Towards Time-Aware Knowledge Graph Completion

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Abstract

Knowledge graph (KG) completion adds new facts to a KG by making inferences from existing facts. Most existing methods ignore the time information and only learn from time-unknown fact triples. In dynamic environments that evolve over time, it is important and challenging for knowledge graph completion models to take into account the temporal aspects of facts. In this paper, we present a novel *time-aware* knowledge graph completion model that is able to predict links in a KG using both *the existing facts* and *the temporal information of the facts*. To incorporate the happening time of facts, we propose a time-aware KG embedding model using temporal order information among facts. To incorporate the valid time of facts, we propose a joint time-aware inference model based on Integer Linear Programming (ILP) using temporal consistency information as constraints. We further integrate two models to make full use of global temporal information. We empirically evaluate our models on time-aware KG completion task. Experimental results show that our time-aware models achieve the state-of-the-art on temporal facts consistently.

1 Introduction

Knowledge graphs (KGs) such as Freebase (Bollacker et al., 2008) and YAGO (Fabian et al., 2007) are extremely useful resources for many NLP related applications such as relation extraction and question answering, etc. Although KGs are large in size, they are far from complete (West et al., 2014). Knowledge graph completion, i.e., automatically inferring missing facts between entities in a knowledge graph, has thus become an increasingly important task. Recently a promising approach called KG embedding aims to embed the components (entities and relations) of a KG into a continuous vector space while preserving the inherent structure of a knowledge graph (Nickel et al., 2011; Bordes et al., 2011). This kind of approach has shown good effectiveness and scalability for KG completion.

However, most existing KG embedding models ignore the temporal information of facts. In the real world, many facts are not static but highly ephemeral. For example, (*Steve_Jobs,* `diedIn`, *California*) happened on 2011-10-05; (*Ronaldo,* `playsFor`, *A.C.Milan*) is true only during 2007-2008. Intuitively, temporal aspects of facts should play an important role when we perform KG completion. In this paper, we focus on time-aware KG completion. Specially, we incorporate two kinds of temporal information for KG completion: (a) *temporal order information* and (b) *temporal consistency information*. By *temporal order information*, we mean that many facts have temporal dependencies on others according to the time that they happened. For example, the facts involving a person *P* may follow the following timeline: (*P,* `wasBornIn`, _) → (*P,* `graduateFrom`, _) → (*P,* `workAt`, _) → (*P,* `diedIn`, _). Given the time after *P* died , it's not proper to predict relations like `workAt`. By *temporal consistency information*, we mean that many facts are only valid during a short time period. For example, a person's marriage may be valid for a short period. Besides, the periods of a person's different marriages should not overlap. Without considering the temporal aspects of facts, the existing KG embedding methods may make mistakes. It is also non-trivial for existing KG embedding methods to incorporate such temporal information.

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To deal with the issues of the existing KG embedding methods, we propose two *time-aware KG completion* models to incorporate the above two kinds of temporal information, respectively. The extensive experimental results show the effectiveness of the two proposed models. We further propose a joint model that achieves better results. Our contributions include the following:

- To the best of our knowledge, this is the first work for time-aware KG completion. To incorporate the temporal order information, we propose a novel time-aware embedding (TAE) model that encodes the temporal order information as a regularizer on the geometric structure of the embedding space. To incorporate more temporal consistency information, we propose using Integer Linear Programming (ILP) to encode the temporal consistency information as constraints.

- We further propose a joint framework to unify the two complementary time-aware models seamlessly. ILP model considers more temporal constraints than TAE model, while TAE model generates more accurate embeddings for the objective function of ILP model. Our framework can be generalized to many KG embedding models such as TransE (Bordes et al., 2013) model and its extensions.

- We create real-world temporal data sets based on YAGO2 and Freebase for time-aware KG completion. The evaluation results show that our models outperform the start-of-the-art approaches and it confirms the effectiveness of incorporating temporal information.

The rest of the paper is organized as follows. Section 2 and Section 3 describe two time-aware KG completion models, respectively. Experiments, related work and conclusion are shown in Section 4-6.

2 Time-Aware KG Embedding Model

Time-aware KG embedding aims to automatically learn entity and relation embeddings by exploiting both observed triple facts and temporal order information among facts.

2.1 Time-Aware KG Completion Task

We represent facts with temporal annotations by quadruples, *quads* for short. We use (e_i, r, e_j, t) to denote the fact that e_i and e_j has relation r during the time interval $t = [t_b, t_e]$ with $t_b < t_e$. Although our reasoning framework supports arbitrary continuous intervals over real number, for simplicity, we assume time intervals range over **years**. For example, the interval [1980, 1999] starts in 1980 and ends in 1999. For some facts that happened at a certain time and did not last, we have $t_b = t_e$. For some facts that does not end yet, we represent t as $t = [t_b, +\infty]$.

KG completion is the task of predicting whether a given edge (e_i, r, e_j) exists in the graph or not. However, most facts are time-dependent and hold only for a given time period. For example, the fact of George W. Bush's presidency is only meaningful from 2001 to 2009. To incorporate temporal information for a more accurate representation, we extend this task to include the time dimension of the facts and call it *time-aware KG completion*, i.e., to complete the quad (e_i, r, e_j, t) when e_i, r or e_j is missing given a specific time interval t. For example, we can answer the question *"Who is the president of USA in 2010?"* by predicting head entity in *(?,* `presidentOf` *, USA*, [2010,2010]).

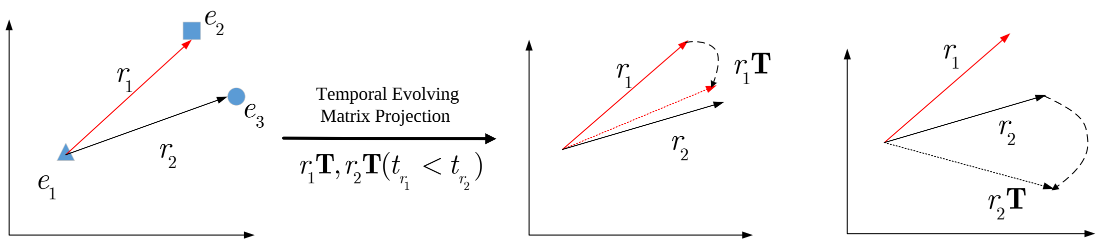
2.2 Traditional KG Embedding Methods

Traditional KG embedding methods use only the observed time-unknown facts (triples) to learn entity and relation representations. TransE (Bordes et al., 2013) is an efficient and simple model among them. The basic idea behind TransE is that the relation between two entities $\mathbf{e}_i, \mathbf{e}_j \in \mathbb{R}^n$ corresponds to a translation vector $\mathbf{r} \in \mathbb{R}^n$ between them, i.e., $\mathbf{e}_i + \mathbf{r} \approx \mathbf{e}_j$ when (e_i, r, e_j) holds. The scoring function is defined as measuring its plausibility in the vector space:

$$f(e_i, r, e_j) = \|\mathbf{e}_i + \mathbf{r} - \mathbf{e}_j\|_{\ell_1/\ell_2}, \tag{1}$$

where $\|\cdot\|_{\ell_1/\ell_2}$ denotes the ℓ_1-norm or ℓ_2-norm. A margin-based ranking loss is optimized to derive the entity and relation representations:

$$\min \sum_{x^+ \in \Delta} \sum_{x^- \in \Delta'} [\gamma + f(x^+) - f(x^-)]_+. \tag{2}$$



(a)TransE

(b)TransE-TAE

Figure 1: Simple illustration of Temporal Evolving Matrix $\mathbf{T}$ in the time-aware embedding (TAE) space. For example, r_1=$wasBornIn$ happened before r_2=$diedIn$. After projection by $\mathbf{T}$, we get prior relation's projection $\mathbf{r}_1\mathbf{T}$ near subsequent relation $\mathbf{r}_2$ in the space, i.e.,$\mathbf{r}_1\mathbf{T} \approx \mathbf{r}_2$, but $\mathbf{r}_2\mathbf{T} \neq \mathbf{r}_1$.

Here, $x^+ \in \Delta$ is the observed (i.e., positive) triple, and $x^- \in \Delta'$ is the negative triple constructed by replacing entities in x^+. γ is the margin separating positive and negative triples and $[z]_+ = \max(0, z)$. Please refer to (Wang et al., 2014a; Lin et al., 2015b) for TransH, TransR and other models.

After we obtain the embeddings, the plausibility of a missing triple can be predicted by using the scoring function. In general, triples with higher plausibility are more likely to be true.

2.3 Time-Aware KG Embedding Model

TransE assumes that each relation is time independent and entity/relation representation is only affected by structural patterns in KGs. To better model knowledge evolution, we assume temporal ordered relations are related to each other and evolve in a time dimension. For example, for the same person, there exists a temporal order among relations `wasBornIn`→ `graduatedFrom` → `diedIn`. In time dimension, `wasBornIn` can evolve into `graduateFrom` and `diedIn`, but `diedIn` cannot evolve into `wasBornIn`.

To compare temporal orders, we define a pair of temporal ordering relations sharing the same head entity [1] as **temporal ordering relation pair**, e.g., ⟨`wasBornIn`, `diedIn`⟩. We define the relation happening earlier, e.g., `wasBornIn`, as **prior relation** and the other as **subsequent relation**. We define ⟨prior relation, subsequent relation⟩ as positive temporal ordering pairs and ⟨subsequent relation, prior relation⟩ as negative ones.

To capture the temporal order of relations, we further define a *temporal evolving matrix* $\mathbf{T} \in \mathbb{R}^{n\times n}$ to model relation evolution, where n is the dimension of relation embedding. $\mathbf{T}$ is a parameter to be learned by the model from the data. We assume that prior relation can evolve into subsequent relation through the temporal evolving matrix. The more frequent they have temporal orders, the more they can evolve. Specially, as in Figure 1, prior relation $\mathbf{r}_1$ projected by $\mathbf{T}$ should be near subsequent relation $\mathbf{r}_2$, i.e., $\mathbf{r}_1\mathbf{T} \approx \mathbf{r}_2$, while $\mathbf{r}_2\mathbf{T}$ should be far from $\mathbf{r}_1$. In this way, we are able to separate prior relation and subsequent relation automatically during training.

We formulate time-aware KG completion as an optimization problem based on a regularization term. Given any positive training quad $(e_i, r_k, e_j, t_{r_k}) \in \Delta_t$, we can find a temporally related quad $(e_i, r_l, e_m, t_{r_l}) \in \Delta_t$ sharing the same *head entity* and a temporal ordering relation pair $\langle r_k, r_l\rangle$. If $t_{r_k}{<}t_{r_l}$, we have a positive temporal ordering relation pair $y^+ = \langle r_k, r_l\rangle$ and the corresponding negative relation pair $y^- = \langle r_k, r_l\rangle^{-1} = \langle r_l, r_k\rangle$ by inverse. Our optimization requires that positive temporal ordering relation pairs should have lower scores (energies) than negative pairs. Therefore, we define a **temporal** scoring function as

$$g(\langle r_k, r_l\rangle) = \|\mathbf{r}_k\mathbf{T} - \mathbf{r}_l\|_{\ell_1/\ell_2}, \tag{3}$$

which is expected to give a low score when the temporal ordering relation pair is in chronological order, and a high score otherwise. Note that $\mathbf{T}$ is asymmetric and the loss function is also asymmetric so as to capture temporal order information.

[1] We only consider relations sharing the same head entity because most temporal facts and temporal relations are partially ordered around a common *protagonist* (usually the head entity), e.g., "wasBornIn", "workAt", and "diedIn" are temporally ordered with a common person. Temporal relations that are ordered with a common tail entity could be transformed by replacing the relation with its inverse relation and exchanging the head and tail entity.

To make the embedding space compatible with the observed triples, we make use of the fact triples set Δ and follow the same strategy adopted in previous methods. Specially, we apply the same **fact** scoring function $f(e_i, r_k, e_j)$ in Equation (1) to each candidate triple. The optimization is to minimize the **joint** scoring function,

$$L = \sum_{x^+ \in \Delta} \Big[\sum_{x^- \in \Delta'} [\gamma_1 + f(x^+) - f(x^-)]_+ + \lambda \sum_{y^+ \in \Omega_{e_i, t_{r_k}}, y^- \in \Omega'_{e_i, t_{r_k}}} [\gamma_2 + g(y^+) - g(y^-)]_+ \Big], \tag{4}$$

where $x^+ = (e_i, r_k, e_j) \in \Delta$ is a positive triple, $x^- = (e'_i, r_k, e'_j) \in \Delta'$ is the corresponding negative triple by replacing entities. The positive temporal ordering relation pair set with respect to (e_i, r_k, e_j, t_{r_k}) is defined as

$$\begin{aligned} \Omega_{e_i, t_{r_k}} &= \{\langle r_k, r_l \rangle | (e_i, r_k, e_j, t_{r_k}) \in \Delta_t, (e_i, r_l, e_m, t_{r_l}) \in \Delta_t, t_{r_k} < t_{r_l}\} \\ &\cup \{\langle r_l, r_k \rangle | (e_i, r_k, e_j, t_{r_k}) \in \Delta_t, (e_i, r_l, e_m, t_{r_l}) \in \Delta_t, t_{r_k} > t_{r_l}\} \end{aligned} \tag{5}$$

where r_k and r_l share the same head entity e_i. $\Omega'_{e_i, t_{r_k}}$ are the corresponding negative relation pairs by inverse the relation pairs. In experiments, our constrains are $\|\mathbf{e}_i\|_2 \leq 1$, $\|\mathbf{r}_k\|_2 \leq 1$, $\|\mathbf{r}_l\|_2 \leq 1$, $\|\mathbf{e}_j\|_2 \leq 1$, $\|\mathbf{r}_k\mathbf{T}\|_2 \leq 1$, and $\|\mathbf{r}_l\mathbf{T}\|_2 \leq 1$ to avoid overfitting similarly to previous work.

The first term in Equation (1) enforces the generated embedding space compatible with all the observed triples, and the second term further requires the space to be temporally consistent and more accurate. Hyperparameter λ strikes a trade-off between the two cases. Stochastic gradient descent (in mini-batch mode) is adopted to solve the minimization problem.

3 Joint Inference for Time-Aware KG Completion

In this section, we incorporate temporal information as temporal consistency constraints for KG completion. We take advantage of temporal logic transitivity and use ILP to derive more accurate predictions.

3.1 Temporal Consistency Constraints

The candidate predictions we obtained in the traditional KG embedding inevitably include many incorrect predictions. By applying temporal consistency constraints, we can identify and then discard such errors to produce more accurate results.

As the complexity of resolving conflicts strictly depends on the constraints to apply, we need to choose them with great care. In the following, we consider three kinds of temporal constraints.

Temporal Disjointness. The time intervals of any two facts with a common functional relation and a common head entity are non-overlapping. For example, a person can only be spouse of one person at a time: $(e_1, \texttt{wasSpouseOf}, e_2, [1990, 2010)) \wedge (e_1, \texttt{wasSpouseOf}, e_3, [2005, 2013)) \wedge e_2 \neq e_3 \rightarrow$ false.

Temporal Ordering. For some temporal ordering relations, one fact always happens before another fact. For example, a person must be born before he graduated: $(e_1, \texttt{wasBornIn}, e_2, t_1) \wedge (e_1, \texttt{graduateFrom}, e_3, t_2) \wedge t_1 > t_2 \rightarrow$ false.

Temporal Spans. Some facts are true only during a specific time span. In general, the fact is invalid for other time periods outside the range of its time span in KGs. For example, given time interval t' outside the range t in $(e_1, \texttt{presidentOf}, e_2, t) \in$ KG, the fact $(e_1, \texttt{presidentOf}, e_2, t')$ is invalid.

3.2 Integer Linear Program Formulation

We formulate the time-aware inference as an ILP problem with temporal constraints. Traditional KG embedding methods can capture the intrinsic properties of data, which can be treated as a probability to predict unseen facts. For each candidate fact (e_i, r_k, e_j), we use $w_{ij}^{(k)} = f(e_i, r_k, e_j)$ to represent the plausibility predicted by an embedding model, and introduce a Boolean decision variable $x_{ij}^{(k)}$ to indicate whether the fact (e_i, r_k, e_j, t) is true or not for time t. Our aim is to find the best assignment to the decision variables, maximizing the overall plausibility while complying with all the temporal constraints. The objective function can be written as:

$$\max_{x_{ij}^{(k)}} \sum w_{ij}^{(k)} x_{ij}^{(k)}. \tag{6}$$

We add the constraints described in Section 3.1 for the above objective function.

The temporal disjointness constraints avoid the disagreement between the predictions of two facts sharing the same head entity and relation. These constraints can be represented as:

$$x_{ij}^{(k)} + x_{il}^{(k)} \leq 1, \forall k \in \mathcal{C}^d, t_{x_{ij}^{(k)}} \cap t_{x_{il}^{(k)}} \neq \emptyset \tag{7}$$

where $\mathcal{C}^d$ are functional relations described such as `wasSpouseOf` and $t_{x_{ij}^{(k)}}, t_{x_{il}^{(k)}}$ are time intervals for two facts, respectively.

The Temporal Ordering constraints ensure the occurring order for some relation pairs. These constraints can be represented as:

$$x_{ij}^{(k)} + x_{il}^{(k')} \leq 1, \forall (k, k') \in \mathcal{C}^o, t_{x_{ij}^{(k)}} \geq t_{x_{il}^{(k)}} \tag{8}$$

where $\mathcal{C}^o = \{\langle r_k, r'_k \rangle\}$ are relation pairs that have precedent orders such as $\langle$`wasBornIn`,`diedIn`$\rangle$. These relation pairs are discovered automatically in the training set by statistics and finally manually calibrated.

The temporal span constraints ensure the specific time span when the corresponding fact is true. These constraints can be represented as:

$$x_{ij}^{(k)} = 0, \forall k \in \mathcal{C}^s, t_{x_{ij}^{(k)}} \cap t_{\Delta} = \emptyset \tag{9}$$

where $\mathcal{C}^s$ are those relations valid for only a specific time span such as `presidentOf` and t_Δ is the valid time span in KG.

Using ILP, we can combine the ability of capturing the intrinsic properties of KG data and the temporal constraints that are embedded into global consistencies of the relations together. As shown in Eq.(10), any unseen fact's plausibility is encoded in scores w_{ij}^k which captures the intrinsic properties of KG data. Temporal consistency constraints are formulated as Eq.(7)-(9) and apply to the objective function naturally. By solving Eq.(10), we will obtain a list of selected candidate entities or relations for a missing fact as our final output.

3.3 Integrating Two Time-Aware Models

As mentioned above, the two time-aware models are complementary for each other: ILP model considers more temporal constraints than TAE model while TAE model generates more accurate embeddings for the ILP objective function.

For each unseen quad (e_i, r_k, e_j, t), we use a Boolean decision variable $x_{ij}^{(k,t)}$ to indicate whether it's true or not. We can use the embeddings of TAE model in Section 2.3 to calculate the plausibility $v_{ij}^{(k,t)}$ for the ILP objective function. The objective function is

$$\max \sum_{x_{ij}^{(k,t)}} v_{ij}^{(k,t)} x_{ij}^{(k,t)}. \tag{10}$$

Eq.(7)-(9) remain the same.

4 Experiments

We use similar evaluation metrics as traditional KG completion methods (Bordes et al., 2013) for time-aware KG completion.

4.1 Data Sets

To create temporal KG data sets, we need to decide whether a fact has temporal information. We categorize relations into time-sensitive relations and time-unsensitive relations according to YAGO2 (Hoffart et al., 2013). For example, `diedIn` is time-sensitive, but `hasNeighbor` is not. We extract temporal annotations for time-sensitive facts from YAGO2 and Freebase[2].

In YAGO2, temporal facts are in the form (*factID,occurSince,*t_b), (*factID,occurUntil,*t_e) indicating the fact is true during $[t_b, t_e]$. Here *factID* denotes a specific fact (e_i, r, e_j). We directly represent these temporal facts as quads $(e_i, r, e_j, [t_b, t_e])$. We selected 10 frequent time-sensitive relations to make a pure temporal data set. Then we selected the subset of entities which have at least two mentions in temporal

[2] www.freebase.com

Dataset	#Rel	#Ent	#Train/#Valid/#Test	#Quads
YG15k	10	9513	13345/1320/1249	15914
YG36k	10	9513	29757/3252/3058	15914
FB42	42	8376	23827/2173/2610	28610
FB87	87	8844	142598/14848/17566	175012

Table 1: Statistics of data sets.

DataSets	YG15k				YG36k				FB42				FB87			
Metric	MeanRank		Hits@10(%)		MeanRank		Hits@10(%)		MeanRank		Hits@10(%)		MeanRank		Hits@10(%)	
	Raw	Filter	Raw	Filter	Raw	Filter	Raw	Filter	Raw	Filter	Raw	Filter	Raw	Filter	Raw	Filter
TransE	990	971	26.6	29.5	179	163	65.7	75.6	383	341	39.5	46.6	105	54	47.7	70.2
TransE-TAE	**245**	**244**	**34.4**	**35.3**	**62**	**58**	**75.4**	**81.9**	**328**	**300**	**45.0**	**51.3**	**92**	**50**	**53.8**	**77.5**
TransE-ILP	-	-	**40.5**	**41.9**	-	-	**80.1**	**85.4**	-	-	**53.5**	**55.2**	-	-	**62.1**	**82.7**
TransE-TAE-ILP	-	-	**44.8**	**46.1**	-	-	**84.7**	**89.4**	-	-	**65.1**	**70.2**	-	-	**65.7**	**85.3**
TransH	986	966	25.7	28.0	174	158	65.3	77.8	378	333	40.3	48.1	102	58	45.3	71.8
TransH-TAE	**243**	**241**	**33.4**	**34.7**	**63**	**58**	**75.3**	**81.6**	**320**	**291**	**46.4**	**52.7**	**93**	**52**	**55.3**	**78.5**
TransH-ILP	-	-	**41.7**	**42.6**	-	-	**81.5**	**85.6**	-	-	**53.7**	**56.4**	-	-	**63.5**	**81.1**
TransH-TAE-ILP	-	-	**43.3**	**46.6**	-	-	**85.4**	**88.7**	-	-	**65.3**	**71.4**	-	-	**67.2**	**86.0**
TransR	976	955	29.5	30.2	175	153	68.3	80.1	371	325	42.5	49.2	96	52	49.3	72.1
TransR-TAE	**253**	**251**	**33.5**	**33.9**	**56**	**45**	**79.5**	**86.9**	**318**	**282**	**47.2**	**54.9**	**88**	**47**	**56.5**	**79.9**
TransR-ILP	-	-	**41.9**	**44.3**	-	-	**82.6**	**82.5**	-	-	**57.8**	**57.1**	-	-	**63.4**	**87.9**
TransR-TAE-ILP	-	-	**45.4**	**47.7**	-	-	**85.8**	**89.5**	-	-	**66.5**	**72.3**	-	-	**68.2**	**88.2**

Table 2: Evaluation results on entity prediction.

facts. This resulted in 15,914 triples (quadruples) which were randomly split with the ratio shown in Table 1. This data set is denoted *YG15k*. Although YAGO2 has many temporal annotations for facts, a lot of temporal annotations are still missing for time-sensitive facts. We consider the data set *YG36k* consisting of half facts with temporal annotations and the other half missing temporal annotations to evaluate whether partial temporal information of data improves the performance or not. The relationship set is the same in YG15k and YG36k.

We extracted temporal facts mainly from FB15k (Bordes et al., 2013), a subset of Freebase consisting of 1345 relations. Among them, 707 relations are long relations in the form "$r_1.r_2$" concatenating short relations r_1 and r_2. Long relations do not exist in the original schema of Freebase. Many associated facts in Freebase are organized as a CVT structure (similar to an event), e.g., (Einstein,`hasWonPrize`, Nobel) is stored as (Einstein, */award/award_winner/awards_won*, x), (x,*/award/award_honor/award,Nobel*) in Freebase, where x is called *mediator* and not a real entity. FB15k facts are created by concatenating two relations: (*Einstein,/award/award_winner/awards_won. /award/award_honor/award,Nobel*). We extracted temporal annotations from the original Freebase CVT structure for these facts with long relations. For short relations such as */film/director/film*, we used creation/destruction dates of head or tail entity as their time, e.g., the released date of the film. This resulted in 42 time-sensitive relations and 28,610 temporal facts. We denoted the data set as *FB42*. We further added triples without time annotations and created *FB87*. In FB15k, there are about 50% temporal facts in our setting. The data set will be publicly available. All experiments are repeated five times by drawing new training/validation/test splits, and results averaged over the five rounds are reported.

4.2 Time-aware KG Completion

Time-aware KG completion (link prediction) is to complete the triple (e_i, r, e_j, t) when e_i, r or e_j is missing given a specific time interval t. We divided the stage into two sub-tasks, i.e., entity prediction and relation prediction.

4.2.1 Entity Prediction

Evaluation protocol. For each test triple with missing head or tail entity, various methods are used to compute the scores for all candidate entities and rank them in descending order. We use two metrics for our evaluation as in (Bordes et al., 2013): the mean of correct entity ranks (Mean Rank) and the proportion of valid entities ranked in top-10 (Hits@10). As mentioned in (Bordes et al., 2013), the metrics are desirable but flawed when a corrupted triple exists in the KG. As a countermeasure, we may filter out all these corrupted triples which have appeared in KG before ranking. We name the first evaluation set as *Raw* and the second as *Filter*.

For each test quad (triple), we replace the head/tail entity e_i by those entities with *compatible types* as removing triples with incompatible types during test time leads to better results (Chang et al., 2014;

Wang et al., 2015). Entity type information is easy to obtain for YAGO and Freebase. Then we rank the generated corrupted triples in descending order, according to the plausibility (for baselines and TAE model) or the decision variables (for time-aware ILP model). Then we check whether the original correct triple ranks in top-10. To calculate Hit@10 for ILP model, for each test quad, we add additional constraints that at most 10 corrupted are true: $\sum_{i,j} x_{e_i e_j}^{(r_1)} \leq 10$. Mean Rank is missing for ILP method as we could not rank the binary decision variables.

Baseline methods. For comparison, we select TransE (Bordes et al., 2013), its extensions TransH (Wang et al., 2014b) and TransR (Lin et al., 2015b) as our baselines. We then compare time-aware embedding and time-aware ILP inference with each baseline. For example, TransE with TAE and time-aware ILP is denoted as "TransE-TAE" and "TransE-ILP", respectively. The combined model of the two time-aware models are denoted as "TransE-TAE+ILP".

Implementation details. For all embedding methods, we create 100 mini-batches on each data set. The dimension of the embedding n is set in the range of $\{20,50,100\}$, the margin γ_1 and γ_2 are set in the range $\{1,2,4,10\}$. The learning rate is set in the range $\{0.1, 0.01, 0.001\}$. The regularization hyperparameter λ is tuned in $\{10^{-1},10^{-2},10^{-3},10^{-4}\}$. The best configuration is determined according to the mean rank in validation set. For YAGO data set, the optimal configurations are $n = 100,\gamma_1 = \gamma_2 = 4,\lambda = 10^{-2}$, learning rate is 0.001 and taking ℓ_1-norm; For Freebase data set, the optimal configurations are $n = 100,\gamma_1 = \gamma_2 = 1,\lambda = 10^{-1}$, learning rate is 0.001 and taking ℓ_1-norm.

We then incorporate temporal constraints into the six models with optimal parameter settings using ILP. To generate the objective function of ILP, plausibility predicted by embedding models is normalized by $w'_{ij} = (w_{ij} - \textsc{Min})/(\textsc{Max} - \textsc{Min})$, where MAX and MIN are max/min scores for each corrupted test triple. We use the lp_solve package[3] to solve the ILP problem.

Results. Table 2 reports the results for each data set. From the results, we can see that 1) TAE methods outperform all the baselines on all the data sets and with all the metrics. The improvements are quite significant. The Mean Rank drops by about 75%, and Hits@10 rises about 19% to 30%. This demonstrates the superiority and generality of our method. 2) Adding more temporal facts improve the performance for TAE models. YG15k consists of 100% temporal facts while YG36k consists of 50% temporal facts. All the temporal information in YG15k is utilized to model temporal associations and make the embeddings more accurate. Therefor, it obtains larger improvement for TAE than YG36k. 3) Improvement for YAGO is larger than Freebase because YAGO data set contains more temporal ordering relation pairs than Freebase data set.

As we can see from Table2, the time-aware ILP method improves each baseline model by about 10% to 16%. This demonstrates the effectiveness of incorporating temporal consistency constraints. Combining two time-aware models further improves the performance by 2% to 3%. This indicates that 1) although TAE models encode temporal order information, only pair-wise temporal ordering relations are optimized during each training iteration. ILP can take advantage of global temporal transitivity which pair-wise methods can't. 2) Adding time span information in the ILP model can remove more false predictions.

4.2.2 Relation Prediction

Relation prediction aims to predict relations between two entities. Evaluation results are shown in Table 3 on YG15K and FB87 due to space limit, and here we report Hits@1 instead of Hits@10. For ILP models, we report Hits@1 for the same reason in entity prediction. Again, two time-aware models improve baselines greatly.

The ILP models improve the precision by about 10%, showing that incorporating temporal constraints directly is better for this task. The main reason is that our temporal constraints are designed to better handle temporal conflicts in relations. Relation prediction and relation extraction from text have common multi-label problems that the same entity pair may have multiple relation labels. For example, *(Obama,US)* could have two valid relations: *wasPresidentOf, wasBornIn*. Through temporal constraints, we are aware that the two relations have different valid time, and therefore we could remove the false one to

[3] http://lpsolve.sourceforge.net/5.5/

Data Sets	YG15K				FB87			
Metric	Mean Rank		Hits@1 (%)		Mean Rank		Hits@1 (%)	
	Raw	Filter	Raw	Filter	Raw	Filter	Raw	Filter
TransE	1.5	1.4	69.4	73.0	1.9	1.7	60.0	73.8
TransE-TAE	**1.4**	**1.3**	**71.4**	**75.7**	**1.7**	**1.6**	**63.4**	**76.7**
TransE-ILP	-	-	**81.6**	**85.4**	-	-	**71.0**	**82.9**
TransE-TAE-ILP	-	-	**82.5**	**86.5**	-	-	**72.3**	**83.1**
TransH	1.5	1.3	69.7	73.4	1.8	1.6	61.3	75.6
TransH-TAE	**1.3**	**1.3**	**74.6**	**76.9**	**1.4**	**1.30**	**64.2**	**77.2**
TransH-ILP	-	-	**81.1**	**85.7**	-	-	**71.7**	**83.1**
TransH-TAE-ILP	-	-	**83.2**	**86.2**	-	-	**73.2**	**84.4**
TransR	1.4	1.2	71.1	74.3	1.6	1.5	62.1	77.3
TransR-TAE	**1.2**	**1.1**	**74.5**	**78.9**	**1.2**	**1.1**	**64.3**	**79.6**
TransR-ILP	-	-	**82.8**	**86.6**	-	-	**72.2**	**83.2**
TransR-TAE-ILP	-	-	**83.1**	**88.3**	-	-	**73.8**	**85.1**

Table 3: Evaluation results on relation prediction.

Testing quads	TransE	TransE-TAE	TransE-ILP
(Stanford_Moore,?,New_York_City,[1982,1982])	wasBornIn,**diedIn**	**diedIn**,wasBornIn	**diedIn**,wasBornIn
(John_Schoenherr,?,Caldecott_Medal,[1988,1988])	owns,**hasWonPrize**	**hasWonPrize**,created	**hasWonPrize**,created
(John_G._Thompson,?,University_of_Cambridge,[1968,1994])	graduatedFrom,**worksAt**	**worksAt**,graduatedFrom	**worksAt**,graduatedFrom
(Tommy_Douglas,?,New_Democratic_Party,[1961,1972])	isMarriedTo,**isAffiliatedTo**	**isAffiliatedTo**,isMarriedTo	**isAffiliatedTo**,isMarriedTo
(Carmen Electra,?,Owen Wilson,[2004,2005])	isMarriedTo,**sameAward_winner**	isMarriedTo,**sameAward_winner**	**sameAward_winner**,isMarriedTo

Table 4: Examples of relation prediction in descending order. Correct predictions are in **bold**.

improve Hit@1 accuracy.

Qualitative analysis. Examples of relation prediction for TransE, TransE-TAE and TransE-ILP are compared in Table 4. From the results we have the following two conclusions. 1) Temporal order information is useful to distinguish similar relations. For example, when testing *(Stanford_Moore, ? , Chicago, [1982, 1982])*, it's easy for TransE to mix relations `wasBornIn` and `diedIn` as they behave similarly for a person and a place. But knowing that he `graduated` in 1935 from the training set, and TransE-TAE have learnt temporal order that *wasBornIn→graduated→diedIn*, the regularization term $|\mathbf{r}_{graduate}\mathbf{T} - \mathbf{r}_{died}|$ and $|\mathbf{r}_{graduate}\mathbf{T} - \mathbf{r}_{born}|$ helps rank `diedIn` higher than `wasBornIn`. TransE-ILP also benefits from such temporal order constraints and obtains more accurate predictions. 2) Time span information is useful to make accurate predictions. For example, TransE and TransE-TAE both predict (*Carmen Electra,?,Owen Wilson*,[2004,2005]) has `wasMarriedTo` relation. Temporal order constraints don't work for this example. But the time span constraints help TransE-ILP to remove `wasMarriedTo` because *Carmen Electra* was married to *Dave Navarro* during [2003,2008] and a person cannot marry two people at the same time.

5 Related Work

There are two lines of research related to our work.

Knowledge Graph Completion. Nickel et al. (2016) provide a broad overview of machine learning models for KG completion. These models predict new facts in a given knowledge graph using information from existing entities and relations. The most related work from this line of work is KG embedding models (Nickel et al., 2011; Bordes et al., 2013; Socher et al., 2013). Aside from fact triples, external information is employed to improve KG embedding such as combining text (Riedel et al., 2013; Wang et al., 2014a; Zhao et al., 2015), entity type and relationship domain (Guo et al., 2015; Chang et al., 2014), relation path (Lin et al., 2015a; Gu et al., 2015), and logical rules (Wang et al., 2015; Rocktäschel et al., 2015). However, these methods have not utilized temporal information among facts.

Temporal Information Extraction. This line of work mainly falls into two categories: methods that extract temporal facts from web (Ling and Weld, 2010; Wang et al., 2011; Artiles et al., 2011; Garrido et al., 2012) and methods that infer temporal scopes from aggregate statistics in large Web corpora (Talukdar et al., 2012b; Talukdar et al., 2012a). The TempEval task (Pustejovsky and Verhagen, 2009) and systems (Chambers et al., 2007; Bethard and Martin, 2007; Chambers and Jurafsky, 2008; Cassidy et al., 2014) have been successful in extracting temporally related events. Temporal reasoning is also explored to solve temporal conflicts in KG (Dylla et al., 2011; Wang et al., 2010). This paper differs from this line of work as we directly use temporal information from KG to perform KG completion.

6 Conclusion and Future Work

In this paper, we propose two novel time-aware KG completion models. Time-aware embedding (TAE) model imposes temporal order constraints on the geometric structure of the embedding space and enforces it to be temporally consistent and accurate. Time-aware joint inference with ILP framework considers global temporal constraints as well as KG embeddings. It naturally preserves the benefits of embedding models and is more accurate with respect to various temporal constraints. We further integrate two models to make full use of temporal information.

As future work: 1) Many temporal facts are not stored by current KGs (about 30% facts in YAGO and 50% in Freebase lack temporal annotations), we will extract more temporal information from texts. 2) We will consider using our time-aware KG completion model to predict temporal scopes of new facts.

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