Iterative Entity Alignment via Joint Knowledge Embeddings

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ME

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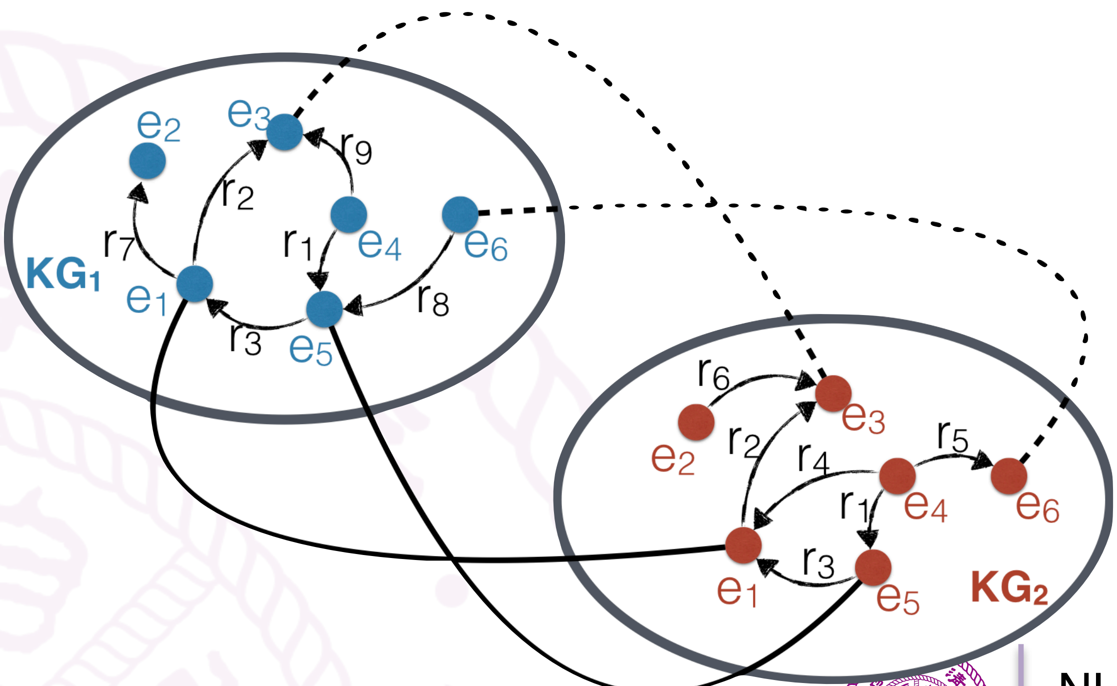
Entity Alignment

- Goal
  – Align synonymous entity pairs from heterogeneous Knowledge Graphs



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Knowledge Graphs

Knowledge Representation Learning

Knowledge Alignment

BACKGROUND

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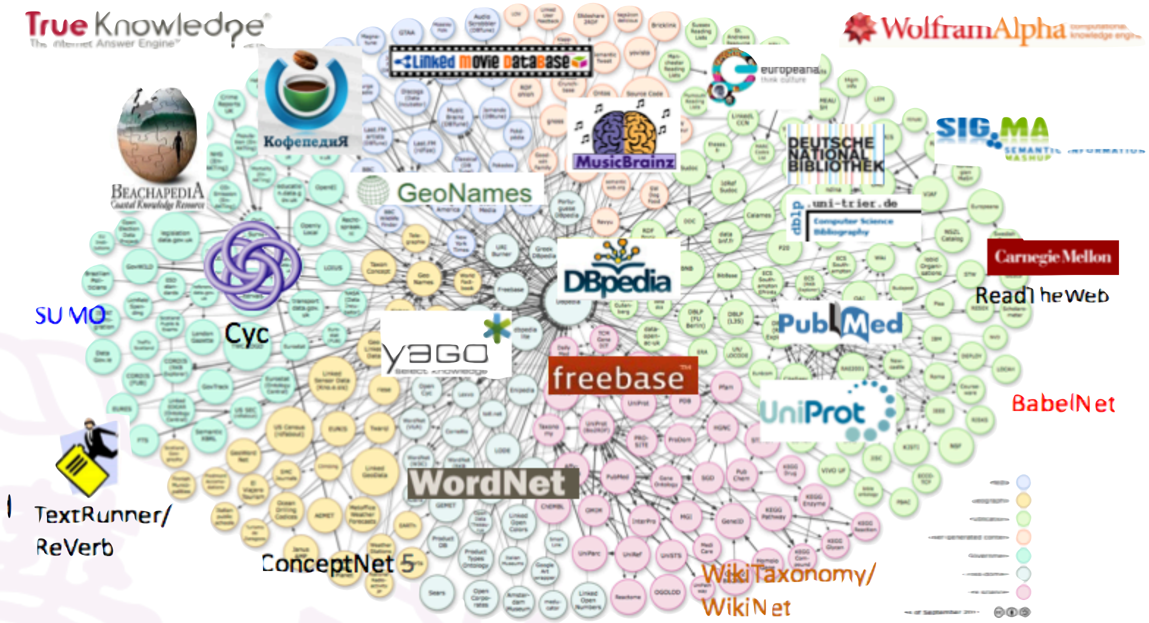

Existing Knowledge Graphs

Knowledge Alignment

- Graph-based models
  - time-consuming on large-scale KGs
- Other conventional models
  - crowd-sourcing
  - well-designed hand-crafted features
- MTransE [Chen et al. 2016]
  - similar idea, but from different assumption
  - experimental result shows our method is better

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Knowledge Representation Learning

- Knowledge Representation Learning
  - TransE [Bordes *et al.*, 2013] and its extensions
  - RESCAL [Nickel *et al.*, 2011; 2012]
  - HOLE [Nickel *et al.*, 2016]
  - NTN [Socher *et al.*, 2013]

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TransE

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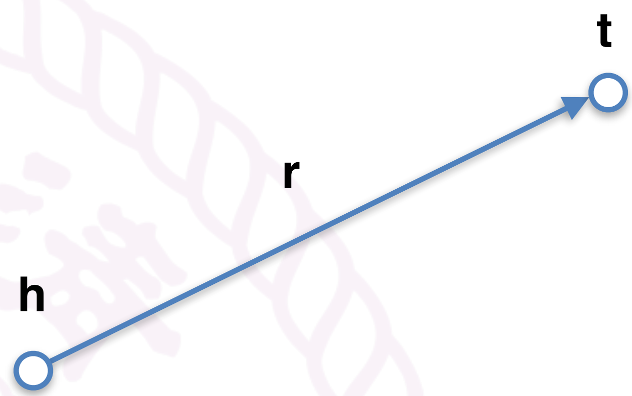
- Embedding:
  - Entity: vectors
  - Relation: translation vectors
- Goal: $\mathbf{h} + \mathbf{r} = \mathbf{t}$



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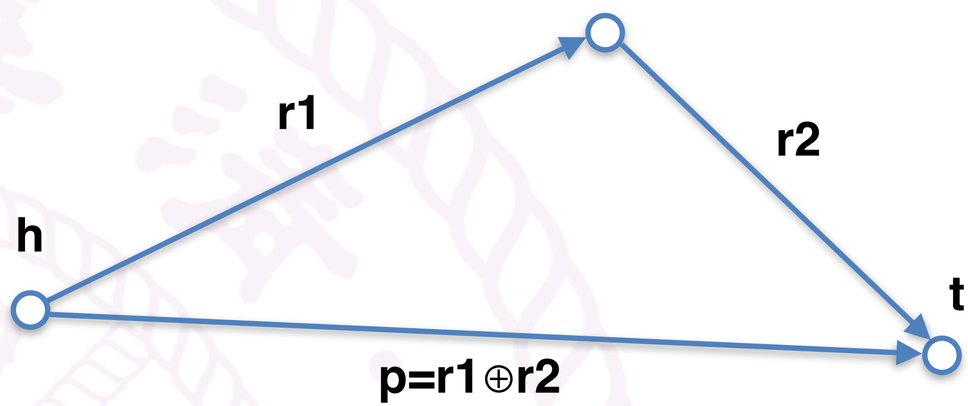
PTransE [Lin et. al 2015]

- Besides entities and relations, also embed relation path into the same space.



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What could KRL help us?

Representation ⟷ Intrinsic Meaning

Closer Representations ⟷ Higher Probability to be Synonymous

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Knowledge Representation Learning

Parameter Sharing Model

Iterative Alignment Model

Our Model(ITransE)

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Knowledge Representation Learning

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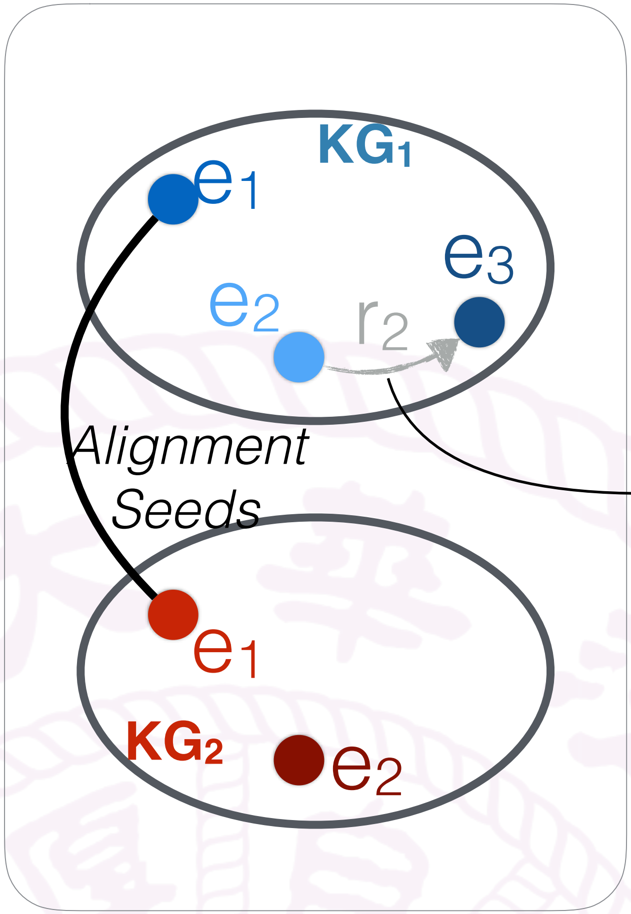
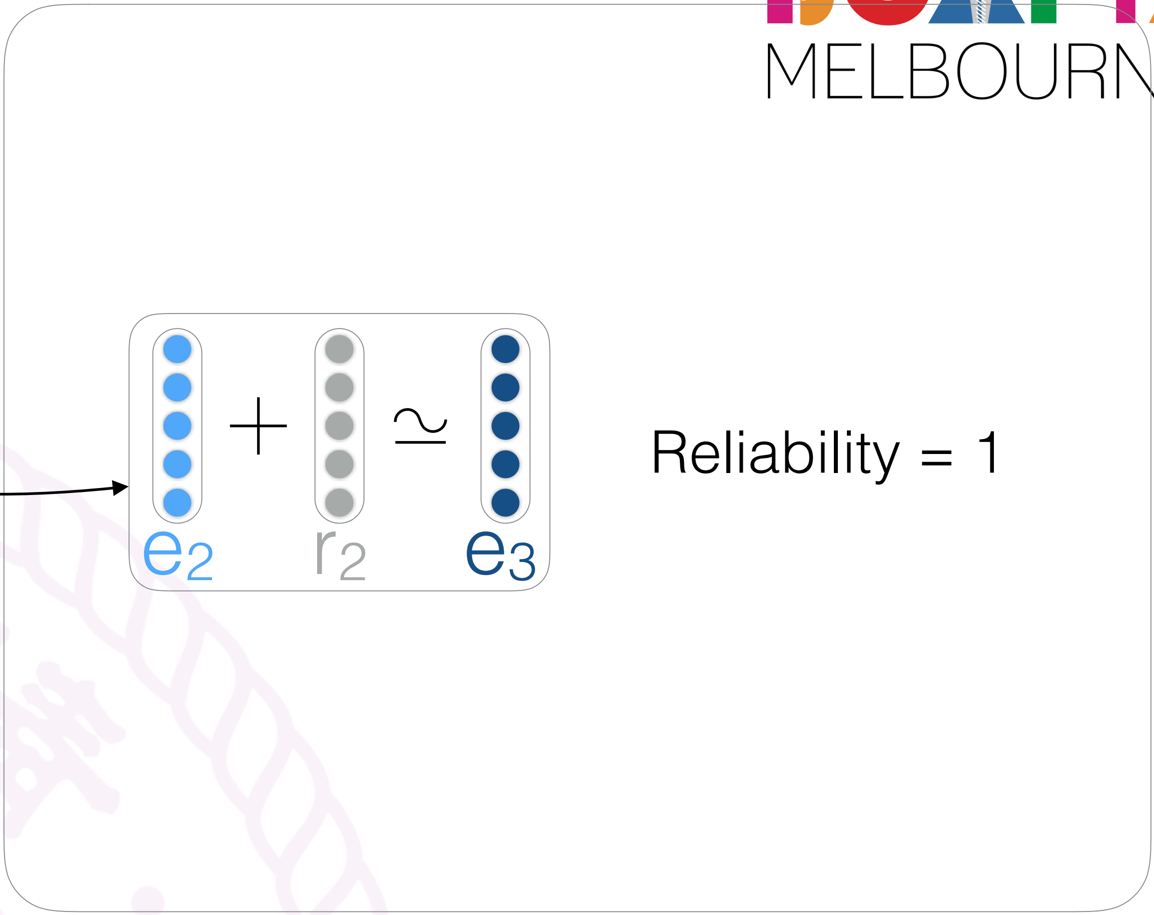


Knowledge Graph



Relationship Among Embeddings

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Parameter Sharing Model

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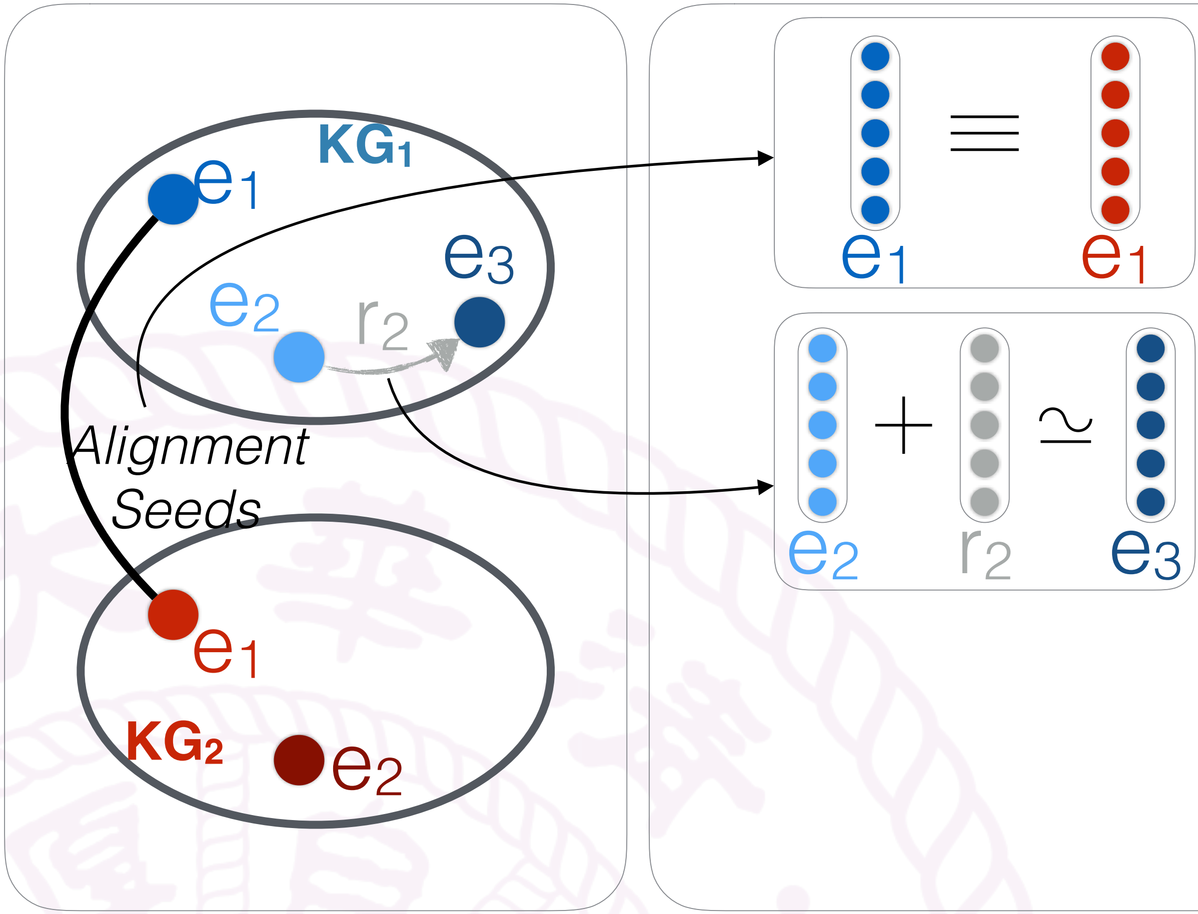

Reliability = 1

Knowledge Graph

Relationship Among Embeddings

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Iterative learning Model

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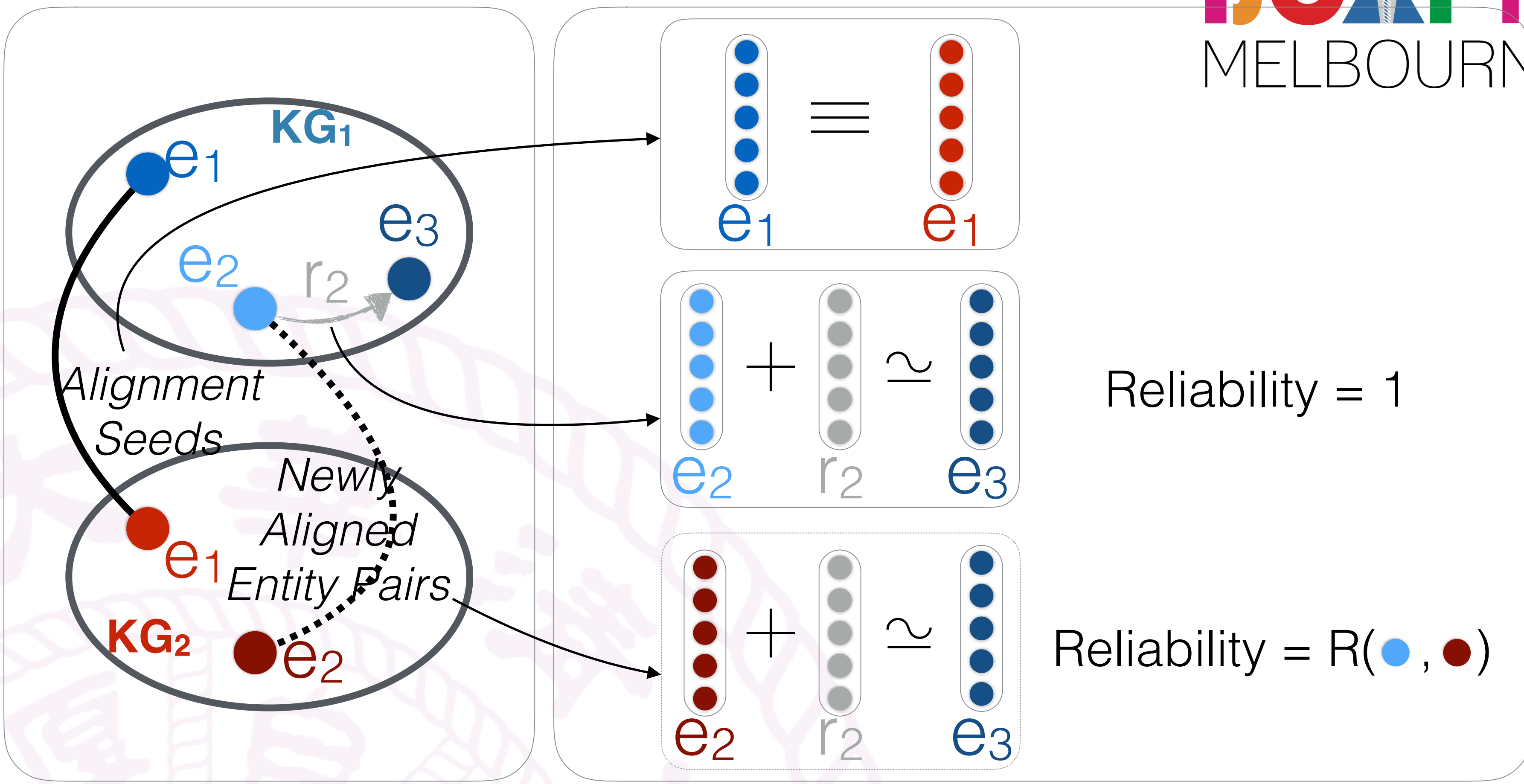

Knowledge Graph

Relationship Among Embeddings

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Empirical Evaluation

- Data
  - DFB-1,2,3

Dataset	$\lvert R \rvert$	$\lvert E \rvert$	$\lvert T_1 \rvert$	$\lvert T_2 \rvert$	$\lvert \mathbb{L} \rvert$	#Valid	O
DFB-1	1,345	14,951	444,159	444,160	5,000	1,000	0.5
DFB-2	1,345	14,951	444,159	444,160	500	1,000	0.5
DFB-3	1,345	14,951	325,717	325,717	500	1,000	0.1

  - DFB-4: Training set, test set and auxiliary training set are 399, 856/59, 071/399, 857 respectively.
- Task
  - Entity Alignment
  - Knowledge Completion

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Entity Alignment

- Goal
  - infer the synonymous entity pairs

Metric	DFB-1			DFB-2			DFB-3		
	Hits@1	Hits@10	Mean Rank	Hits@1	Hits@10	Mean Rank	Hits@1	Hits@10	Mean Rank
MTransE (LT)	38.9	61.0	237.7	12.3	33.8	419.2	6.5	22.0	699.8
MTransE (TB)	13.6	35.1	547.7	13.9	35.4	675.7	4.5	16.1	1255.5
TransE + PS	61.9	79.2	105.2	41.1	67.0	154.9	12.2	34.6	431.9
ITransE (HA)	62.6	78.9	100.0	41.2	66.9	151.9	12.3	33.7	432.3
ITransE (SA)	**67.1**	**83.1**	**80.1**	**57.7**	**77.7**	**109.3**	**16.2**	**40.9**	**367.2**
PTransE + PS	65.8	83.4	62.9	46.3	72.1	96.8	15.8	40.2	346.9
IPTransE (HA)	66.1	83.3	59.1	46.2	72.6	94.2	15.1	39.7	337.6
IPTransE (SA)	**71.7**	**86.5**	**49.0**	**63.5**	**82.2**	**67.5**	**20.4**	**47.4**	**281.0**

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Entity Alignment

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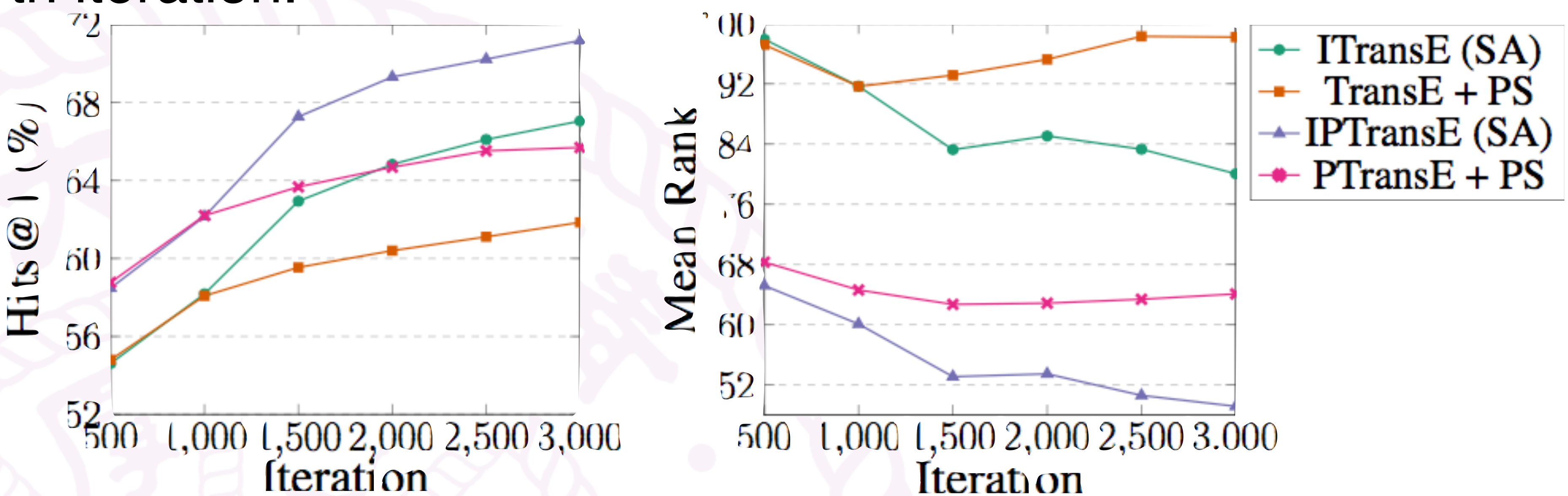
Hits@1 and Mean Rank of our methods through different iterations. (Hits@10 has similar trends to Hits@1.) We conduct soft alignment every 500 iterations from the 1000-th iteration.



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Knowledge Completion

- Goal
  - help learn better knowledge embeddings

Metric	Entity Prediction				Relation Prediction			
	Mean Rank		Hits@10		Mean Rank		Hits@1	
	Raw	Filter	Raw	Filter	Raw	Filter	Raw	Filter
MTransE (LT)	240.8	131.3	36.4	47.3	37.2	36.9	48.3	56.9
MTransE (TB)	851.3	759.7	9.4	10.8	293.7	293.4	27.4	27.7
TransE	246.1	131.6	42.5	54.3	55.9	55.6	44.2	50.7
TransE + Aux	232.8	121.5	43.3	54.9	50.1	49.8	44.4	50.9
ITransE (SA)	**209.2**	**101.0**	**44.2**	**55.1**	**19.8**	**19.6**	**54.2**	**60.7**
PTransE	213.0	97.2	50.9	72.1	2.33	1.96	67.4	86.9
PTransE + Aux	206.3	80.4	52.7	80.7	2.34	1.93	**68.8**	90.5
IPTransE (SA)	**197.5**	**70.6**	**53.0**	**80.8**	**2.03**	**1.62**	68.6	**90.8**

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Conclusion

- This paper presents iterative entity alignment via joint knowledge embeddings, by encoding both entities and relations of various KGs into a unified semantic space.
- A simple and effective Parameter Sharing Model
- An Iterative Alignment Model
- We evaluate on entity alignment and knowledge graph completion.
- Experiment results show the effectiveness of our methods as compared with other baselines.

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Future Work

- incorporate rich external information of KGs for entity alignment
- explore the effectiveness of other KRL models in our methods for entity alignment.

- Our **code** and **data** will be available at https://github.com/thunlp/IEAJKE

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Questions?

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