Learning Sequence Encoders for Temporal Knowledge Graph Completion

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\section*{Abstract}

Research on link prediction in knowledge graphs has mainly focused on static multi-relational data. In this work we consider temporal knowledge graphs where relations between entities may only hold for a time interval or a specific point in time. In line with previous work on static knowledge graphs, we propose to address this problem by learning latent entity and relation type representations. To incorporate temporal information, we utilize recurrent neural networks to learn time-aware representations of relation types which can be used in conjunction with existing latent factorization methods. The proposed approach is shown to be robust to common challenges in real-world KGs: the sparsity and heterogeneity of temporal expressions. Experiments show the benefits of our approach on four temporal KGs. The data sets are available under a permissive BSD-3 license\textsuperscript{1}.

\section{Introduction}

Knowledge graphs (KGs) are used to organize, manage, and retrieve structured information. The incompleteness of most real-world KGs has stimulated research on predicting missing relations between entities. A KG is of the form $G = (\mathcal{E}, \mathcal{R})$, where $\mathcal{E}$ is a set of entities and, $\mathcal{R}$ is a set of relation types or predicates. One can represent $G$ as a set of triples of the form (subject, predicate, object), denoted as $(s, p, o)$. The link prediction problem seeks the most probable completion of a triple $(s, p, o)$ or $(?, p, o)$ (Nickel et al., 2016). We focus on temporal KGs where some triples are augmented with time information and the link prediction problem asks for the most probable completion given time information. More formally, a temporal KG $G = (\mathcal{E}, \mathcal{R}, T)$ is a KG where facts can also have the form (subject, predicate, object, timestamp) or (subject, predicate, object, time predicate, timestamp), in addition to $(s, p, o)$ triples. For instance, facts such as (Barack Obama, born, US, 1961) or (Barack Obama, president, US, occursSince, 2009-01) express temporal information about the facts associated with Barack Obama. While the former expresses that a relation type occurred at a specific point in time, the latter expresses an (open) time interval using the time predicate “occursSince.” The latter example also illustrates a common challenge posed by the heterogeneity of time expressions due to variations in language and serialization standards.

Most approaches to link prediction are characterized by a scoring function that operates on the entity and relation type embeddings of a triple (Bordes et al., 2013; Yang et al., 2014; Guu et al., 2015). Learning representations that carry temporal information is challenging due to the sparsity and irregularities of time expressions. It is possible, however, to turn time expressions into sequences of tokens expressing said temporal information. Moreover, character-level architectures for language modeling (Zhang et al., 2015; Kim et al., 2016) operate on characters as atomic units to derive word embeddings. Inspired by these models, we propose a method to incorporate time information into standard embedding approaches for link prediction. We learn time-aware representations by training a recursive neural network with sequences of tokens representing the time predicate and the digits of the timestamp, if they exist. The last hidden state of the recurrent network is combined with standard scoring functions from the KG completion literature.

\textsuperscript{*} Work done while interning at NEC Labs Europe
\textsuperscript{1}https://github.com/nle-ml/mmkb
2 Related Work

Reasoning with temporal information in knowledge bases has a long history and has resulted in numerous temporal logics (van Benthem, 1995). Several recent approaches extend statistical relational learning frameworks with temporal reasoning capabilities (Chekol et al., 2017; Chekol and Stuckenschmidt, 2018; Dylla et al., 2013).

There is also prior work on incorporating temporal information in knowledge graph completion methods. Jiang et al. (2016) capture the temporal ordering that exists between some relation types as well as additional common-sense constraints to generate more accurate link predictions. Esteban et al. (2016) introduce a prediction model for link prediction that assumes that changes to a KG are introduced by incoming events. These events are modeled as a separate event graph and used to predict the existence of links in the future. Trivedi et al. (2017) model the occurrence of a fact as a point process whose intensity function is influenced by the score assigned to the fact by an embedding function. Leblay and Chekol (2018) develop scoring functions that incorporate time representations into a TransE-type scoring function. Prior work has also incorporated numerical but non-temporal entity information for knowledge base completion (Garcia-Duran and Niepert, 2017).

Contrary to all previous approaches, we encode sequences of temporal tokens with an RNN. This facilitates the encoding of relation types with temporal tokens such as “since,” “until,” and the digits of timestamps. Moreover, the RNN encoding provides an inductive bias for parameter sharing among similar timestamps (e.g., those occurring in the same century). Finally, our method can be combined with all existing scoring functions.

3 Time-Aware Representations

Embedding approaches for KG completion learn a scoring function $f$ that operates on the embeddings of the subject $e_s$, the object $e_o$, and the predicate $e_p$ of the triples. The value of this scoring function on a triple $(s, p, o)$, $f(s, p, o)$, is learned to be proportional to the likelihood of the triples being true. Popular examples of scoring functions are

- **TRANSE** (Bordes et al., 2013)

  \[
  f(s, p, o) = ||e_s + e_p - e_o||_2. \tag{1}
  \]

- **DISTMULT** (Yang et al., 2014):

  \[
  f(s, p, o) = (e_s \circ e_p) e_p^T, \tag{2}
  \]

where $e_s, e_p \in \mathbb{R}^d$ are the embeddings of the subject and object entities, $e_p \in \mathbb{R}^d$ is the embedding of the relation type predicate, and $\circ$ is the element-wise product. These scoring functions do not take temporal information into account.

Given a temporal KG where some triples are augmented with temporal information, we can decompose a given (possibly incomplete) timestamp into a sequence consisting of some of the following temporal tokens

\[
\begin{array}{cccccccc}
\text{year} & 0 & 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 \\
\text{month} & 01 & 02 & 03 & 04 & 05 & 06 & 07 & 08 & 09 & 10 & 11 & 12 \\
\text{day} & 0 & 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 & 11 & 12
\end{array}
\]

Hence, temporal tokens have a vocabulary size of 32. Moreover, for each triple we can extract a sequence of predicate tokens that always consists of the relation type token and, if available, a temporal modifier token such as “since” or “until.” We refer to the concatenation of the predicate token sequence and (if available) the sequence of temporal tokens as the predicate sequence $p_{seq}$. Now, a temporal KG can be represented as a collection of triples of the form $(s, p_{seq}, o)$, wherein the predicate sequence may include temporal information. Table 1 lists some examples of such facts from a temporal KG and their corresponding predicate sequence. We use the suffix $y, m$ and $d$ to indicate whether the digit corresponds to year, month or day information. It is these sequences of tokens that are used as input to a recurrent neural network.

3.1 LSTMs for Time-Encoding Sequences

A long short-term memory (LSTM) is a neural network architecture particularly suited for modeling sequential data. The equations defining an
LSTM are
\[ i = \sigma_g(h_{n-1} U_i + x_n W_i) \]
\[ f = \sigma_g(h_{n-1} U_f + x_n W_f) \]
\[ o = \sigma_g(h_{n-1} U_o + x_n W_o) \]
\[ g = \sigma_c(h_{n-1} U_g + x_n W_g) \]
\[ c_n = f \circ c_{n-1} + i \circ g \]
\[ h_n = o \circ h_n(c_n) \]
(3) the model can use triples with and without temporal information as training data. Figure 1 illustrates the generic working of our approach.

4 Experiments

We conducted experiments on four different KG completion data sets where a subset of the facts are augmented with time information.

4.1 Datasets

Integrated Crisis Early Warning System (ICEWS) is a repository that contains political events with a specific timestamp. These political events relate entities (e.g. countries, presidents...) to a number of other entities via logical predicates (e.g. 'Make a visit' or 'Express intent to meet or negotiate'). Additional information can be found at http://www.icews.com/. The repository is organized in dumps that contain the events that occurred each year from 1995 to 2015. We created two temporal KGs out of this repository, i) a short-range version that contains all events in 2014, and ii) a long-range version that contains all events occurring between 2005-2015. We refer to these two data sets as ICEWS 2014 and ICEWS 2005-15, respectively. Due to the large number of entities we selected a subset of the most frequently occurring entities in the graph and all facts where both the subject and object are part of this subset of entities. We split the facts into training, validation and test in a proportion of 80%/10%/10%, respectively. The protocol for the creation of these data sets is identical to the one used in previous work (Bordes et al., 2013). To create YAGO15K, we used FREEBASE15K (Bordes et al., 2013) (FB15K) as a blueprint. We aligned entities from FB15K to YAGO (Hoffart et al., 2013) with SAMEAS relations contained in a YAGO dump\(^2\), and kept all facts involving those entities. Finally, we augment this collection of facts with time information from the "yagoDateFacts\(^3\)" dump. Contrary to the

\(^2\) /yago-naga/yago3.1/yagoDBpediaInstances.ttl.7z
\(^3\) /yago-naga/yago3.1/yagoDateFacts.ttl.7z

| Fact | Predicate Sequence |
|------|------------------|
| (Barack Obama, country, US) | [country] |
| (Barack Obama, born, US, 1961) | [born, 1y, 9y, 6y, 1y] |
| (Barack Obama, president, US, since, 2009-01) | [president, since, 2y, 0y, 0y, 9y, 01m] |
Table 2: Statistics of the data sets. TS stands for timestamps. The number of facts with time information is in brackets.

| Data set       | YAGO15K | ICEWS '14 | ICEWS 05-15 | WIKIDATA |
|----------------|---------|-----------|-------------|----------|
| Entities       | 15,403  | 6,869     | 10,094      | 11,134   |
| Relationships  | 34      | 230       | 251         | 95       |
| #Facts         | 138,056 | 96,730    | 461,329     | 150,079  |
| #Distinct TS   | 198     | 365       | 4,017       | 328      |
| Time Span      | 1513-2017 | 2014     | 2005-2015   | 2025-2020 |
| Training       | 110,441 | 72,826    | 368,962     | 121,422  |
| (29,381)       |         |           |             |          |
| Validation     | 13,815  | 8,941     | 46,275      | 14,374   |
| (3,635)        |         |           |             |          |
| Test           | 13,800  | 8,963     | 46,092      | 14,283   |
| (3,685)        |         |           |             |          |

Table 3: Results (filtered setting) of the temporal knowledge graph completion experiments for the data sets YAGO15K and WIKIDATA. The best results are written bold.

|          | YAGO15K                  | WIKIDATA                  |
|----------|--------------------------|---------------------------|
|          | MRR MR Hits@10 Hits@1    | MRR MR Hits@10 Hits@1     |
| TTRANSE  | 32.1 578 51.0 23.0        | 48.8 80 80.6 33.9         |
| TRANSE   | 29.6 614 46.8 22.8        | 31.6 50 65.9 18.1         |
| DISTMULT | 27.5 578 43.8 21.5        | 31.6 77 66.1 18.1         |
| TA-TRANSE| 32.1 564 51.2 23.1        | 48.4 79 80.7 32.9         |
| TA-DISTMULT| 29.1 551 47.6 21.6       | 70.0 198 78.5 65.2        |

Table 4: Results (filtered setting) of the temporal knowledge graph completion experiments for the data sets ICEWS 2014 and ICEWS 2005-15. The best results are written bold.

|        | ICEWS 2014 | ICEWS 2005-15 |
|--------|------------|---------------|
|        | MRR MR Hits@10 Hits@1 | MRR MR Hits@10 Hits@1 |
| TTRANSE| 25.5 148 60.1 7.4  | 27.1 181 61.6 8.4  |
| TRANSE | 28.0 122 63.7 9.4  | 29.4 84 66.3 9.0  |
| DISTMULT | 43.9 189 67.2 32.3 | 45.6 90 69.1 33.7 |
| TA-TRANSE | 27.5 128 62.5 9.5 | 29.9 79 66.8 9.6 |
| TA-DISTMULT | 47.7 276 68.6 36.3 | 47.4 98 72.8 34.6 |

ICEWS data sets, YAGO15K does contain temporal modifiers; namely, ‘occursSince’ and ‘occursUntil’. Contrary to previous work (Leblay and Chekol, 2018), all facts maintain time information in the same level of granularity as one can find in the original dumps these data sets come from.

We also experimented with the temporal facts from the WIKIDATA data set extracted in (Leblay and Chekol, 2018). Only information regarding the year is available for these facts, since the authors discarded information of finer granularity. All facts are framed in a time interval (i.e. they contain the temporal modifiers ‘occursSince’ and ‘occursUntil’). Facts annotated with a single point-in-time are associated with that time-point as start and end time. Due to the large number of entities of this data set, which hinders the computation of standard KG completion metrics, we selected a subset of the most frequent entities and kept all facts where both the subject and object are part of this subset of entities. This set of filtered facts was split into training, validation and test in the same proportion as before.

Table 2 lists some statistics of the temporal KGs. All four data sets, with their corresponding training, validation, and test splits are available at https://github.com/nle-ml/mmkb.

4.2 General Set-up

We evaluate various methods by their ability to answer completion queries where i) all the arguments of a fact are known except the subject entity, and ii) all the arguments of a fact are known except the object entity. For the former we replace the subject by each of the KBs entities \( E \) in turn, sort the triples based on the scores returned by the different methods, and computed the rank of the correct entity. We repeated the same process for the second completion task and average the results.

4http://staff.aist.go.jp/julien.leblay/datasets
This is standard procedure in the KG completion literature. We also report the filtered setting as described in (Bordes et al., 2013). The mean of all computed ranks is the Mean Rank (lower is better) and the fraction of correct entities ranked in the top $n$ is called hits@$n$ (higher is better). We also compute the Mean Reciprocal Rank (higher is better) which is less susceptible to outliers.

Recent work (Leblay and Chekol, 2018) evaluates different approaches for performing link prediction in temporal KGs. The approach that learns independent representations for each timestamp and use these representations as translation vectors, similarly to (Bordes et al., 2013), leads to the best results. This approach is called VECTOR-BASED TTRANSE, though for the sake of simplicity in the paper we refer to it as TTRANSE. We compare our approaches TA-TTRANSE and TA-DISTMULT against TTRANSE, and the standard embedding methods TTRANSE and DISTMULT. For all approaches, we used ADAM (Kingma and Ba, 2014) for parameter learning in a mini-batch setting with a learning rate of 0.001, the categorical cross-entropy (Kadlec et al., 2017) as loss function and the number of epochs was set to 500. We validated every 20 epochs and stopped learning whenever the MRR values on the validation set decreased. The batch size was set to 512 and the number of negative samples to 500 for all experiments. The embedding size is $d=100$. We apply dropout (Srivastava et al., 2014) for all embeddings. We validated the dropout from the values $\{0, 0.4\}$ for all experiments. For TA-TTRANSE and TA-DISTMULT, the activation gate $\sigma_g$ is the sigmoid function; $\sigma_c$ and $\sigma_h$ were chosen to be linear activation functions.

4.3 Results

Table 3 and 4 list the results for the KG completion tasks. TA-TTRANSE and TA-DISTMULT systematically improve TTRANSE and DISTMULT in MRR, hits@10 and hits@1 in almost all cases. Mean rank is a metric that is very susceptible to outliers and hence these improvements are not consistent. TTRANSE learns independent representations for each timestamp contained in the training set. At test time, timestamps unseen during training are represented by null vectors. This explains that TTRANSE is only competitive in YAGO15K, wherein the number of distinct timestamps is very small (see #Distinct TS in Table 2) and thus enough training examples exist to learn robust timestamp embeddings. TTRANSE’s performance is similar to that of TA-TTRANSE, our time-aware version of TTRANSE, in WIKIDATA. Similarly, TTRANSE can learn robust timestamp representations because of the small number of distinct timestamps of this data set.

Figure 3 shows a comparison of the training loss of TTRANSE and TA-TTRANSE for YAGO15K. Under the same set-up, TA-TTRANSE’s ability to learn from time information leads to a training loss lower than that of TTRANSE.

Figure 2 shows a t-SNE (Maaten and Hinton, 2008) visualization of the embeddings learned for the predicate sequence $p_{seq} = \{\text{playsFor, occursSince, date}\}$, where date corresponds to the date token sequence. This illustrates that the learned relation type embeddings carry temporal information.

5 Conclusions

We propose a digit-level LSTM to learn representations for time-augmented KG facts that can be used in conjunction with existing scoring functions for link prediction. Experiments in four temporal knowledge graphs show the effectiveness of the approach.
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