Knowledge Graph Embedding
For Precise Link Prediction

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Precise Link Prediction attempts to find the exact entity given another entity and the relation.

Motivations.
- Being *ill-posed algebraic system*.
  - There are $Td$ equations $(h_i + r_i = t_i)$.
  - There are $(E + R)d$ variables.
  - Since $T \gg E + R$, it is an *ill-posed algebraic system*.
- Adopting *over-strict geometric form*.
ManifoldE: From A Point To A Manifold

**Methodology.** To apply the manifold-based principle:

\[
M(h, r, t) = D_r^2
\]

When a head entity and a relation are given, the tail entities lay in a high-dimensional manifold.

\[
f_r(h, t) = ||M(h, r, t) - D_r^2||^2
\]
ManifoldE: From A Point To A Manifold

- **Sphere.**
  \[
  \mathcal{M}(h, r, t) = \|h + r - t\|^2
  \]

- **Hyperplane.**
  \[
  \mathcal{M}(h, r, t) = (h + r_{\text{head}})^\top(t + r_{\text{tail}})
  \]
ManifoldE: From A Point To A Manifold

- **Geometric Perspective.**
  - Manifold-Based principle extends one point to a whole manifold, to strengthen the stability.
  - This way would benefit complex relations.

- **Algebraic Perspective.**
  - There are one equation for one triple.
  - Thus, if \( d \geq \frac{T}{E+R} \), the system is far away from ill-posed.

- **Training.**

\[
\mathcal{L} = \sum_{(h,r,t) \in \Delta} \sum_{(h',r',t') \in \Delta'} \left[ f_r(h', t') - f_r(h, t) + \gamma \right]_+
\]
Experiments: Link Prediction.

<table>
<thead>
<tr>
<th>Datasets</th>
<th>WN18</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>HITS@10(%)</td>
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<tr>
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<td>TransH</td>
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<td>PTransE</td>
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<tr>
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<tr>
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<td>80.7</td>
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<td>ManifoldE H.</td>
<td><strong>84.2</strong></td>
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**Experiments:** Link Prediction.

<table>
<thead>
<tr>
<th>Datasets</th>
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**Experiments:** Triple Classification.

<table>
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<tr>
<th>Methods</th>
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Knowledge Semantic Representation
An Interpretable Knowledge Graph Representation

Han Xiao, Minlie Huang, Xiaoyan Zhu

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April 17, 2016
Knowledge Semantic Representation

- **Motivations** Geometrical positions as knowledge representation could not explicitly indicate the semantics.
  - The representation entity *Table* in TransE:
    
    \[(0.12, -0.22, 0.55, 0.60, 0.71, -0.01, 0.00, -0.77...)\]

- **Could we tell about something semantic?**
  - being a furniture?
  - being a daily tool?
  - being not an animal?

- The **GAP** between knowledge and language remains.
- Thus, developing a *semantics-specific representation* triggers an urgent task.
- A well-fitting model for knowledge graph is encouraging, but is still not enough from the semantic perspective.
Knowledge Semantic Representation

- **Knowledge Semantic Analysis (KSA)**
  - **Definitions**: A knowledge representation methodology that is supposed to explicitly provide human-comprehensive or at least semantics-relevant representation
  - *(Stanford University) = (University:Yes, Animal:No, Location:California, ...)*

- **Knowledge Feature** is a term we introduced for describing some knowledge semantic aspects.

- **Benefits**
  - The trade-off between *Human-Comprehensive* and *Machine-Computational* Knowledge Representation.
  - At least, in this way, it is more elegant to joint multiple information sources and knowledge triples.
A Naive Example in the scenario of information retrieval.

Query: What private university is most famous in California?

1. Extracting the keywords: private, university, famous, California.
2. Mapping to knowledge feature: (University:Yes, Animal:No, Location:California, Type:Private, Famous:Very, ...).
3. Inferring the possible entity/relation (Stanford University) as the answer with link prediction task.

Notably, our model KSR is a generative model, which could generate the representations, while it is also capable to infer towards entities/relations.
Model Descriptions KSR leverages a two-level hierarchical generative process to semantically represent the entities, relations and triples.

1. In the first level of our model, we generate some knowledge features such as University (YES/NO), Animal Type, Location, etc.
2. In the second level of our model, we assign a corresponding category in each knowledge feature for every triple.
Knowledge Semantic Representation

- **Model Descriptions** KSR leverages a two-level hierarchical generative process to semantically represent the entities, relations and triples.
  
  1. In the first level of our model, we generate some knowledge features such as University(YES/NO), Animal Type, Location, etc.
  
  2. In the second level of our model, we assign a corresponding category in each knowledge feature for every triple.

  For the example of **Stanford University**, we assign Yes in the University feature, California in Location feature and so on.

  
  \[
  (\text{University} : \text{Yes}, \text{Animal} : \text{No}, \text{Location} : \text{California},
  \text{Type} : \text{Private}, \text{Famous} : \text{Very}, ...)
  \]

  In this way, the knowledge representation is semantically interpretable.
Knowledge Semantic Representation

Clustering Perspective (Basic Idea)

How to Categorize?

<table>
<thead>
<tr>
<th>Hallow</th>
<th>Slas</th>
<th>Solid</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
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</tbody>
</table>

Shape

Content

Knowledge Feature

Semantic Representation

Square

Star

{(S,H) (T,H)}  
{(S,S) (T,S)}  
{(S,D) (T,D)}
Knowledge Semantic Representation

- **Clustering Perspective (Simple Illustration)**

A pool of Knowledge

- **Triples Information**
- **Location**

<table>
<thead>
<tr>
<th>Knowledge Feature</th>
<th>University</th>
<th>Location</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tsinghua University</td>
<td>Beijing</td>
<td>Yes</td>
</tr>
<tr>
<td>Tiananmen Square</td>
<td>Beijing</td>
<td>No</td>
</tr>
<tr>
<td>Fudan University</td>
<td>Shanghai</td>
<td>Yes</td>
</tr>
<tr>
<td>Oriental Pearl</td>
<td>Shanghai</td>
<td>No</td>
</tr>
</tbody>
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Knowledge Semantic Representation

- **Clustering Perspective (Model Analysis)**

![Diagram](image)

- **Latent Semantics Mapping.** Naively to adopt very little hand-craft analysis.
**Experiments:** Knowledge Graph Completion

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<td>KSR (S2)</td>
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</tbody>
</table>
Knowledge Semantic Representation

- **Experiments**: Entity Classification
- Relatively 17% Improvement.
- Details presented in our paper.
Knowledge Semantic Representation

- **Experiments**: Semantic Analysis
- Case Study presented in our paper.
- At least we feel good.
Knowledge Semantic Representation

- **Experiments**: Description to Entity Analysis
- Task.
- Will be done.
- Case Study will be presented in our paper.
- Currently, at least, we feel good.
Knowledge Semantic Representation

Thanks for your attention.