The Presentation of Entities and Relations and its Application in Inference

Weidi Xu

Peking University, Computational Intelligence Laboratory

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Overview

- Knowledge Graph: a directed graph with entiites and relations
- Knowledge Inference: link prediction in knowledge graph
- Representation: efficient and scalable inference methods

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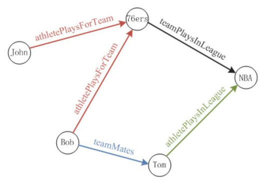
Knowledge Graph

- Knowledge graph is a directed graph comprised by entities and relations.

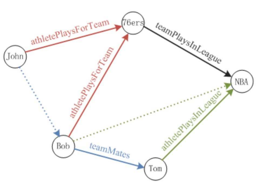


- (John, athletePlaysForTeam, 76ers)
- (Bob, athletePlaysForTeam, 76ers)
- (Tom, athleteMates, Tom)
- (Tom, athletePlaysInLeague, NBA)
- (76ers, teamPlaysInLeague, NBA)

- However the knowledge graph is incomplete: it only covers small part of facts.

Knowledge Inference

- Knowledge inference: link prediction in knowledge graph.



  - (John, teamMates, Bob)
  - (Bob, athletePlaysInLeague, NBA)
  - … …

- Inference in Knowledge Graph can increase the coverage.

Methods

- Inference based on representation learning.
  1. Collective Matrix Factoriation (Nickel et al., 2011)
  2. Neural Tensor Networks (Socher et al., 2013)
  3. Translating Embeddings(Bordes et al., 2013)
- Inference based on markov random field.
  1. Markov Logic Networks (Richardson and Domingos, 2006)
  2. Probabilistic Soft Logic (Brocheler et al., 2012)
- Inference based on random walk.
  1. Path Ranking (Lao et al., 2011)

Table

Framework

- Hidden variable model: modeling data in hidden variable space.

Leanring

- Learning entity and relation embeddings in hidden vector spaces.
- Define an fitness funtion to determine the certainty of entity-relation-entity pairs.
- Define an objective funtion to determine the certainty of entity-relation-entity pairs.

Prediction

- Using the model and objective function to inference.

Framework

- Hidden variable model: modeling data in hidden variable space.

Leanring

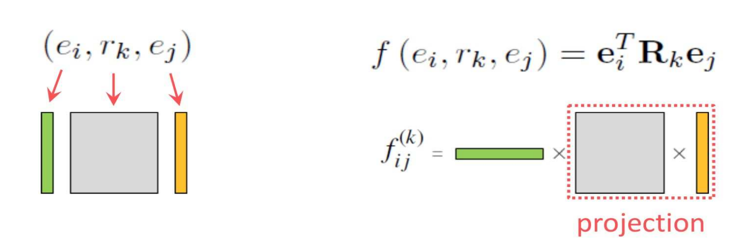
- Learning entity and relation embeddings in hidden vector spaces.
- Define an fitness funtion to determine the certainty of entity-relation-entity pairs.
- Define an objective funtion and use the facts dataset to learn the model parameters.

Objective function

- Reconstruction error
- Ranking loss

RESCAL: reconstruction error

- Representation in hidden vector/matrix space and the corresponding fitness function:



- Learn based on reconstruction error:

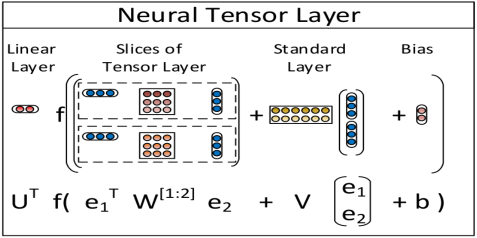
$$\min_{e_i, R_k} \sum_k \sum_i \sum_j (y_{i,j}^k - f(e_i, r_k, e_j))^2 + \lambda R \qquad (1)$$

assumption

It is assumed that all pairs not contained in dataset are negative.

NTN: ranking loss

- Representation in hidden vector/matrix space and the corresponding fitness function:



$$f(e_i, r_k, e_j) = U_k^T g(e_i^T W_k^{[1:K]} e_j + V_k[e_i : e_j] + b_k) \tag{2}$$

- Learn based on reconstruction error:

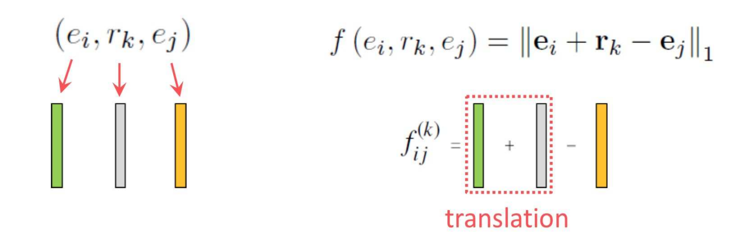
$$\min_{e_i, R_k} \sum_{t^+ \in O} \sum_{t^- \in D} (\lambda + f(e_i, r_k, e_j) - f(e_i', r_k, e_j')) \tag{3}$$

assumption

It is assumed that all pairs not contained in dataset are negative.

TransE: ranking loss

- Representation in hidden vector space and the corresponding fitness function:



- Learn based on ranking loss:

$$\min_{e_i, R_k} \sum_{t^+ \in O} \sum_{t^- \in D} (\lambda + f(e_i, r_k, e_j) - f(e_i', r_k, e_j')) \tag{4}$$

assumption

It is assumed that pairs not contained in dataset are partially negative.

Prons and Cons

- Pros
  1. Hidden space model can capture the complex concepts.
  2. It is computationally efficient.
- Cons
  1. It is not logical: we can capture the co-occurrence information but not logical properties of relation.
  2. It is not precise: data-driven methods will be noisy-prone.

Bordes, A., Usunier, N., Garcia-Duran, A., Weston, J., and Yakhnenko, O. (2013). Translating embeddings for modeling multi-relational data. In *Advances in Neural Information Processing Systems*, pages 2787–2795.

Brocheler, M., Mihalkova, L., and Getoor, L. (2012). Probabilistic similarity logic. *arXiv preprint arXiv:1203.3469*.

Lao, N., Mitchell, T., and Cohen, W. W. (2011). Random walk inference and learning in a large scale knowledge base. In *Proceedings of the Conference on Empirical Methods in Natural Language Processing*, pages 529–539. Association for Computational Linguistics.

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