Project3 CFKG Algorithm

Introduction of the task

- In this task, you need to construct a Recommender System by the given user-item interaction data and knowledge graph (KG).

- The key to the Recommender System is a score function $f(u, w)$

- For the samples in the given user-item interaction data
  - While inputting a positive sample, f should return a high score
  - While inputting a negative sample or a sample not in the given data, f should return a low score.

How to score a sample

- The input of the $f(u,w)$, u and w is only the index of the user/item.

- There is no information in the index of the user/item, it’s impossible to give a significative score only based on the index.

- For the user u and item w, we need to find their feature vectors, and record as $\mathbf{u}$ and $\mathbf{w}$.

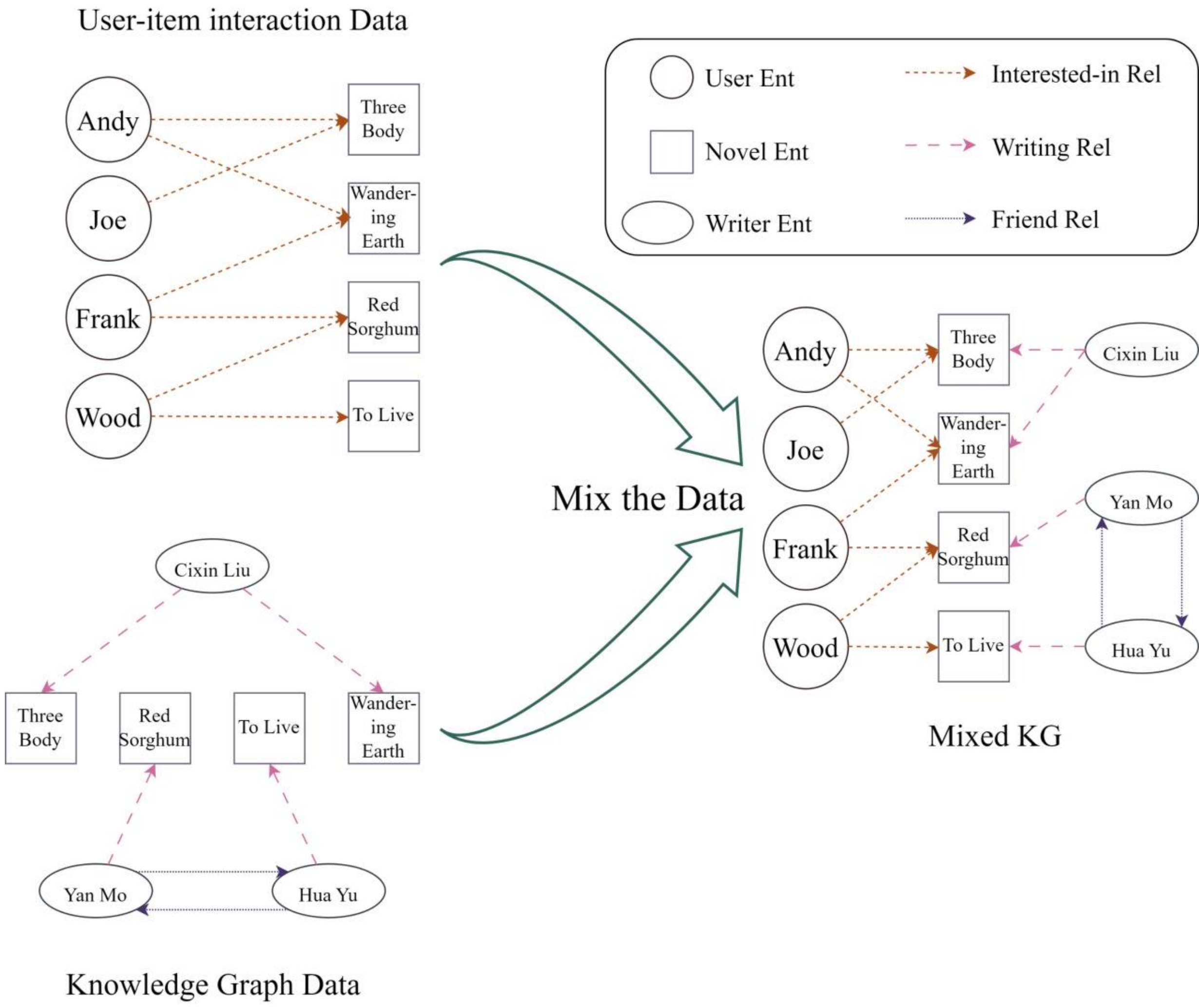
- The calculation process of $f(u,w)$ depends on $\mathbf{u}$ and $\mathbf{w}$.

How to find a good feature?

- An intuitive method is designing some statistical metric as the feature, such as the correlation coefficient
  - Designing the statistical metric is difficult.
  - It's hard to use the information in the KG.
- Another method is representing the user/item as a low-dimensional real value vector (also called Embedding)
  - How to get the embedding?
    - Firstly, we define the calculation process of $f(u, w)$
    - Get the embeddings of all the users and items by the Gradient Descent method, let the return value of $f(u, w)$ for all the combinations of users and items are accordance with the given interaction data
  - Each element in the embedding can represent some information about the user/item, but we cannot explain them.
  - The information of KG can also be represented in the embedding.

How to mix information of KG and interaction data?——CFKG Algorithm

- CFKG algorithm models the interaction records as a new type of relations in the KG, there relation type is "Interested-in".
- The interaction data and origin KG will be mixed into a bigger KG
- We also can define a score function $g(h,r,t)$ for the relation in the KG:
  - Input is a relation in KG: g returns a high score
  - Input is a relation not in KG: g returns a low score
- If we define $r' =$ Interested-in:
  - For a positive sample, $g(u,r',w)$ returns a high score
  - For a negative sample or a sample not in the given data , $g(u,r',w)$ returns a low score.



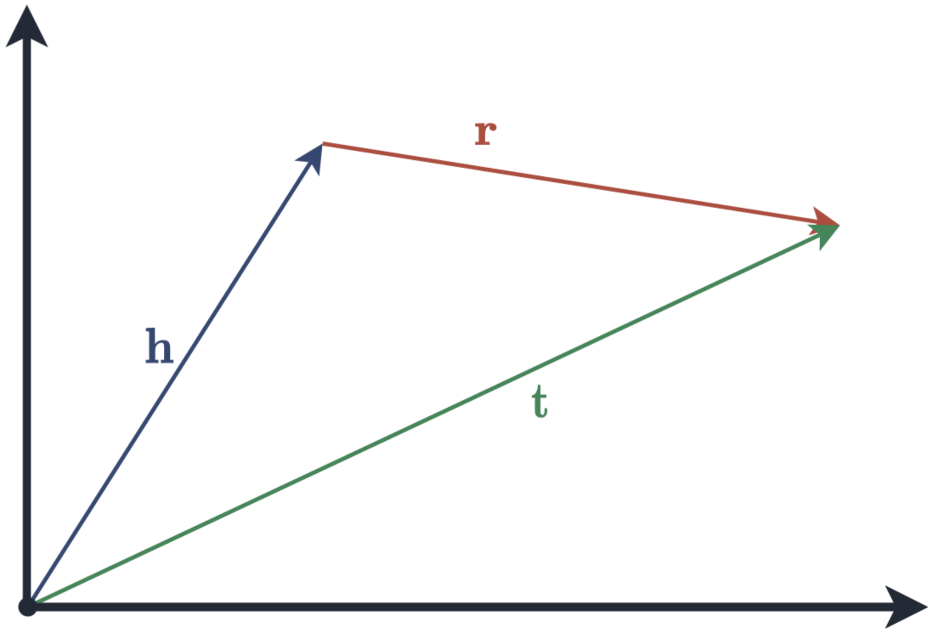
Integrating interaction data with knowledge graph data to form a new knowledge graph

A specific design scheme of g — the TransE Algorithm

- TransE Algorithm is an example of $g(h, r, t)$
  - Entity and relation type will be represented as a vector in the d-dimensional Euclidean Space
  - Ideally, when the relational triplet (h, r, t) holds, its corresponding vector representation should satisfy:

$$\mathbf{h} + \mathbf{r} = \mathbf{t}$$

  - However, the ideal situation often does not hold true. Therefore, the likelihood of a relational triplet (h, r, t) being valid is positively correlated with $-\|\mathbf{h} + \mathbf{r} - \mathbf{t}\|$
  - Therefore, $g(h, r, t) = -\|\mathbf{h} + \mathbf{r} - \mathbf{t}\|$



Schematic diagram of the calculation principle of the TransE relation model

Get Embedding from given data

- For the merged knowledge graph, the Embedding representations of all entities and relations should satisfy:
  - For a relation in KG: g returns a high score
  - For a relation not in KG: g returns a low score
- Then ideally, for the merged knowledge graph $\mathcal{G}'$, there is::

$$\forall(h,r,t) \in \mathcal{G}' \forall(h',r',t') \notin \mathcal{G}', g(h,r,t) > g(h',r',t')$$

- Which means: $\sum_{(h,r,t)\in\mathcal{G}'} \sum_{(h',r',t')\notin\mathcal{G}'} [g(h',r',t') - g(h,r,t)]_+ = 0$, where $[x]_+ = \max(x,0)$
- There is a loss function: $\min \sum_{(h,r,t)\in\mathcal{G}'} \sum_{(h',r',t')\notin\mathcal{G}'} [g(h',r',t') - g(h,r,t)]_+$
- If we require that $g(h,r,t)$ be at least γ higher than $g(h',r',t')$, then the final form of the loss function is:

$$\min \sum_{(h,r,t)\in\mathcal{G}'} \sum_{(h',r',t')\notin\mathcal{G}'} [g(h',r',t') - g(h,r,t) + \gamma]_+$$

Reference

1. Y. Zhang, Q. Ai, X. Chen, and P. Wang, “Learning over Knowledge-Base Embeddings for Recommendation.,” *arXiv*, vol. abs/1803.06540, 2018, [Online]. Available: http://arxiv.org/abs/1803.06540
2. A. Bordes, N. Usunier, A. García-Durán, J. Weston, and O. Yakhnenko, “Translating Embeddings for Modeling Multi-relational Data.,” in *Advances in Neural Information Processing Systems 26*, 2013, pp. 2787–2795. [Online]. Available: https://proceedings.neurips.cc/paper/2013/hash/1cecc7a77928ca8133fa24680a88d2f9-Abstract.html