

# **Differentiable Reasoning on Large Knowledge Bases and Natural Language**

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# End-to-End Differentiable Proving - NIPS2017 (NTP)

## ➤ 任务

处理KB查询,  $r(h, ?)$  or  $r(?, t)$ , 如: `grandpaOf(ABE, ?)`

## ➤ 动机

神经网络预测模型能建模相似性, 很难处理多跳推理, 没有解释性;

符号证明太严苛, 缺乏相似但不相同符号的查询的能力, 容易受噪音干扰。

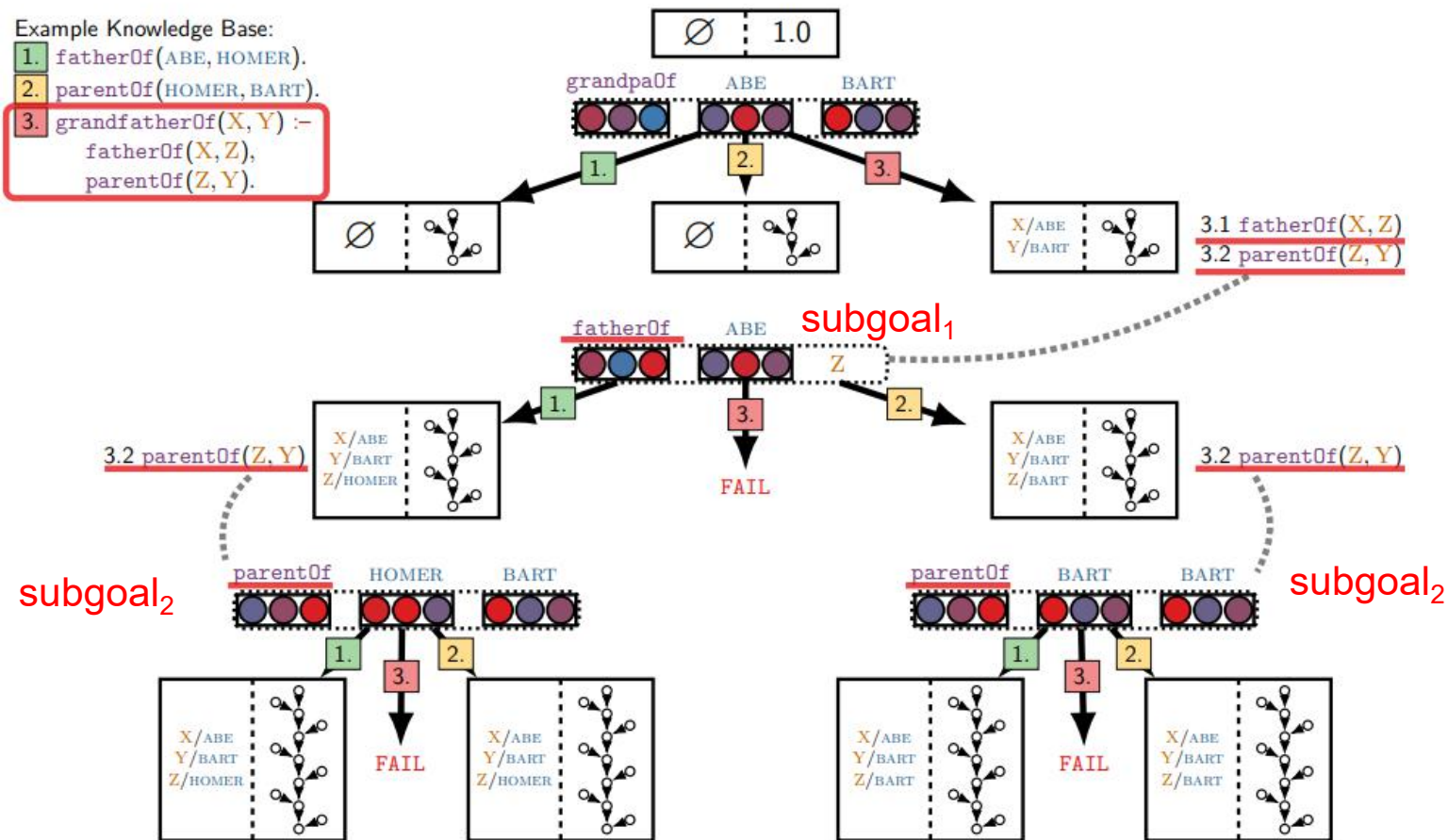
## ➤ 主要贡献

可解释的可微推理, 针对查询给出答案的同时给出证明“路径”

通过训练参数反推出知识库上的一些规则, 如: `0.90 locatedIn(X, Y) :- locatedIn(X, Z), locatedIn(Z, Y).`



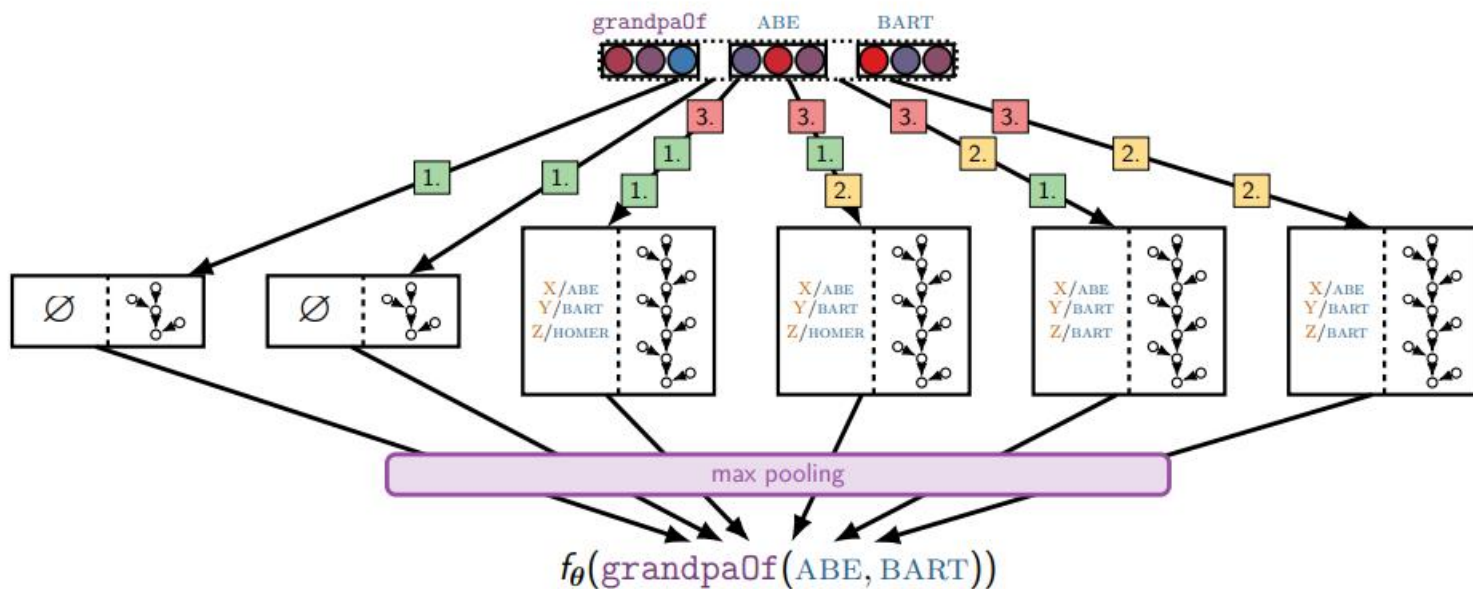
# Neural Program Induction



路径3-1-1表示的证明：  
 $\text{grandpaOf(ABE, BART)} \leq \text{fatherOf(ABE, HOMER)} \ \& \ \text{parentOf(HOMER, BART)}$

1. 枚举规则（OR module），利用嵌入相似性计算目标与规则的匹配度（Unification module）
2. 处理子目标(AND module)
3. 取分数最大的路径作为结果

# Training Objective



- 扰动已知事实获得negative facts
- 为了加速表示学习，与complex联合学习

$$\text{ntp}_{\theta}^{\mathfrak{K}}(\mathbf{G}, d) = \arg \max_{\substack{S \in \text{or}_{\theta}^{\mathfrak{K}}(\mathbf{G}, d, (\emptyset, 1)) \\ S \neq \text{FAIL}}} S_{\rho}$$

$$\mathcal{L}_{\text{ntp}_{\theta}^{\mathfrak{K}}} = \sum_{([s, i, j], y) \in \mathcal{T}} -y \log(\text{ntp}_{\theta}^{\mathfrak{K}}([s, i, j], d)_{\rho}) - (1 - y) \log(1 - \text{ntp}_{\theta}^{\mathfrak{K}}([s, i, j], d)_{\rho})$$

$$\mathcal{L}_{\text{ntp}_{\theta}^{\lambda^{\mathfrak{K}}}} = \mathcal{L}_{\text{ntp}_{\theta}^{\mathfrak{K}}} + \sum_{([s, i, j], y) \in \mathcal{T}} -y \log(\text{complex}_{\theta}(s, i, j)) - (1 - y) \log(1 - \text{complex}_{\theta}(s, i, j))$$

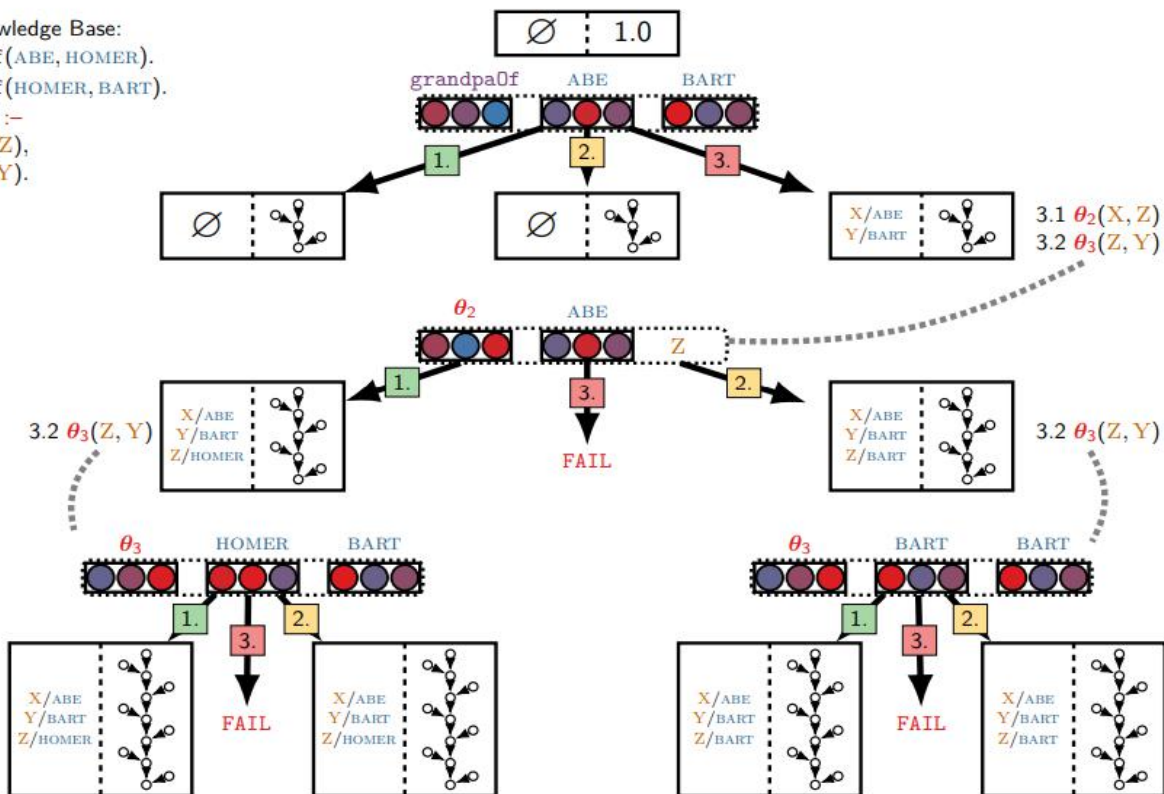


# 从参数中获取规则

## Neural Program Induction

Example Knowledge Base:

1. `fatherOf(ABE, HOMER).`
2. `parentOf(HOMER, BART).`
3.  $\theta_1(X, Y) :-$   
     $\theta_2(X, Z),$   
     $\theta_3(Z, Y).$



- 指定规则模板及对应数量
- 训练结束后使用Radial Basis Function kernel获取表示与已有谓词表示相似度
- 证明路径中的最小值作为规则置信度

# **Differentiable Reasoning on Large Knowledge Bases and Natural Language - AAAI2020 (GNTP)**

## ➤ 动机

NTP只能用在小规模知识库上

大多数人类知识不是在KBs中获得的，而是在难以自动推理的自然语言文本中获得的

## ➤ 主要贡献

有限损失内加速NTP，保留可解释性

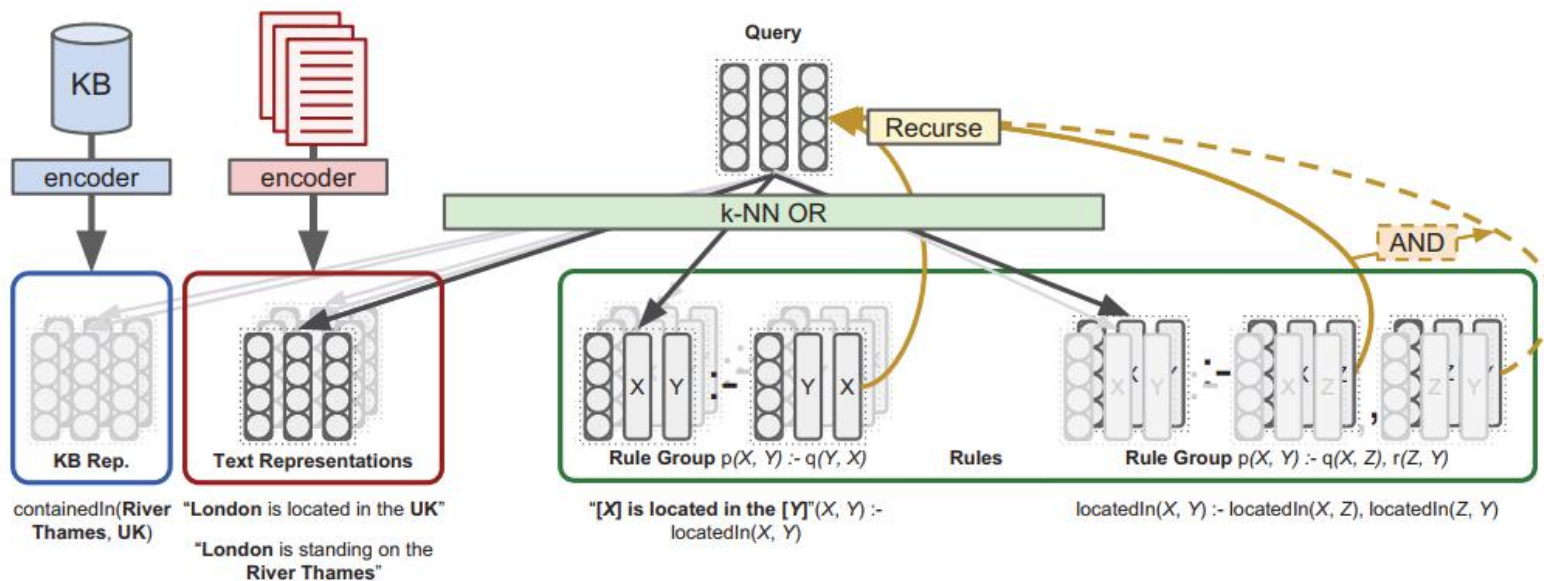
知识库和文本提及联合推理，在共享的嵌入空间中嵌入事实和自然语言句子

## ➤ 关键方法

➤ L2距离最近邻，路径剪枝

➤ 诱导规则的注意力机制，减少参数

➤ 对自然语言扩展，联合嵌入谓词和文本



- 事实选择 (Nearest Neighbour Search (NNS))
- 规则选择(在共享相同模板的规则之间动态选择规则)
- 注意力机制

$$H = [\theta_p, X, Y] \text{ and } B = [[\theta_q, X, Z], [\theta_r, Z, Y]]$$

把规则中k维的表示变成在已知数量为r的各个谓词上的注意力分数（适用 $r < k$ 的情况）

- 联合训练

文本编码：词嵌入求平均，当成谓词一起训练

$$t = [[arg1], borders, with, [arg2]]$$

neighborOf(X, Y) :- "Y is a neighboring state to X"(X, Y)  
 locatedIn(X, Y) :- "X is a neighboring state to Z"(X, Z),  
 "Z is located in Y"(Z, Y)



Datasets	Metrics	Models					Rules Learned by GNTP
		NTP <sup>7</sup>	GNTP		NeuralLP	MINERVA	
			Standard	Attention			
Countries	S1	90.83 $\pm$ 15.4	99.98 $\pm$ 0.05	<b>100.0 <math>\pm</math> 0.0</b>	<b>100.0 <math>\pm</math> 0.0</b>	<b>100.0 <math>\pm</math> 0.0</b>	locatedIn(X,Y) :- locatedIn(X,Z), locatedIn(Z,Y)
	S2	87.40 $\pm$ 11.7	90.82 $\pm$ 0.88	<b>93.48 <math>\pm</math> 3.29</b>	75.1 $\pm$ 0.3	92.36 $\pm$ 2.41	neighborOf(X,Y) :- neighborOf(X,Z), locatedIn(Z,Y)
	S3	56.68 $\pm$ 17.6	87.70 $\pm$ 4.79	91.27 $\pm$ 4.02	92.20 $\pm$ 0.2	<b>95.10 <math>\pm</math> 1.20</b>	neighborOf(X,Y) :- neighborOf(Y,X)
Kinship	MRR	0.35	0.719	<b>0.759</b>	0.619	0.720	term0(X, Y) :- term0(Y, X)
	HITS@1	0.24	0.586	<b>0.642</b>	0.475	0.605	term4(X, Y) :- term4(Y, X)
	HITS@3	0.37	0.815	<b>0.850</b>	0.707	0.812	term13(X,Y) :- term13(X, Z), term10(Z, Y)
	HITS@10	0.57	0.958	<b>0.959</b>	0.912	0.924	term2(X,Y) :- term4(X, Z), term7(Z, Y)
Nations	MRR	0.61	<b>0.658</b>	0.645	—	—	commonbloc1(X, Y) :- relngo(Y, X)
	HITS@1	0.45	<b>0.493</b>	0.490	—	—	timesincewar(X,Y) :- independence(X,Y)
	HITS@3	0.73	<b>0.781</b>	0.736	—	—	unweightedunvote(X,Y) :- relngo(X,Y)
	HITS@10	0.87	<b>0.985</b>	0.975	—	—	ngo(X, Y) :- independence(Y, X)
UMLS	MRR	0.80	0.841	<b>0.857</b>	0.778	0.825	isa(X,Y) :- isa(X,Z), isa(Z,Y)
	HITS@1	0.70	0.732	<b>0.761</b>	0.643	0.728	complicates(X,Y) :- affects(X,Y)
	HITS@3	0.88	<b>0.941</b>	<b>0.947</b>	0.869	0.900	affects(X, Y) :- affects(X, Z), affects(Z, Y)
	HITS@10	0.95	<b>0.986</b>	0.983	0.962	0.968	process_of(X,Y) :- affects(X,Y)

使用了FB122  
数据集提供的  
规则

		规则无关三元组				规则相关三元组							
		Test-I				Test-II				Test-ALL			
		Hits@N (%)			MRR	Hits@N (%)			MRR	Hits@N (%)			MRR
		3	5	10		3	5	10		3	5	10	
With Rules	KALE-Pre (Guo et al. 2016)	35.8	41.9	49.8	0.291	82.9	86.1	89.9	0.713	61.7	66.2	71.8	0.523
	KALE-Joint (Guo et al. 2016)	<b>38.4</b>	<b>44.7</b>	<b>52.2</b>	0.325	79.7	84.1	89.6	0.684	61.2	66.4	72.8	0.523
	ASR-DistMult (Minervini et al. 2017)	36.3	40.3	44.9	0.330	98.0	99.0	99.2	0.948	70.7	73.1	75.2	0.675
	ASR-ComplEx (Minervini et al. 2017)	37.3	41.0	45.9	<b>0.338</b>	<b>99.2</b>	<b>99.3</b>	<b>99.4</b>	<b>0.984</b>	71.7	73.6	75.7	0.698
	KBLR (García-Durán and Niepert 2018)	—	—	—	—	—	—	—	—	<b>74.0</b>	<b>77.0</b>	<b>79.7</b>	<b>0.702</b>
Without Rules	TransE (Bordes et al. 2013)	36.0	41.5	48.1	0.296	77.5	82.8	88.4	0.630	58.9	64.2	70.2	0.480
	DistMult (Yang et al. 2015)	36.0	40.3	45.3	0.313	<b>92.3</b>	<b>93.8</b>	<b>94.7</b>	0.874	<b>67.4</b>	<b>70.2</b>	<b>72.9</b>	0.628
	ComplEx (Trouillon et al. 2016)	<b>37.0</b>	<b>41.3</b>	<b>46.2</b>	<b>0.329</b>	91.4	91.9	92.4	<b>0.887</b>	67.3	69.5	71.9	<b>0.641</b>
	GNTPs	33.7	36.9	41.2	0.313	<b>98.2</b>	<b>99.0</b>	<b>99.3</b>	<b>0.977</b>	<b>69.2</b>	<b>71.1</b>	<b>73.2</b>	<b>0.678</b>

DistMult and ComplEx using Adversarial Sets (ASR) - a method for incorporating rules in neural link predictors via adversarial training  
与KBLR和ComplEx在WN18和WN18RR上效果差不多，但是提供了可解释性

# 谢谢！

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