A Statistical Relational Approach to Learning Distance-based GCNs

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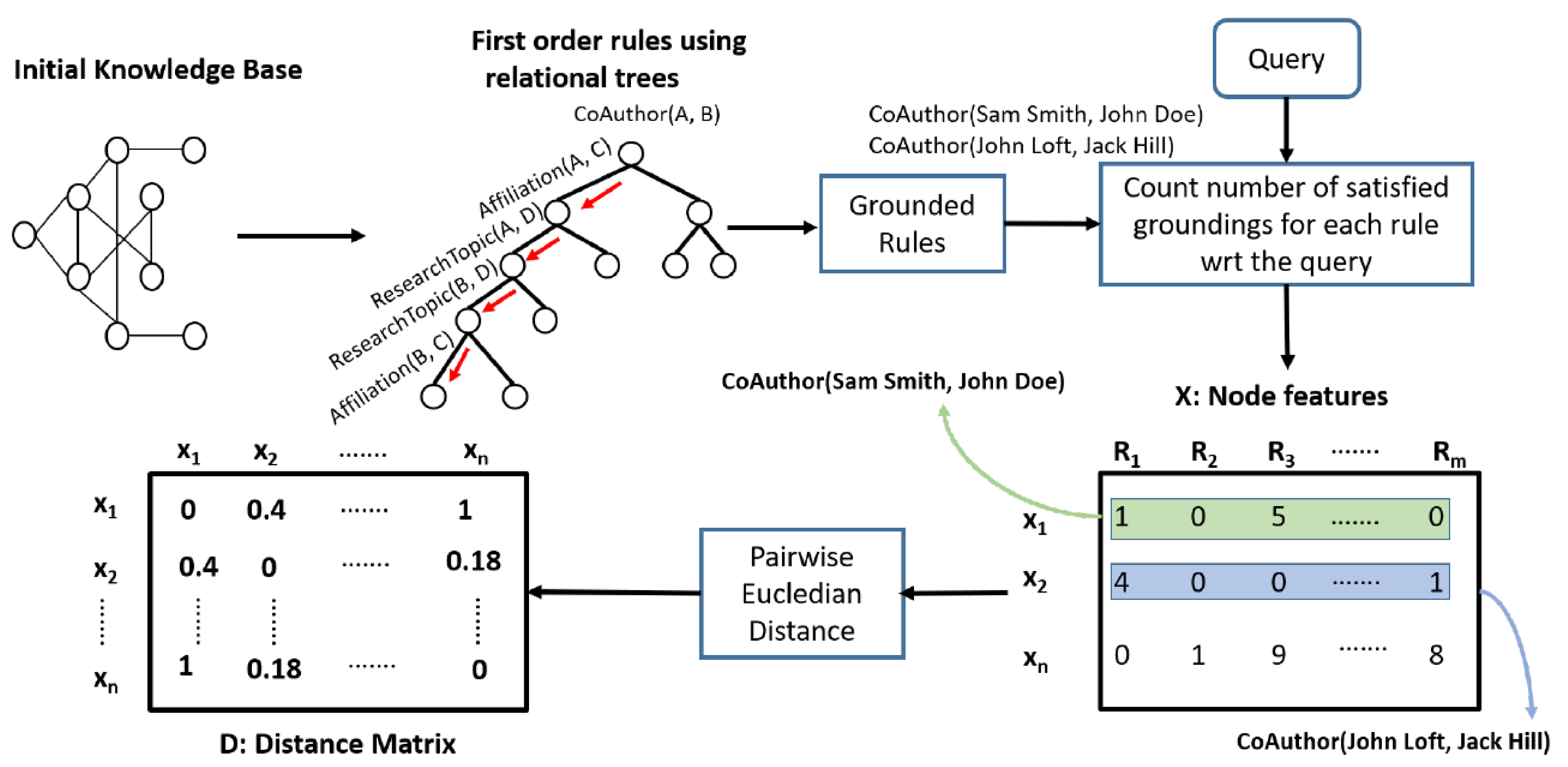
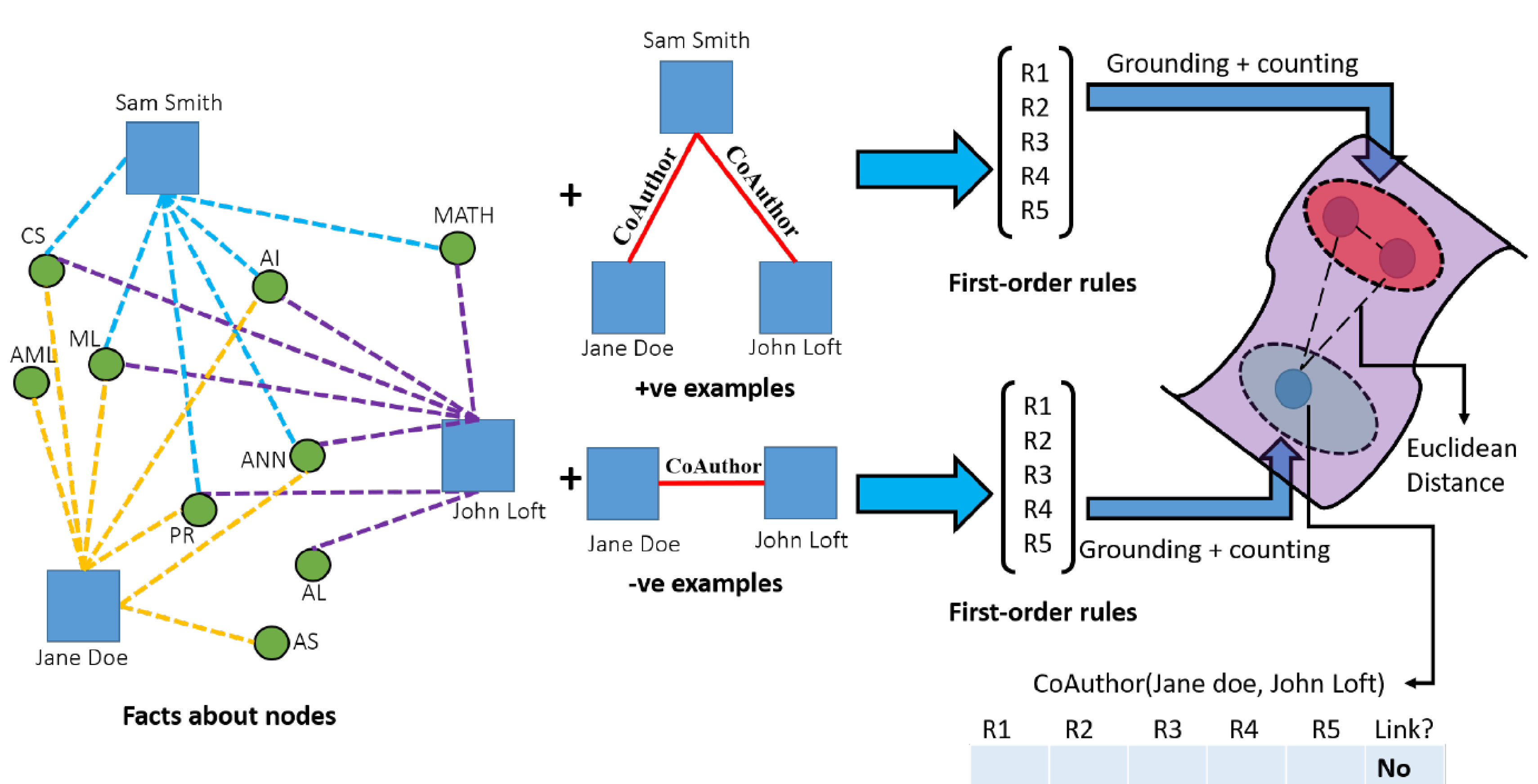
Overview

- Bridging the gap between Statistical Relational learning and graph neural networks
- Learning distance-based Graph Convolutional Networks (GCNs) for relational data
- Embed the original graph into the Euclidean space => secondary Euclidean graph
  - Using relational density estimation
- Vertices correspond to target triples & edges to Euclidean distance between target triples



Relational Density-based GCN

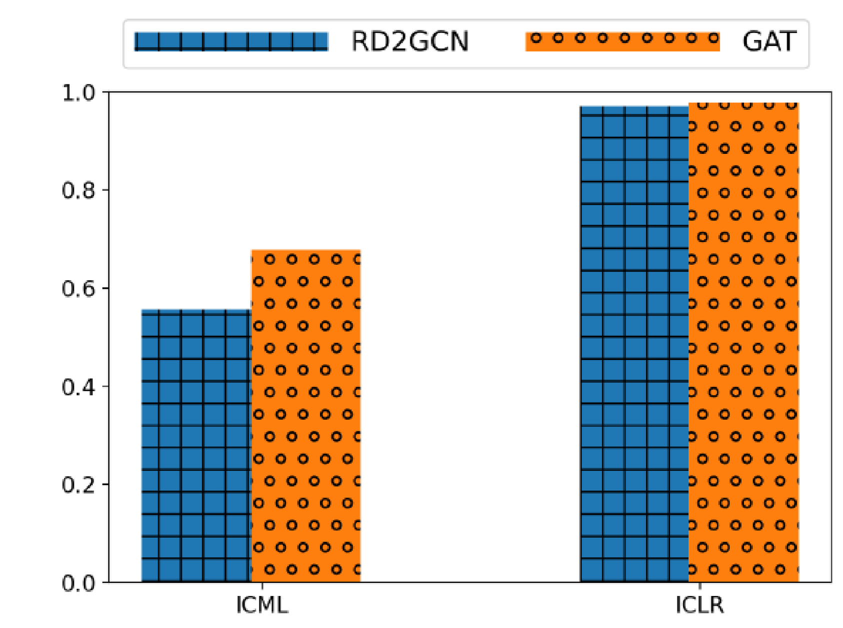
- Learning RD^{2}GCN: **Learn relational decision trees for separate densities -> extract first order rules -> count number of satisfied groundings**
- Vanilla GCN: feature matrix and adjacency matrix & RD^{2}GCN: relation rule matrix (obtained by counting the number of satisfied groundings of the obtained first-order rules (R1 - Rm) w.r.t the query variables) and distance matrix



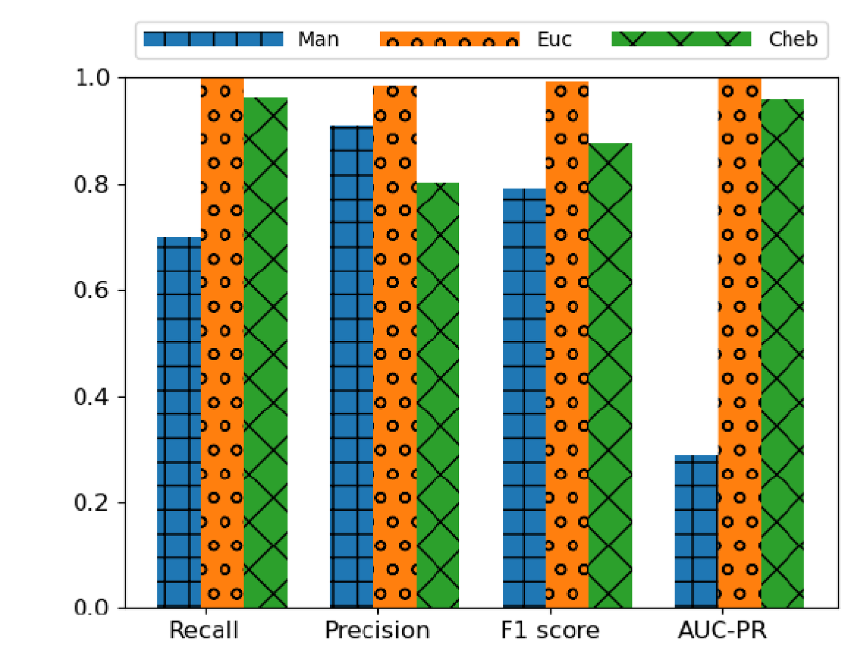
Experiments

Task	Data Set	# Relations	# Facts	#+ve Examples	#-ve Examples	# Rules
Link Prediction	*ICML'18*	4	1395	155	6498	7
	ICLR	4	4730	990	10000	7
	DDI	14	1774	2832	3188	25

Data	Methods	Recall	Precision	F1	AUC-PR
ICML'18	Gaifman	0.10	0.16	0.174	0.127
	Neural-LP$_3$	**0.927**	0.024	0.047	0.267
	Neural-LP$_{10}$	0.891	0.035	0.069	0.143
	metapath2vec	0.836	0.209	0.335	0.286
	PRAGCN	0.0	0.0	0.0	0.512
	ComplEx	0.85	0.013	0.03	0.04
	ConvE	0.636	0.01	0.02	0.015
	SimplE	**0.927**	0.012	0.023	0.128
	N+LF	0.379	**1.0**	0.549	0.396
	R-GCN	0.636	0.07	0.13	0.13
	CompGCN	0.727	0.022	0.044	0.185
	RD^{2}GCN	0.389	**1.0**	**0.561**	**0.556**
ICLR	Gaifman	0.564	0.795	0.66	0.488
	Neural-LP$_3$	0.939	0.308	0.463	0.421
	Neural-LP$_{10}$	**0.987**	0.275	0.429	0.453
	metapath2vec	0.828	0.338	0.480	0.641
	PRAGCN	0.0	0.0	0.0	0.544
	ComplEx	0.269	0.032	0.057	0.105
	ConvE	0.677	0.037	0.069	0.054
	SimplE	0.973	0.054	0.102	0.535
	N+LF	0.97	**1.0**	**0.984**	**0.972**
	R-GCN	0.667	0.783	0.720	0.763
	CompGCN	0.906	0.719	0.802	0.912
	RD^{2}GCN	0.594	**1.0**	0.745	**0.972**
DDI	Gaifman	0.469	0.707	0.564	0.581
	Neural-LP$_3$	0.727	0.336	0.459	0.368
	Neural-LP$_{10}$	0.779	0.338	0.472	0.403
	metapath2vec	0.782	0.652	0.711	0.707
	PRAGCN	0.427	0.700	0.531	0.695
	ComplEx	0.832	0.492	0.618	0.705
	ConvE	0.931	0.384	0.544	0.678
	SimplE	0.992	0.288	0.446	0.503
	N+LF	0.682	0.924	0.785	0.781
	R-GCN	0.571	**1.0**	0.727	0.922
	CompGCN	0.882	0.552	0.679	0.826
	RD^{2}GCN	**0.998**	0.986	**0.992**	**0.998**



Comparison with GAT



Effect of Distance Measures

Conclusion and Future work

- We present RD^{2}GCN, a graph neural network that can learn from multi-relational data utilizing the different densities separately
- We do not make assumptions on the supervision or the arity of predicates and automatically constructs rules that allow for a rich latent representation
- RD^{2}GCN replaces adjacency matrix with distance matrix which allows the RD^{2}GCN to learn richer set of features, allow for meaningful interpretations and have clear semantics
- Future works
  - Joint learning and inference over multiple types of relations
  - Using more classical rule learning techniques
  - Extending our framework to node classification
  - Learning in the presence of hidden/latent data and rich human domain knowledge

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