



SAFRAN: An interpretable, rule-based link prediction method outperforming embedding models

Simon Ott¹, Christian Meilicke², Matthias Samwald¹

² Data and Web Science Research Group, University Mannheim, Germany



¹ Institute of Artificial Intelligence and Decision Support, Medical University of Vienna, Austria

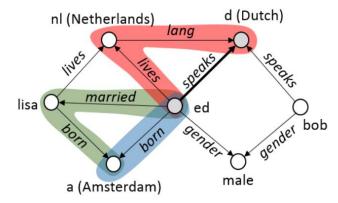
Rule-based approach AnyBURL

Advantages

- Efficient rule learning
- Explainable!

Limitations

- Functional redundant rules
- Slow rule application



Meilicke, C. et al. (2019). Anytime Bottom-Up Rule Learning for Knowledge Graph Completion

$$speaks(X, Y) \leftarrow lives(X, A_2), lang(A_2, Y)$$

 $speaks(X, d) \leftarrow married(X, A_2), born(A_2, a)$

SAFRAN

- Scalable and fast non-redundant rule application
- Clustering of redundant rules
 Elevating predictive performance
- Scalability
 Enables the application of symbolic rules to large scale KBs

Non-redundant Noisy-OR

$genre_artist(Pop\ rock,\ Y) \leftarrow genre_artist(Adult\ contemporary\ mu$	sic, Y) 0.3				
$genre_artist(Pop\ rock,\ Y) \leftarrow genre_artist(Pop\ music, Y)$					
$genre_artist(Pop\ rock,\ Y) \leftarrow nominated_for(Y,Grammy\ (Best\ Mal$	e Pop Vocal Perf.)) 0.2				
$genre_artist(Pop\ rock,\ Y) \leftarrow instrumentalist(Guitar,Y)$	0.19830				
$genre_artist(Pop\ rock,\ Y) \leftarrow profession(Y,\ Guitarist)$	0.17901				
$genre_artist(Pop\ rock,\ Y) \leftarrow track_contribution_role(Y,\ Guitar)$	0.17816				

genre_artist(?, Bryan Adams)

	-			,
	Entity		Confidence	
Þ	Pop rock		0.99817	✓
	Country music		0.95141	
	Blues rock		0.94286	
	Dance-pop		0.93301	
	Rythm and blues	3	0.93282	
	Psychedelic ro	ck	0.91512	
	Folk rock		0.88181	
	Contemporary R	&B	0.86727	
	Rock and roll		0.86479	
	Progressive ro	ck	0.84606	
	Jazz		0.83302	

Results

				8	FB15K-2	37		WN18R	R			YAGO3-	10
	Approach			MRR	hits@1	${ m hits@10}$	MRR	hits@1	hits@10		MRR	hits@1	hits@10
	RESCAL		*	.357	.263	.541	.468	.439	.521				
	TransE		*	.313	.221	.497	.227	.053	.526	9	.501	.405	.673
1t	DistMult		*	.343	.250	.531	.452	.413	.531	9	.501	.412	.661
Latent	ComplEx		*	.348	.253	.534	.477	.438	.543	9	.576	.505	.704
Le	ConvE		*	.339	.248	.521	.447	.411	.508	¶	.488	.399	.657
	RotatE		4	.336	.238	.531	.475	.426	.574	1	.498	.405	.670
	TuckER		¶	.352	.259	.536	.459	.430	.514	9	.544	.465	.680
	HAKE		∇	.346	.250	.542	.497	.452	.582		.545	.462	.694
	C-NN		Δ	.296	.222	.446	.469	.444	.519				
	DRUM		‡	$.343^{\dagger}$	$.255^{\dagger}$	$.516^{\dagger}$	$.486^{\dagger}$.425†	$.586^{\dagger}$				
	Neural LP		\Diamond	$.240^{\dagger}$		$.362^{\dagger}$	$.435^{\dagger}$	$.371^{\dagger}$	$.566^{\dagger}$				
(1)	GPFL		\Diamond	.322	.247	.504	.480	.449	.552				
pple	AMIE+		*		.174	.409		.358	.388				
ets	RuleN		4		.182	.420		.427	.536				
rpr	RLvLR		#	.240		.393							
Interpretable		Maximum		.355	.270	.519	.494	.452	.572		.559	.487	.686
H	AnyBURL	Noisy-OR		.342	.258	.502	.454	.399	.562		.524	.444	.672
	with	VS		.363	.277	.526	.497	.455	.572		.560	.489	.689
	SAFRAN	NRNO * (grid)		.370	.287	.531	.501	.457	.581		.564	.492	.691
		NRNO * (random)		.389	.298	.537	.502	.459	.578		.564	.491	.693

