also show a large boost in performance over TransE (Bordes et al., 2013). This significant gain empirically validates our claim that including temporal information in a principled approach can lead to substantial improvements in performance.
Test quadruples

| Gordon Carroll, ?, Baltimore,[1928, 1928] | TransE | HyTE |
|------------------------------------------|--------|------|
| S.Laubenthal, ?, Washington.,[2002, 2002] | diedIn, wasBornIn | wasBornIn, diedIn |
| Eugene_Sander, ?, Cornell Univ.,[1959, 1965] | wasBornIn, diedIn | diedIn, wasBornIn |
| Ernesto Maceda, ?, Nacionalist_Party, [1971,1987] | worksAt, graduatedFrom | graduatedFrom, isAffiliatedTo |
|                                            | isMarriedTo, diedIn | isAffiliatedTo, diedIn |

Table 5: Example of Qualitative Results on relation prediction. The order of prediction is in descending order. Correct one is in **bold**. Please refer Section 6.2 for details.

fashion helps to learn richer embeddings of the KG elements. We notice that HolE is performing significantly poor in terms of MR but it exceeds the other baselines in Hits@10 by a large margin.

Again, in comparison with the temporal model t-TransE (Jiang et al., 2016), HyTE proves to be effective. t-TransE performs better than TransE and HolE due to its implicit time incorporation through relation ordering. HyTE with its direct inclusion of time in the relation-entity semantic space outperforms all of them.

**Relation prediction:** Again, in this scenario, we show improvement over baselines. We hypothesize that time scope information helps to disambiguate among relations e.g. traditional methods like TransE or HolE will confuse between relations like wasBornIn, diedIn. Where time information surely helps to resolve that conflict. From Table 3, we validate this claim. In Section 6.2, we also demonstrate some qualitative result in favor of our assertion.

**Temporal scoping of facts:** We report the rank of correct time instance of the triple. If the triple scope is an interval of time, we consider the lowest rank that corresponds to the time within that interval. The ranks are reported in table 4 for both the datasets. The baseline model t-TransE (Jiang et al., 2016) is not applicable here as it does not use the time meta-facts directly. We also observe that the HyTE hyperplanes form a sequential map in the space. We discuss it with details in subsection 6.2.

**6.2 Qualitative results**

Table 5 contains some of the qualitative analyses for the relation prediction task. We mention some of the cases where transE is confusing between the temporal relations like wasBornIn and diedIn. Consider the second example in Table 5, where transE wrongly predicts wasBornIn. HyTE predicts diedIn as it has a prior knowledge that S.Laubenthal “was born in 1943”, “created Excalibur on 1973” from the training data. As the query year is 2002, our method comes to such a conclusion through its relative temporal ordering. We see many examples of this kind, where HyTE is naturally learning some relation ordering in parallel with the temporal direction. We observe many type inconsistency in relation prediction for our model, e.g., for this fact (Lauren Miller, wasBornIn, Lakeland, Florida.,[1982,1982]), our model predicts isMarriedTo. This can be attributed to the fact that we do not impose any type related constraints in our model. We will look forward to incorporating type and temporal constraints within our model as future work.

In Figure 2, we show a 2-d PCA projection of the 128-dimensional time embeddings which are obtained after training HyTE for temporal scoping task. We observe that the trained time representations are forming natural clusters and ordering. Please ref Section 6.2
data itself. We hypothesize that this phenomenon emerges due to TDNS (Equation 2). However, in case of link prediction, we notice that the extra samples are affecting performance as they originate from the KG itself.

7 Conclusion

We propose HyTE, a hyperplane-based method for learning temporally aware knowledge graph embeddings. Our method exploits temporally scoped facts of KG to perform link prediction as well as prediction of time scopes for unannotated temporal facts. Through extensive experiments on real-world datasets, we demonstrate effectiveness of HyTE over both traditional and time aware embedding methods. In future, we would like to incorporate type consistency information to further improve our model and also integrate HyTE with open-world knowledge graph completion (Shi and Weninger, 2018). We are hopeful that our proposed temporal representation learning algorithm will motivate further research on temporal KG embedding learning.

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