

Knowledge Graph Embedding For Precise Link Prediction

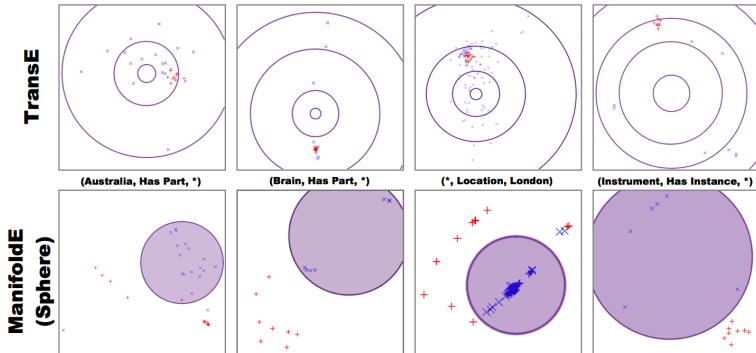
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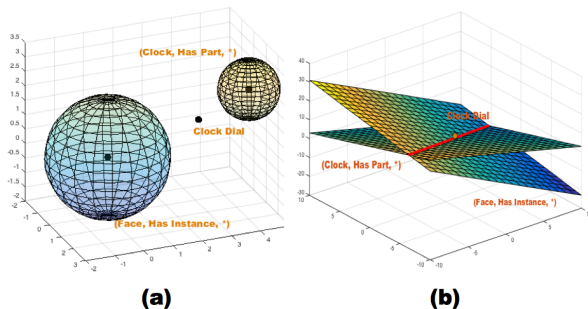
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ManifoldE: From A Point To A Manifold

- **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



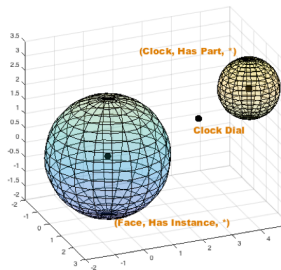
- **Methodology.** To apply the manifold-based principle:

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

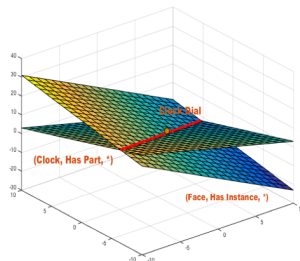
When a head entity and a relation are given, the tail entities lay in a high-dimensional manifold.

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

ManifoldE: From A Point To A Manifold



(a)



(b)

- Sphere.

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

- Hyperplane.

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

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.**

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

ManifoldE: From A Point To A Manifold

- **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:

$(0.12, -0.22, 0.55, 0.60, 0.71, -0.01, 0.00, -0.77\dots)$

- **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**

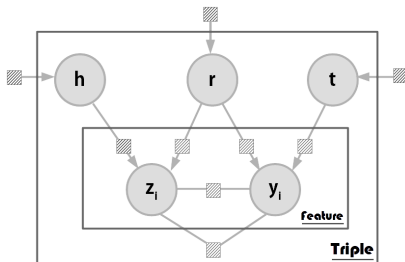
- The trade-off between *Human-Comprehensive* and *Machine-Computational* Knowledge Representation.
- At least, in this way, it is more elegant to joint multiple information sources and knowledge triples.

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

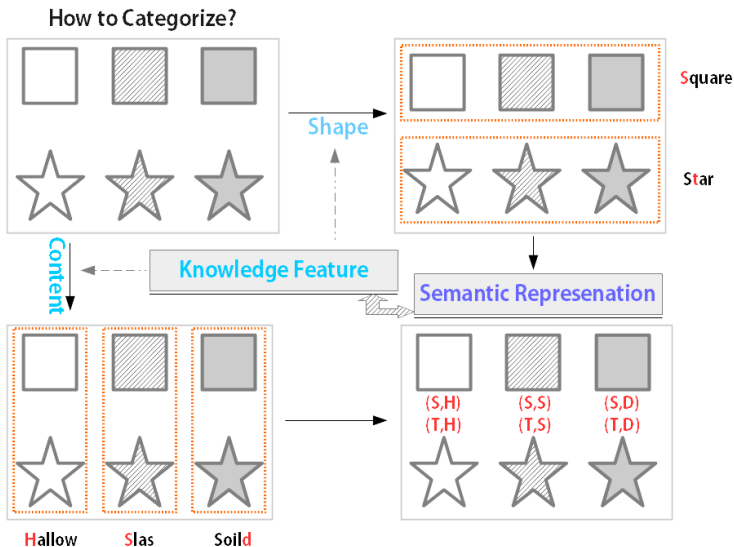
- **Model Descriptions** KSR leverages a two-level hierarchical generative process to semantically represent the entities, relations and triples.
 - 1 In the first level of our model, we generate some *knowledge features* such as *University(YES/NO)*, *Animal Type*, *Location*, etc.
 - 2 In the second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

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

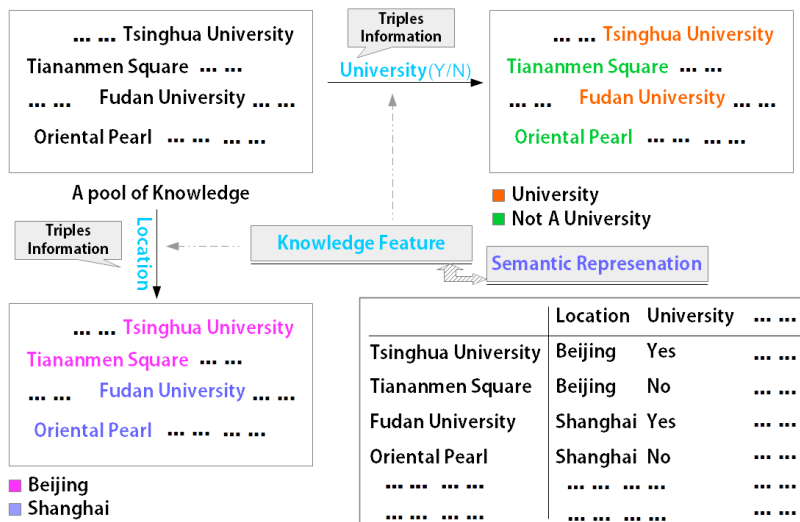
Knowledge Semantic Representation

- Clustering Perspective (Basic Idea)



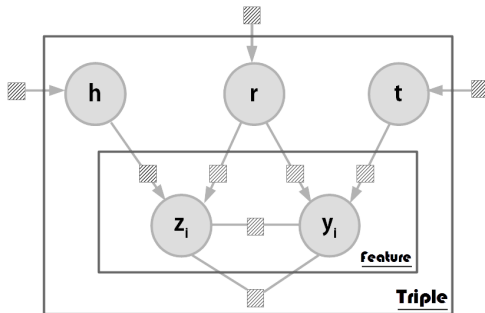
Knowledge Semantic Representation

Clustering Perspective (Simple Illustration)



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

Datasets	FB15K		
Metric	EC@25	EC@50	EC@75
TransE	82.7	83.2	78.2
TransH	82.2	71.5	71.4
TransR	82.4	76.8	73.6
KSR(S1)	89.7	86.6	83.3

Knowledge Semantic Representation

- **Experiments:** Semantic Analysis
- On working.

Knowledge Semantic Representation

- **Experiments:** Description to Entity Analysis
- Task.
- Will be worked out.

Knowledge Semantic Representation

Thanks for your attention.