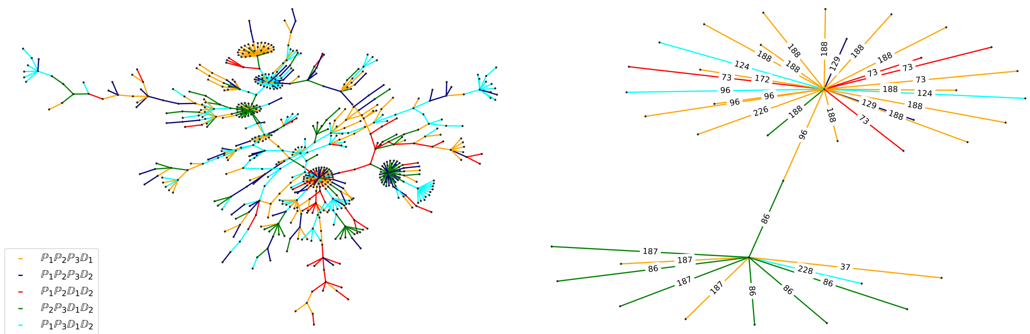

Figure 1: More examples of the connected component on FB15K-237.

Model	WN18RR		FB15K-237	
	embedding dim	Model Size	Embedding Dim	Model Size
TransE/DistMult/ConvE	tuned from {128, 256, 512}	max 20.97M	tuned from {128, 256, 512}	max 7.57M
BoxE/MurP/TuckER	500	20.48M	500	7.39M
RotE/RotH	500	20.49M	500	7.63M
QuatE	1000	40.95M	4000	58.64M
RotatE	1000	40.95M	2000	29.32M
ComplEx-N3	1000	40.95M	1000	14.78M
Ours	500	20.49M	500	7.63M

Table 1: Model size comparison on the relational graph link prediction task.

1 Additional Details on the Relational Graph Link Prediction Task

1.1 Related work on relational graph link prediction

A number of embedding techniques have been explored for relational graphs. Representative Euclidean models are RESCAL [8], DistMult [12], TransE [4], TuckER [3], ConvE [6], RotE [5], R-GCN [9], and BoxE [1]. Complex/Hypercomplex number models such as ComplEx [11; 7], RotatE [10], QuatE [13] have shown better capability in modeling asymmetric relations. Recently, learning relational graph embeddings in hyperbolic spaces has gained increasing popularity. Hyperbolic models such as MurP [2] and RotH [5] can effectively capture the hierarchical relational patterns in relational graphs. As can be concluded from the literature, it is important for the models to have the capability to capture the relational and structural patterns in real-world relational graphs. However, current models usually focus on specific patterns and lose sight of the big picture. Our model is capable of modeling not only different relational patterns (symmetric, antisymmetric, and inversive, etc.) but also various structural patterns (hierarchical, cyclical, etc) of relational graphs for more effective link prediction.

1.2 Model size comparison

As shown in Table 1, we see that the introduced trainable parameters in the gating network can be ignored as compared with RotE/RotH. Compared with QuatE and RotatE, our method uses half of their parameters but obtains better results.

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