



中科院计算所  
INSTITUTE OF COMPUTING TECHNOLOGY

# MultiE: Multi-Task Embedding for Knowledge Base Completion

Zhao Zhang, Fuzhen Zhuang, Zheng-Yu Niu,

Deqing Wang, Qing He

Institute of Computing Technology, CAS; Baidu Inc.; Beihang University.



## Introduction

Knowledge bases are comprised of knowledge triples in the form of (h, r, t), e.g. (Beijing, capitalOf, China). Knowledge base completion (KBC) aims to fill the missing values into incomplete triples.

(Donald Trump, nationality, ?)

(Donald Trump, bornIn, New York)

(New York, cityOf, USA)

infer

(Donald Trump, nationality, USA)

Recent KBC models have the following two flaws:

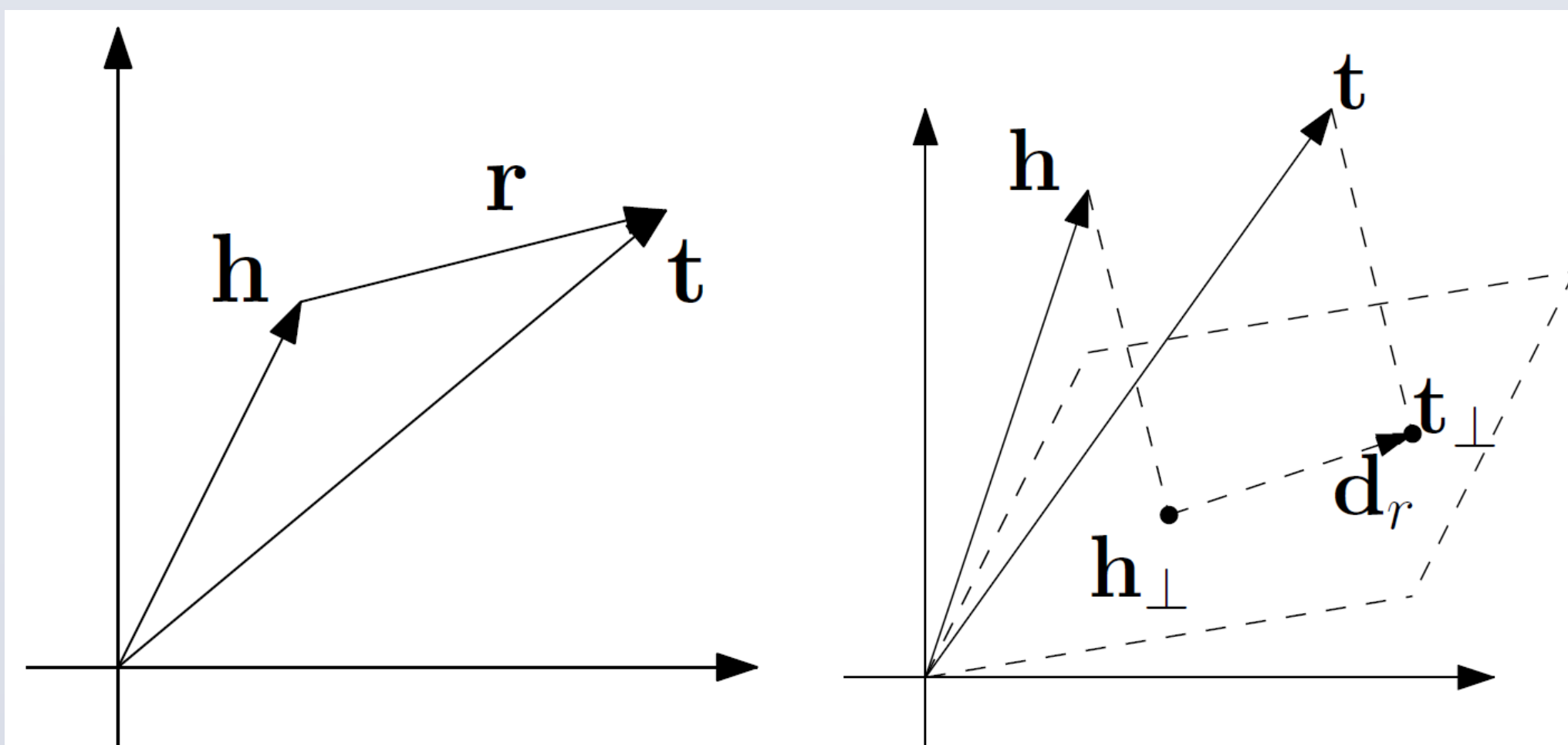
(1) each relation is embedded into a latent vector separately, and the correlations among relations are ignored;

/location/country/official\_language

Correlation

/location/country/languages\_spoken

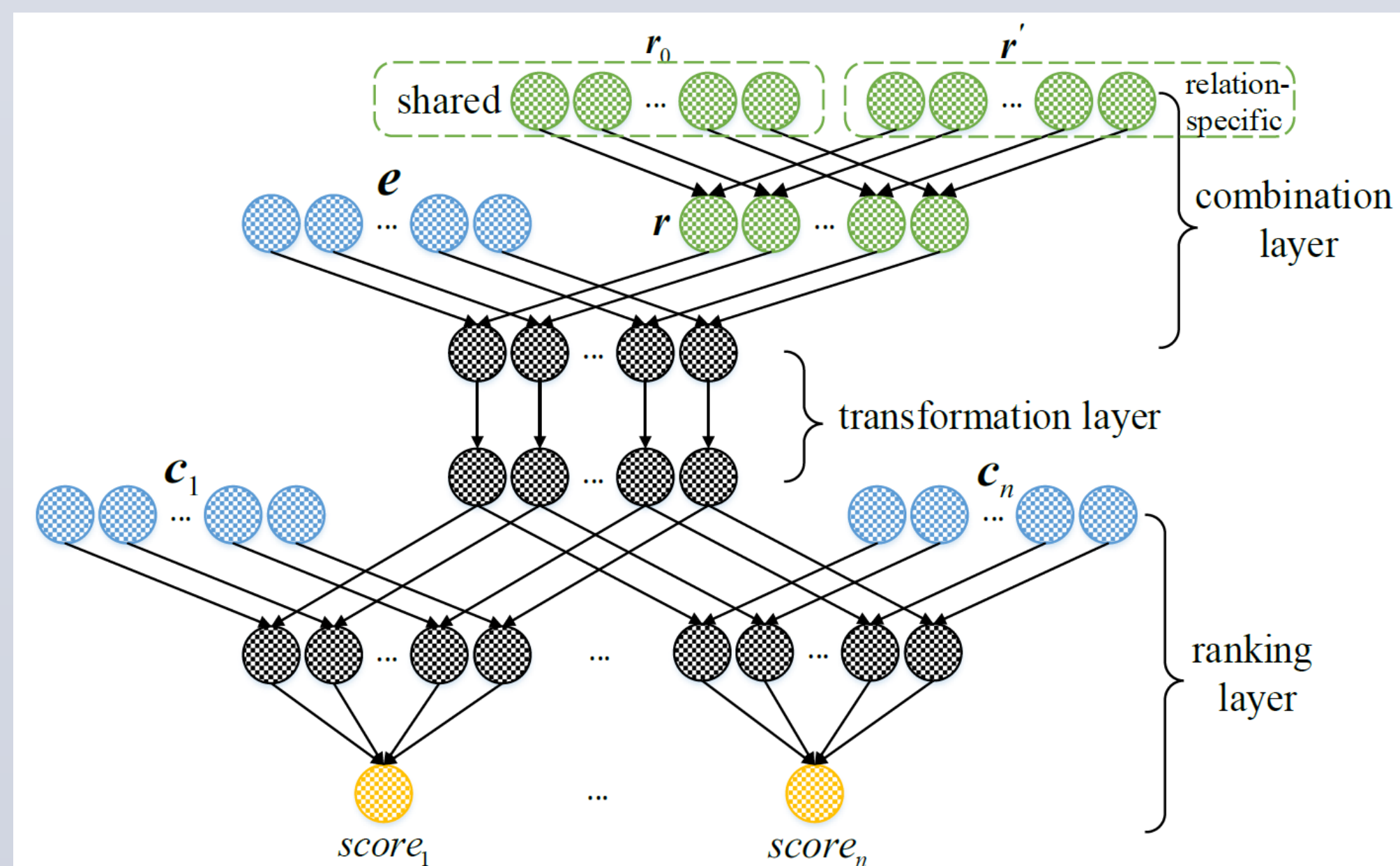
(2) most models embed entities and relations into a unified space instead of separate spaces.



(a) TransE

(b) TransH

## Network Structure

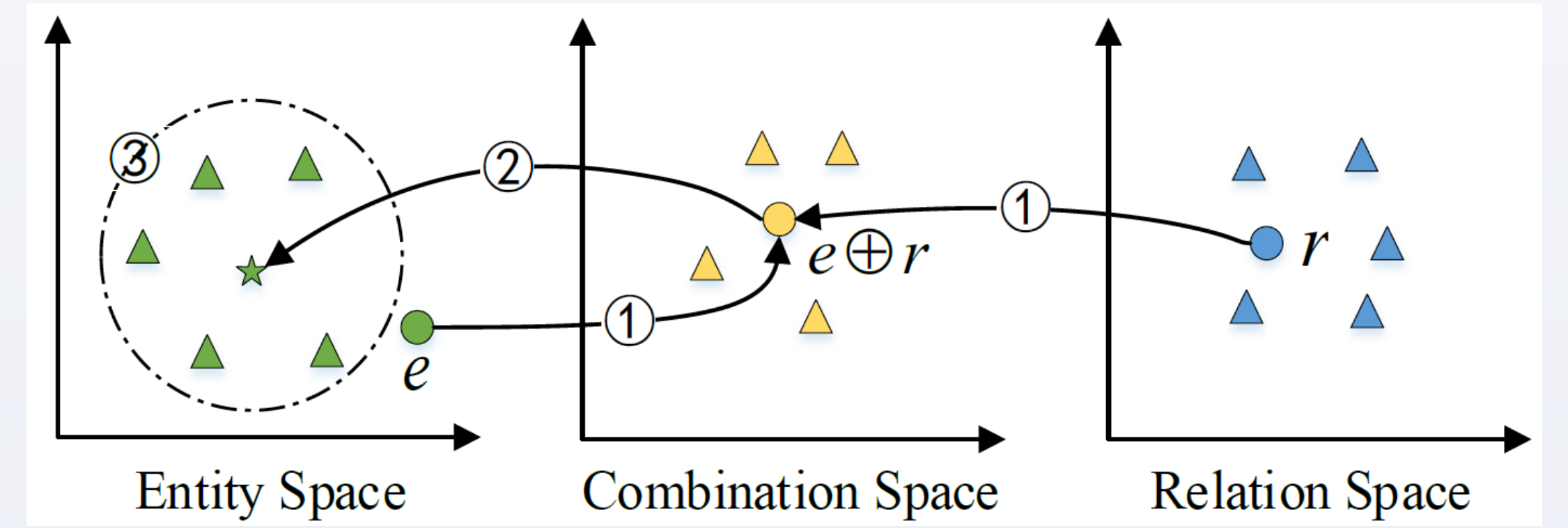


Relation embedding  $\mathbf{r} = \mathbf{r}_0 + \mathbf{r}'$

First Layer  $\mathbf{e} \oplus \mathbf{r} = f(\mathbf{W}_e \mathbf{e} + \mathbf{W}_r \mathbf{r} + \mathbf{b}_c)$

Second Layer  $(\mathbf{e} \oplus \mathbf{r})' = f(\mathbf{W}_t (\mathbf{e} \oplus \mathbf{r}) + \mathbf{b}_t)$

Third Layer  $s(\mathbf{e}, \mathbf{r}, \mathbf{c}_i) = g(\mathbf{c}_i^\top (\mathbf{e} \oplus \mathbf{r})' + \mathbf{b}_r)$



## Experiment

Dataset: FB15k, FB15k-237 and WN18

Dataset	$ \mathcal{E} $	$ \mathcal{R} $	#triples in Train/Valid/Test
FB15k	14,951	1,345	483,142 / 50,000 / 59,071
FB15k-237	14,541	237	272,115 / 17,535 / 20,466
WN18	40,943	18	141,442 / 5,000 / 5,000

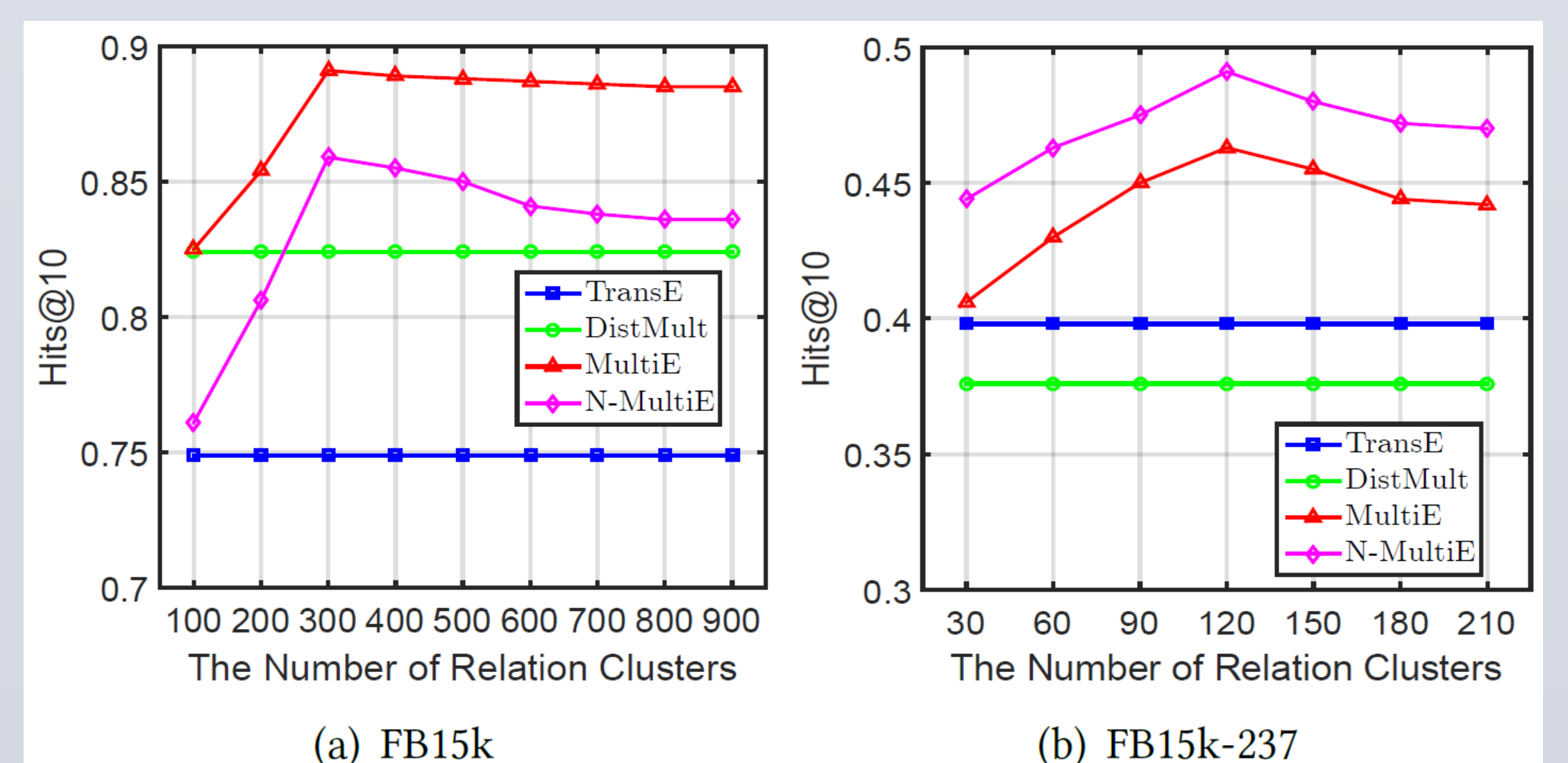
## Results

	FB15k					FB15k-237					WN18				
	MR	MRR	H10	H3	H1	MR	MRR	H10	H3	H1	MR	MRR	H10	H3	H1
TransE [1]	125	0.463	0.749	0.578	0.297	-	0.233	0.398	0.263	0.147	251	0.495	0.943	0.888	0.113
TransR [4]	77	0.346	0.582	0.404	0.218	-	-	-	-	-	225	0.427	0.940	0.876	0.335
DistMult [15]	-	0.654	0.824	0.733	0.546	-	0.191	0.376	0.207	0.106	-	0.532	0.936	0.914	0.728
HoIE [6]	-	0.524	0.739	0.613	0.402	-	0.222	0.391	0.253	0.133	-	0.938	0.949	0.945	0.930
ComplEx [14]	-	0.692	0.840	0.759	0.599	-	0.201	0.388	0.213	0.112	-	0.941	0.947	0.945	0.936
ProjE [8]	34	0.727	0.884	0.772	0.646	237	0.241	0.410	0.258	0.160	271	0.817	0.948	0.928	0.913
R-GCN+ [7]	-	0.696	0.842	0.760	0.601	-	0.249	0.417	0.264	0.151	-	0.819	0.964	0.929	0.697
MultiE-STL	56	0.756	0.883	0.817	0.668	240	0.262	0.441	0.287	0.179	257	0.940	0.949	0.945	0.939
MultiE	42	<b>0.775</b>	<b>0.887</b>	<b>0.832</b>	<b>0.681</b>	247	0.284	0.463	0.312	0.199	248	0.925	0.942	0.938	0.931
N-MultiE-STL	59	0.713	0.836	0.771	0.616	<b>148</b>	0.287	0.470	0.322	0.203	229	<b>0.949</b>	0.956	<b>0.949</b>	<b>0.941</b>
N-MultiE	48	0.736	0.859	0.792	0.637	183	<b>0.309</b>	<b>0.491</b>	<b>0.339</b>	<b>0.219</b>	<b>223</b>	0.938	0.949	0.939	0.933

## Examples of Relation Clusters in FB15k

	relations
1	/location/country/languages_spoken /location/country/official_language
2	/film/producer/film, /film/writer/film /film/director/film, /film/cinematographer/film
3	/sports/sports_team/roster./soccer/football_roster_position/player /sports/sports_team/roster./sports/sports_team_roster/player /soccer/football_team/current_roster./soccer/football_roster_position/player /soccer/football_team/current_roster./sports/sports_team_roster/player

## The Change of Hits@10 with The Number of Relation Clusters Increasing



(a) FB15k

(b) FB15k-237

## Conclusion

In this paper, we propose MultiE, a MTL-based model for the KBC task. MultiE uses a three-layer network and a ranking-based loss function to predict the missing values of incomplete knowledge triples. In MultiE, three semantic spaces are considered, which guarantees the expressivity of our model. Experiments show that our model can outperform other baselines with a large margin, especially on the data sets which have dense semantic distributions over relations.