# Knowledge Graph Embedding For Precise Link Prediction

Han Xiao, Minlie Huang, Xiaoyan Zhu

Tsinghua University

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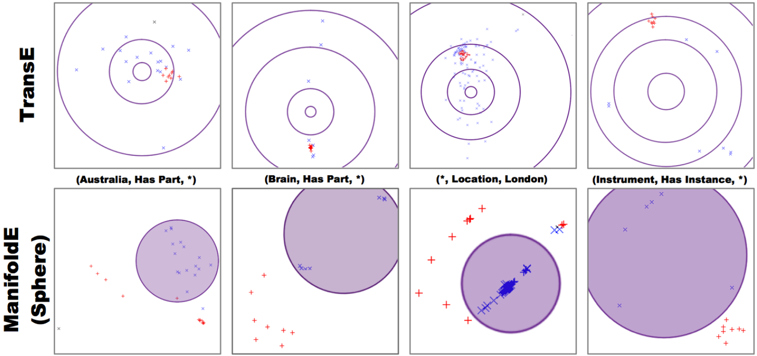
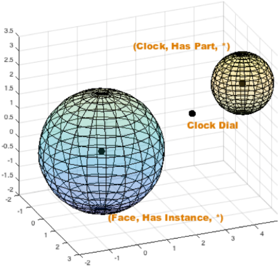
# ManifoldE: From A Point To A Manifold

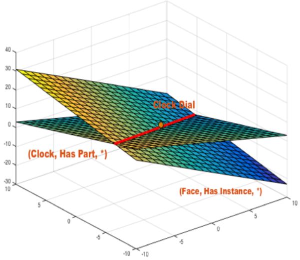
- **Precise Link Prediction** attempts to find the exact entity given another entity and the relation.
- **Motivations.**
  - Being *ill-posed algebraic system*.
    - There are $Td$ equations ($h_i + r_i = t_i$).
    - There are $(E + R)d$ variables.
    - Since $T \gg E + R$, it is *an ill-posed algebraic system*.
  - Adopting *over-strict geometric form*.



# ManifoldE: From A Point To A Manifold




**(a)**




**(b)**

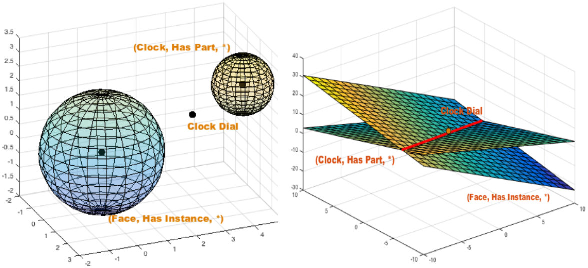
- **Methodology.** To apply the manifold-based principle:

$$\mathcal{M}(\mathbf{h}, \mathbf{r}, \mathbf{t}) = D_r^2$$

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

$$f_r(h, t) = ||\mathcal{M}(h, r, t) - D_r^2||^2$$

# ManifoldE: From A Point To A Manifold




**(a)** **(b)**

- **Sphere.**

$$\mathcal{M}(h,r,t) = ||\mathbf{h}+\mathbf{r}-\mathbf{t}||_2^2$$

- **Hyperplane.**

$$\mathcal{M}(h,r,t) = (\mathbf{h}+\mathbf{r}_{\mathbf{head}})^\top(\mathbf{t}+\mathbf{r}_{\mathbf{tail}})$$

# 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.**

$$\mathcal{L} = \sum_{(h,r,t)\in\Delta} \sum_{(h',r',t')\in\Delta'} [f_{r'}(h', t') - f_r(h, t) + \gamma]_+$$

- **Experiments**: Link Prediction.

| Datasets | WN18 | | | |
|---|---|---|---|---|
| Metric | HITS@10(%) | | HITS@1(%) | Time(s) |
| | Raw | Filter | Filter | One Epos |
| TransE | 75.4 | 89.2 | 29.5 | **0.4** |
| TransH | 73.0 | 82.3 | 31.3 | 1.4 |
| TransR | 79.8 | 92.0 | 33.5 | 9.8 |
| PTransE | - | - | - | - |
| KG2E | 80.2 | 92.8 | 54.1 | 10.7 |
| ManifoldE S. | 80.7 | 92.8 | 55.8 | **0.4** |
| ManifoldE H. | **84.2** | **94.9** | **93.2** | 0.5 |

# ManifoldE: From A Point To A Manifold

- **Experiments**: Link Prediction.

| Datasets | FB15K | | | |
|---|---|---|---|---|
| Metric | HITS@10(%) | | HITS@1(%) | Time(s) |
| | Raw | Filter | Filter | One Epos |
| TransE | 34.9 | 47.1 | 29.4 | **0.7** |
| TransH | 48.2 | 64.4 | 24.8 | 4.8 |
| TransR | 48.4 | 68.7 | 20.0 | 29.1 |
| PTransE | 51.4 | 84.6 | 63.3 | 266.0 |
| KG2E | 48.9 | 74.0 | 40.4 | 44.2 |
| ManifoldE S. | **55.7** | 86.2 | 64.1 | **0.7** |
| ManifoldE H. | 55.2 | **88.1** | **70.5** | 0.8 |

# ManifoldE: From A Point To A Manifold

- **Experiments**: Triple Classification.

| **Methods** | **WN11** | **FB13** | **AVG.** |
|---|---|---|---|
| SE | 53.0 | 75.2 | 64.1 |
| NTN | 70.4 | 87.1 | 78.8 |
| TransE | 75.9 | 81.5 | 78.7 |
| TransH | 78.8 | 83.3 | 81.1 |
| TransR | 85.9 | 82.5 | 84.2 |
| KG2E | 85.4 | 85.3 | 85.4 |
| ManifoldE Sphere | **87.5** | 87.2 | **87.4** |
| ManifoldE Hyperplane | 86.9 | **87.3** | 87.1 |

# Knowledge Semantic Representation
# An Interpretable Knowledge Graph Representation

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# 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

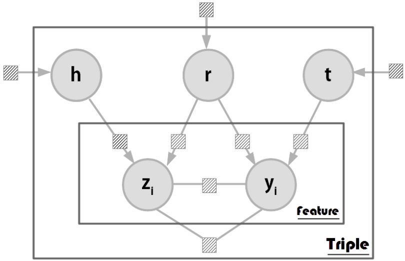
- **Knowledge Semantic Analysis (KSA)**
  - **Definitions**: A knowledge representation methodology that is supposed to explicitly provide human-comprehensive or at least semantics-relevant representation
  - *(Stanford University)* = *(University:Yes, Animal:No, Location:California, ...)*
- **Knowledge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

# Knowledge Semantic Representation

- **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 is also capable to infer towards entities/relations.

# 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.



# Knowledge Semantic Representation

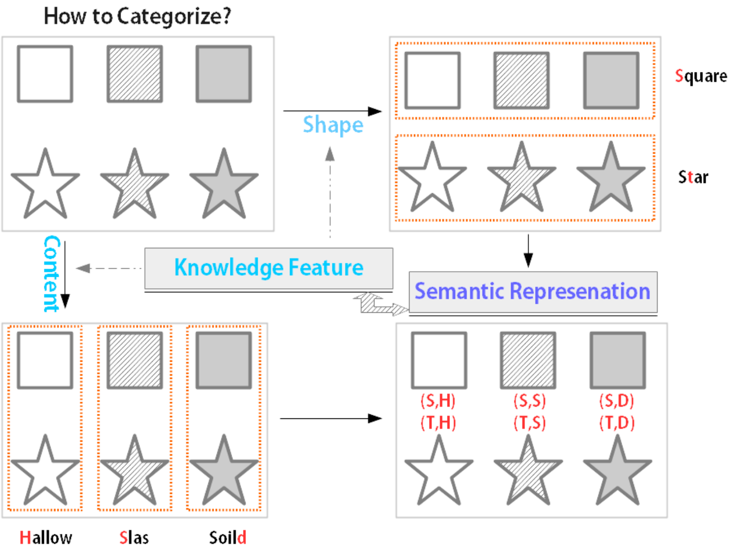
- **Model Descriptions** KSR leverages a two-level hierarchical generative process to semantically represent the entities, relations and triples.
  1. In the first level of our model, we generate some *knowledge features* such as *University(YES/NO), Animal Type, Location, etc.*
  2. In the second level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

$$(University : Yes, Animal : No, Location : California,$$
$$Type : Private, Famous : Very, \ldots)$$

- In this way, the knowledge representation is semantically interpretable.

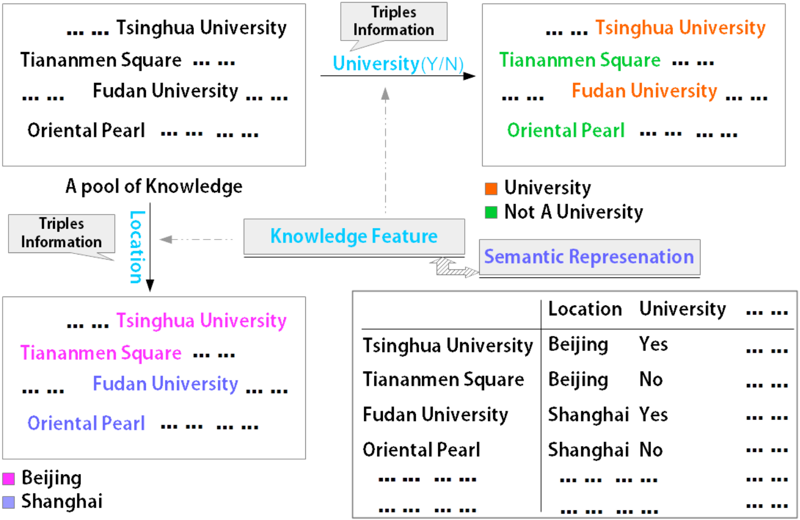
# Knowledge Semantic Representation

- **Clustering Perspective (Basic Idea)**



# Knowledge Semantic Representation

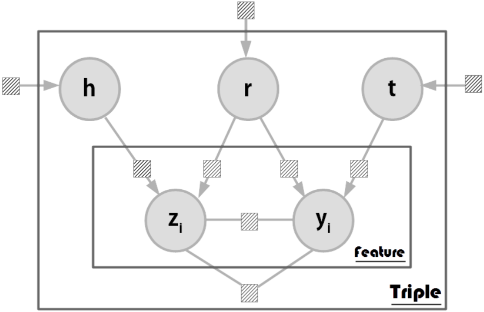
- **Clustering Perspective (Simple Illustration)**




| | Location | University | ... ... |
|---|---|---|---|
| Tsinghua University | Beijing | Yes | ... ... |
| Tiananmen Square | Beijing | No | ... ... |
| Fudan University | Shanghai | Yes | ... ... |
| Oriental Pearl | Shanghai | No | ... ... |
| ... ... ... ... | ... ... ... ... | | ... ... |
| ... ... ... ... | ... ... ... ... | | ... ... |

# Knowledge Semantic Representation

- **Clustering Perspective (Model Analysis)**




- **Latent Semantics Mapping.** Naively to adopt very little hand-craft analysis.

# Knowledge Semantic Representation

- **Experiments**: Knowledge Graph Completion

| Datasets | FB15K | | | |
|---|---|---|---|---|
| Metric | HITS@10(%) | | HITS@1(%) | Time(s) |
| | Raw | Filter | Raw | Filter |
| TransE | 243 | 125 | 34.9 | 47.1 |
| TransH | 212 | 87 | 45.7 | 64.4 |
| KSR (S1) | **178** | **86** | **55.6** | **76.7** |
| TransR | 198 | 77 | 48.2 | 68.7 |
| KG2E | 183 | 69 | 47.5 | 71.5 |
| KSR (S2) | **159** | **66** | **57.2** | **87.2** |

# 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.**