

知识推理近期工作综述

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- GNTP - AAAI2020
- Neural LP - NIPS2017
- Neural Num IP - ICLR2020
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- **QUERY2BOX - ICLR2020**
- **Reified KB - ICLR2020**
- Complex KGQA - ACL2020
- *EmbedKGQA - ACL2020*
- Virtual KB - ICLR2020
- 可解释推理
- 可微规则挖掘
- 利用文本
- KGC(knowledge graph completion)
- KBQA/KGQA（多个答案/复杂）

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

➤ 任务

处理KB查询, $r(h, ?)$ or $r(?, t)$

➤ 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

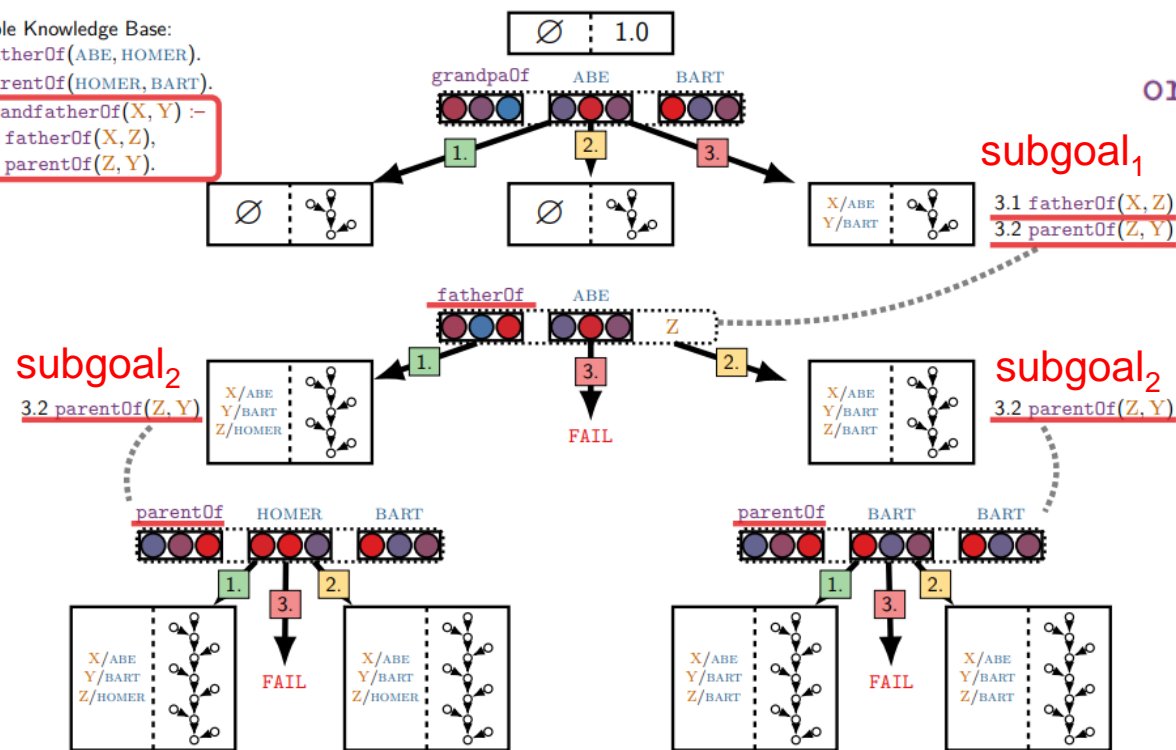
Neural Program Induction

Example Knowledge Base:

```

1. fatherOf(ABE, HOMER).
2. parentOf(HOMER, BART).
3. grandfatherOf(X, Y) :-
    fatherOf(X, Z),
    parentOf(Z, Y).

```



$$\text{or}_{\theta}^{\mathfrak{K}}(\mathbb{G}, d, S) = [S' \mid S' \in \text{and}_{\theta}^{\mathfrak{K}}(\mathbb{B}, d, \text{unify}_{\theta}(\mathbb{H}, \mathbb{G}, S)) \text{ for } \mathbb{H} :- \mathbb{B} \in \mathfrak{K}]$$

$$\text{unify}_{\theta}(h : H, g : G, S) = \text{unify}_{\theta}(H, G, S') = (S'_{\psi}, S'_{\rho})$$

$$\text{and}_{\theta}^{\mathfrak{K}}(\mathbb{G} : \mathbb{G}, d, S) = [S'' \mid S'' \in \text{and}_{\theta}^{\mathfrak{K}}(\mathbb{G}, d, S')]$$

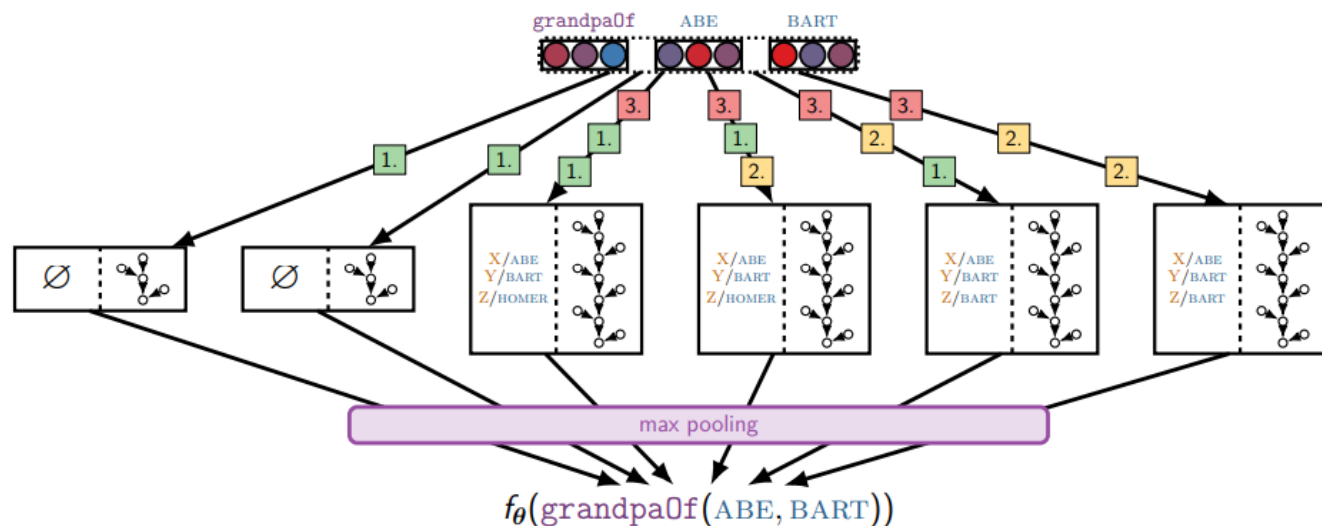
$$\text{for } S' \in \text{or}_{\theta}^{\mathbb{K}}(\text{substitute}(\mathbf{G}, S_{\psi}), d-1, S)]$$

$$\text{substitute}(g : G, \psi) = \left\{ \begin{array}{ll} x & \text{if } g/x \in \psi \\ g & \text{otherwise} \end{array} \right\} : \text{substitute}(G, \psi)$$

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

1. 枚举事实、规则 (or module), 匹配 (unify module)
2. 规则变量ground到常量(and)
3. 根据规则处理子目标(and)
4. 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

- Loss: negative log-likelihood w.r.t. target proof success
- Trained end-to-end using stochastic gradient descent
- Vectors are **learned such that proof success is high for known facts** and low for sampled negative facts

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

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

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

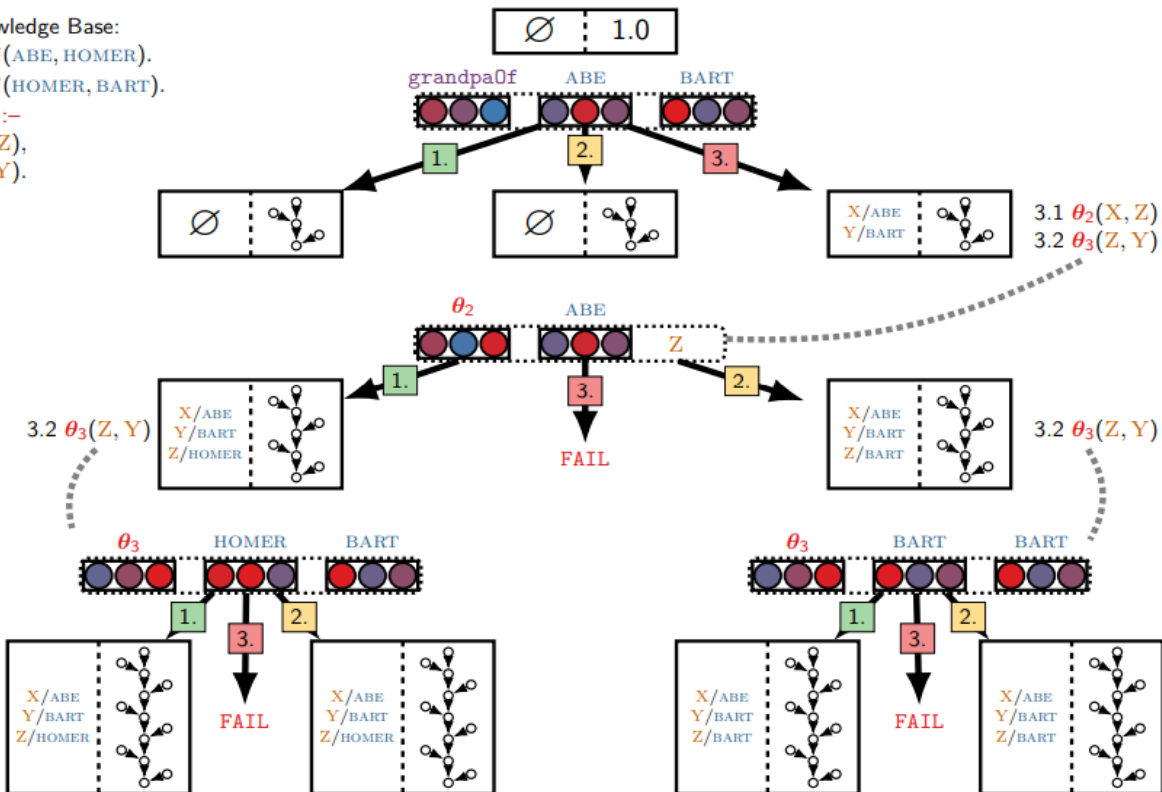
从参数中获取规则

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

实验结果

Corpus		Metric	Model			Examples of induced rules and their confidence
			ComplEx	NTP	NTP λ	
Countries	S1	AUC-PR	99.37 \pm 0.4	90.83 \pm 15.4	100.00 \pm 0.0	0.90 locatedIn(X,Y) :- locatedIn(X,Z), locatedIn(Z,Y).
	S2	AUC-PR	87.95 \pm 2.8	87.40 \pm 11.7	93.04 \pm 0.4	0.63 locatedIn(X,Y) :- neighborOf(X,Z), locatedIn(Z,Y).
	S3	AUC-PR	48.44 \pm 6.3	56.68 \pm 17.6	77.26 \pm 17.0	0.32 locatedIn(X,Y) :- neighborOf(X,Z), neighborOf(Z,W), locatedIn(W,Y).
Kinship		MRR	0.81	0.60	0.80	0.98 term15(X,Y) :- term5(Y,X)
		HITS@1	0.70	0.48	0.76	0.97 term18(X,Y) :- term18(Y,X)
		HITS@3	0.89	0.70	0.82	0.86 term4(X,Y) :- term4(Y,X)
		HITS@10	0.98	0.78	0.89	0.73 term12(X,Y) :- term10(X,Z), term12(Z,Y).
Nations		MRR	0.75	0.75	0.74	0.68 blockpositionindex(X,Y) :- blockpositionindex(Y,X).
		HITS@1	0.62	0.62	0.59	0.46 expeldiplomats(X,Y) :- negativebehavior(X,Y).
		HITS@3	0.84	0.86	0.89	0.38 negativecomm(X,Y) :- commonbloc0(X,Y).
		HITS@10	0.99	0.99	0.99	0.38 intergovorgs3(X,Y) :- intergovorgs(Y,X).
UMLS		MRR	0.89	0.88	0.93	0.88 interacts_with(X,Y) :-
		HITS@1	0.82	0.82	0.87	interacts_with(X,Z), interacts_with(Z,Y).
		HITS@3	0.96	0.92	0.98	0.77 isa(X,Y) :- isa(X,Z), isa(Z,Y).
		HITS@10	1.00	0.97	1.00	0.71 derivative_of(X,Y) :- derivative_of(X,Z), derivative_of(Z,Y).

数据集的规模都非常小

AUC-PR: area under the Precision-Recall-curve

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

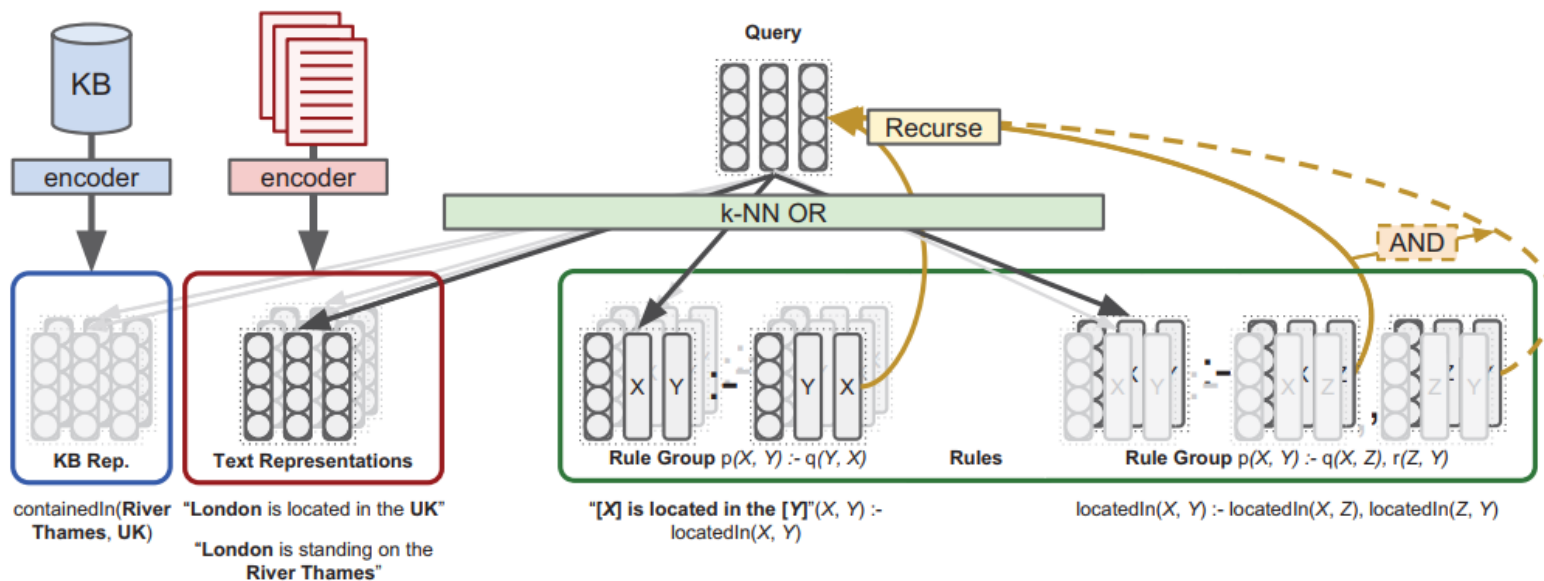
知识库和文本提及联合推理，在共享的嵌入空间中嵌入事实和自然语言句子

➤ 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 ⁷	GNTP		NeuralLP	MINERVA	
			Standard	Attention			
Countries	S1	90.83 \pm 15.4	99.98 \pm 0.05	100.0 \pm 0.0	100.0 \pm 0.0	100.0 \pm 0.0	locatedIn(X,Y) :- locatedIn(X,Z), locatedIn(Z,Y)
	S2	87.40 \pm 11.7	90.82 \pm 0.88	93.48 \pm 3.29	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	95.10 \pm 1.20	neighborOf(X,Y) :- neighborOf(Y,X)
Kinship	MRR	0.35	0.719	0.759	0.619	0.720	term0(X, Y) :- term0(Y, X)
	HITS@1	0.24	0.586	0.642	0.475	0.605	term4(X, Y) :- term4(Y, X)
	HITS@3	0.37	0.815	0.850	0.707	0.812	term13(X,Y) :- term13(X, Z), term10(Z, Y)
	HITS@10	0.57	0.958	0.959	0.912	0.924	term2(X,Y) :- term4(X, Z), term7(Z, Y)
Nations	MRR	0.61	0.658	0.645	—	—	commonbloc1(X, Y) :- relngo(Y, X)
	HITS@1	0.45	0.493	0.490	—	—	timesincewar(X,Y) :- independence(X,Y)
	HITS@3	0.73	0.781	0.736	—	—	unweightedunvote(X,Y) :- relngo(X,Y)
	HITS@10	0.87	0.985	0.975	—	—	ngo(X, Y) :- independence(Y, X)
UMLS	MRR	0.80	0.841	0.857	0.778	0.825	isa(X,Y) :- isa(X,Z), isa(Z,Y)
	HITS@1	0.70	0.732	0.761	0.643	0.728	complicates(X,Y) :- affects(X,Y)
	HITS@3	0.88	0.941	0.947	0.869	0.900	affects(X, Y) :- affects(X, Z), affects(Z, Y)
	HITS@10	0.95	0.986	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)	38.4	44.7	52.2	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	0.338	99.2	99.3	99.4	0.984	71.7	73.6	75.7	0.698
	KBLR (García-Durán and Niepert 2018)	—	—	—	—	—	—	—	—	74.0	77.0	79.7	0.702
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	92.3	93.8	94.7	0.874	67.4	70.2	72.9	0.628
	ComplEx (Trouillon et al. 2016)	37.0	41.3	46.2	0.329	91.4	91.9	92.4	0.887	67.3	69.5	71.9	0.641
	GNTPs	33.7	36.9	41.2	0.313	98.2	99.0	99.3	0.977	69.2	71.1	73.2	0.678

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

Differentiable Learning of Logical Rules for Knowledge Base Reasoning - NIPS2017(Neural LP)

➤ 任务：研究了知识库推理中概率一阶逻辑规则的学习问题

➤ 动机

通过为逻辑规则配备概率，可以更好地建模统计复杂和噪声数据，但这个学习问题相当困难——它需要学习结构(即模型中包含的特定规则集)和参数(即与每个规则相关联的置信度)

许多过去的学习系统都使用了优化方法，将离散结构空间中的移动与参数空间中的移动交织起来

➤ 主要贡献

第一种端到端可微&同时学习参数和逻辑规则的结构

归纳逻辑编程方法学到的规则有相对广泛的适用性

举例说明将神经LP模型可视化为逻辑规则的方法（从参数中导出规则）

$$\alpha \text{ query}(Y, X) \leftarrow R_n(Y, Z_n) \wedge \dots \wedge R_1(Z_1, X)$$

$$R(Y, X) \leftarrow P(Y, Z) \wedge Q(Z, X)$$

$M_P \cdot M_Q \cdot v_x \doteq \boxed{s}$ x实体应用到以上规则中之后，所有Y实体的得分

$$s = \sum (\alpha_l (\prod_{k \in \beta_l} M_{R_k} v_x)), \text{score}(y | x) = v_y^T s$$

$$\max_{\{\alpha_l, \beta_l\}} \sum_{\{x, y\}} \text{score}(y | x) = \max_{\{\alpha_l, \beta_l\}} \sum_{\{x, y\}} v_y^T \left(\sum_l (\alpha_l (\prod_{k \in \beta_l} M_{R_k} v_x)) \right)$$

$$\prod_{t=1}^T \sum_k a_t^k M_{R_k}$$

//给每个关系分配权重参数 a_t^k

$$u_0 = v_x$$

$$u_t = \sum_k a_t^k M_{R_k} \left(\sum_{\tau=0}^{t-1} b_t^\tau u_\tau \right) \text{ for } 1 \leq t \leq T \text{ //记忆attention参数 } b_t^\tau$$

$$u_{T+1} = \sum_{\tau=0}^T b_{T+1}^\tau u_\tau$$

$$h_t = \text{update}(h_{t-1}, \text{input}) \text{ (RNN)}$$

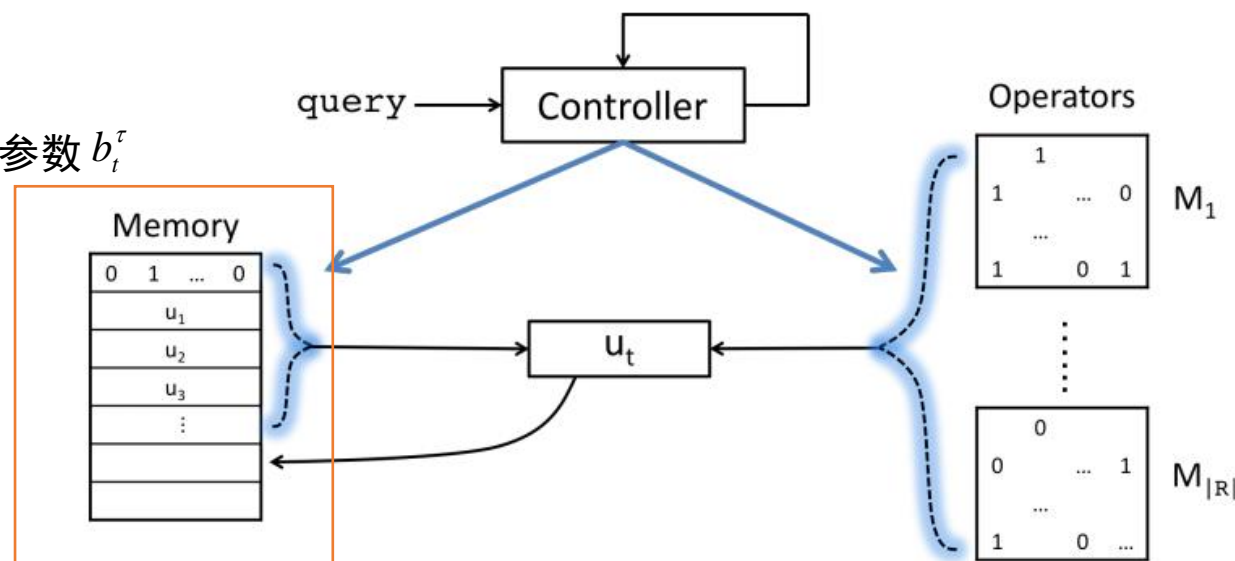
$$a_t = \text{softmax}(W h_t + b)$$

$$b_t = \text{softmax}([h_0, \dots, h_{t-1}]^T h_t)$$

Tensorlog: A differentiable deductive database

训练目标， β 是某条规则的关系id

枚举规则操作不可微



解决规则长度限制问题

从参数中获取规则

Algorithm 1 Recover logical rules from attention vectors

Input: attention vectors $\{\mathbf{a}_t \mid t = 1, \dots, T\}$ and $\{\mathbf{b}_t \mid t = 1, \dots, T + 1\}$

Notation: Let $R_t = \{r_1, \dots, r_l\}$ be the set of partial rules at step t . Each rule r_l is represented by a pair of (α, β) as described in Equation [1](#), where α is the confidence and β is an ordered list of relation indexes.

Initialize: $R_0 = \{r_0\}$ where $r_0 = (1, ())$.

for $t \leftarrow 1$ to $T + 1$ **do**

Initialize: $\widehat{R}_t = \emptyset$, a placeholder for storing intermediate results.

for $\tau \leftarrow 0$ to $t - 1$ **do** //枚举之前所有长度的规则状态，更新置信度

for rule (α, β) in R_τ **do**

 Update $\alpha' \leftarrow \alpha \cdot b_t^\tau$. Store the updated rule (α', β) in \widehat{R}_t .

if $t \leq T$ **then**

Initialize: $R_t = \emptyset$

for rule (α, β) in \widehat{R}_t **do**

for $k \leftarrow 1$ to $|\mathbf{R}|$ **do** //枚举更新过置信度的规则，加入新关系k并更新信息

 Update $\alpha' \leftarrow \alpha \cdot a_t^k$, $\beta' \leftarrow \beta$ append k . Add the updated rule (α', β') to R_t .

else

$R_t = \widehat{R}_t$

return R_{T+1}

	WN18		FB15K		FB15KSelected	
	MRR	Hits@10	MRR	Hits@10	MRR	Hits@10
Neural Tensor Network	0.53	66.1	0.25	41.4	-	-
TransE	0.38	90.9	0.32	53.9	-	-
DISTMULT [29]	0.83	94.2	0.35	57.7	0.25	40.8
Node+LinkFeat [25]	0.94	94.3	0.82	87.0	0.23	34.7
Implicit ReasoNets [23]	-	95.3	-	92.7	-	-
Neural LP	0.94	94.5	0.76	83.7	0.24	36.2

Table 8: Performance comparison. Memory Network is from [28]. QA system is from [4].

Model	Accuracy
Memory Network	78.5
QA system	93.5
Key-Value Memory Network [16]	93.9
Neural LP	94.6

Table 6: Inductive knowledge base completion. The metric is Hits@10.

	WN18	FB15K	FB15KSelected
TransE	0.01	0.48	0.53
Neural LP	94.49	73.28	27.97

训练集与测试集实体不相交

DIFFERENTIABLE LEARNING OF NUMERICAL RULES IN KNOWLEDGE GRAPHS - ICLR2020 (Neural Num LP)

➤ 任务

学习知识图谱上包含数值比较的规则

“People younger than 18 typically live with their parents”

➤ 主要贡献

为规则加入数值比较的形式，增强表达能力

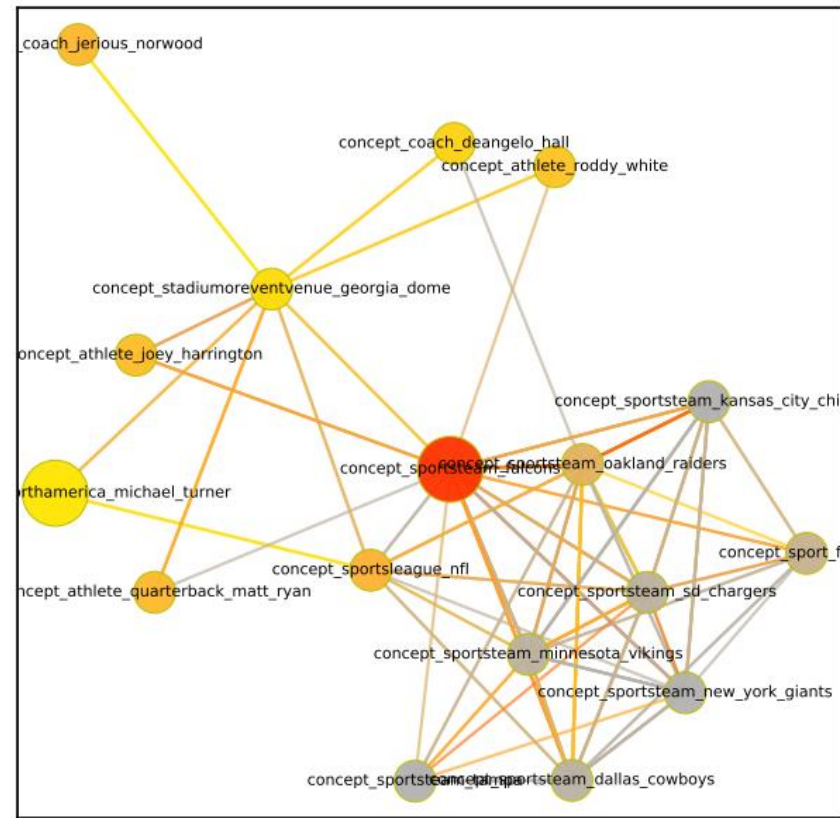
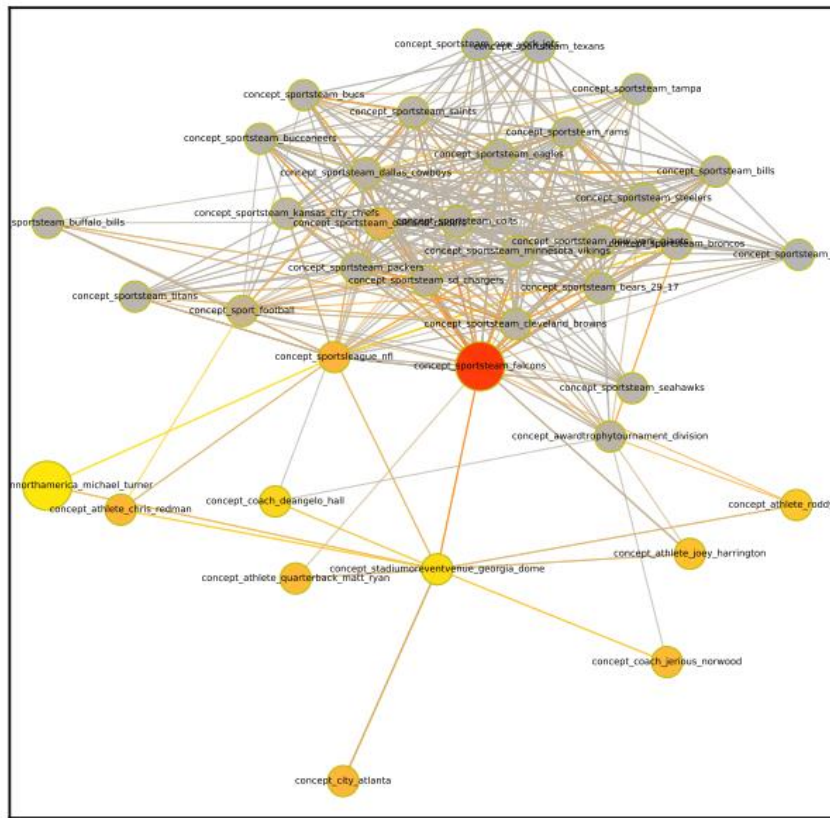
数值规则会导致在NeuralLP框架中密集的矩阵运算，文章使用动态规划和累积和运算加速

Dataset	FB15K-237-num		DBP15K-num		Numerical1		Numerical2	
	Hit@10	MRR	Hit@10	MRR	Hit@10	MRR	Hit@10	MRR
AnyBurl	0.4262	0.2438	0.5217	0.3711	0.0306	0.0085	0.6850	0.5087
Neural-LP	0.362*	0.240*	0.4363	-	0.2398	-	0.2950	-
Neural-LP-N	0.415	0.259	0.682	0.451	1.000	0.941	1.000	0.837

DYNAMICALLY PRUNED MESSAGE PASSING NETWORKS FOR LARGE-SCALE KNOWLEDGE GRAPH REASONING - ICLR2020

- Dynamically Pruned Message Passing Networks (DPMPN)
- 基于输入的查询中应用图注意力机制,动态构造和扩展子图
- 构建了图结构的解释

Metric (%)	FB15K-237				WN18RR			
	H@1	H@3	H@10	MRR	H@1	H@3	H@10	MRR
TransE [♠]	-	-	46.5	29.4	-	-	50.1	22.6
DistMult [♣]	15.5	26.3	41.9	24.1	39	44	49	43
DistMult [♡]	20.6 (.4)	31.8 (.2)	-	29.0 (.2)	38.4 (.4)	42.4 (.3)	-	41.3 (.3)
ComplEx [♣]	15.8	27.5	42.8	24.7	41	46	51	44
ComplEx [♡]	20.8 (.2)	32.6 (.5)	-	29.6 (.2)	38.5 (.3)	43.9 (.3)	-	42.2 (.2)
ConvE [♣]	23.7	35.6	50.1	32.5	40	44	52	43
ConvE [♡]	23.3 (.4)	33.8 (.3)	-	30.8 (.2)	39.6 (.3)	44.7 (.2)	-	43.3 (.2)
RotatE [◇]	24.1	37.5	53.3	33.8	42.8	49.2	57.1	47.6
ComplEx-N3[✕]	-	-	56	37	-	-	57	48
NeuralLP [♡]	18.2 (.6)	27.2 (.3)	-	24.9 (.2)	37.2 (.1)	43.4 (.1)	-	43.5 (.1)
MINERVA [♡]	14.1 (.2)	23.2 (.4)	-	20.5 (.3)	35.1 (.1)	44.5 (.4)	-	40.9 (.1)
MINERVA [△]	-	-	45.6	-	41.3	45.6	51.3	-
M-Walk [♡]	16.5 (.3)	24.3 (.2)	-	23.2 (.2)	41.4 (.1)	44.5 (.2)	-	43.7 (.1)
DPMPN	28.6 (.1)	40.3 (.1)	53.0 (.3)	36.9 (.1)	44.4 (.4)	49.7 (.8)	55.8 (.5)	48.2 (.5)



Query: (concept_personnorthamerica_michael_turner, concept:athleteplaysforteam, concept_sportsteam_falcons)

Selected key edges:

concept:personnorthamerica_michael_turner, concept:agentbelongstoorganization, concept:sportsleague_nfl
concept:personnorthamerica_michael_turner, concept:athlethomestadium, concept:stadiumeventvenue_georgia_dome
concept:sportsleague_nfl, concept:agentcompeteswithagent, concept:sportsleague_nfl
concept:sportsleague_nfl, concept:agentcompeteswithagent_inv, concept:sportsleague_nfl
concept:sportsleague_nfl, concept:teamplaysinleague_inv, concept:sportsteam_sd_chargers
concept:sportsleague_nfl, concept:leaguestadiums, concept:stadiumeventvenue_georgia_dome
concept:sportsleague_nfl, concept:teamplaysinleague_inv, concept:sportsteam_falcons
concept:sportsleague_nfl, concept:agentbelongstoorganization_inv, concept:personnorthamerica_michael_turner
concept:stadiumeventvenue_georgia_dome, concept:leaguestadiums_inv, concept:sportsleague_nfl
concept:stadiumeventvenue_georgia_dome, concept:teamhomestadium_inv, concept:sportsteam_falcons
concept:stadiumeventvenue_georgia_dome, concept:athlethomestadium_inv, concept:athlete_joey_harrington
concept:stadiumeventvenue_georgia_dome, concept:athlethomestadium_inv, concept:athlete_rodny_white
concept:stadiumeventvenue_georgia_dome, concept:athlethomestadium_inv, concept:coach_deangelo_hall
concept:stadiumeventvenue_georgia_dome, concept:athlethomestadium_inv, concept:personnorthamerica_michael_turner
concept:sportsleague_nfl, concept:subpartoforganization_inv, concept:sportsteam_oakland_raiders

QUERY2BOX: REASONING OVER KNOWLEDGE GRAPHS IN VECTOR SPACE USING BOX EMBEDDINGS - ICLR2020

➤ 任务: Existential Positive First-order (EPFO) logical queries (\wedge , \vee , \exists)

➤ 动机

之前的工作将查询建模为向量空间中的单个点，最近的实体作为答案，但一个查询可能有多个答案
处理带有逻辑析取(\vee)的查询仍然是一个有待解决的问题

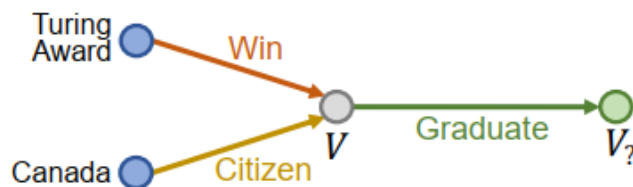
➤ 主要贡献

利用Disjunctive Normal Form (DNF)加入析取逻辑，对答案是实体集的更复杂的情况进行建模
可以处理一些训练时没见过的结构，对缺失有一定鲁棒性

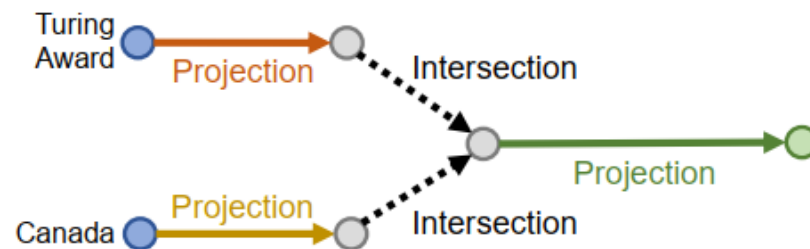
- where did Canadian citizens with *Turing Award* graduate?

(A) Query q and Its Dependency Graph

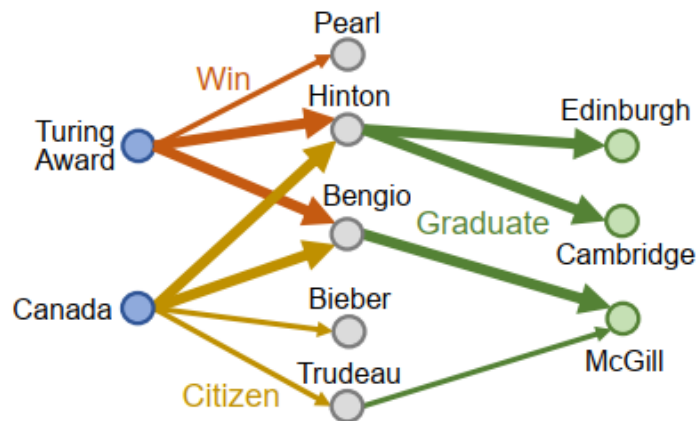
$$q = V_? . \exists V : \text{Win}(\text{TuringAward}, V) \wedge \text{Citizen}(\text{Canada}, V) \wedge \text{Graduate}(V, V_?)$$



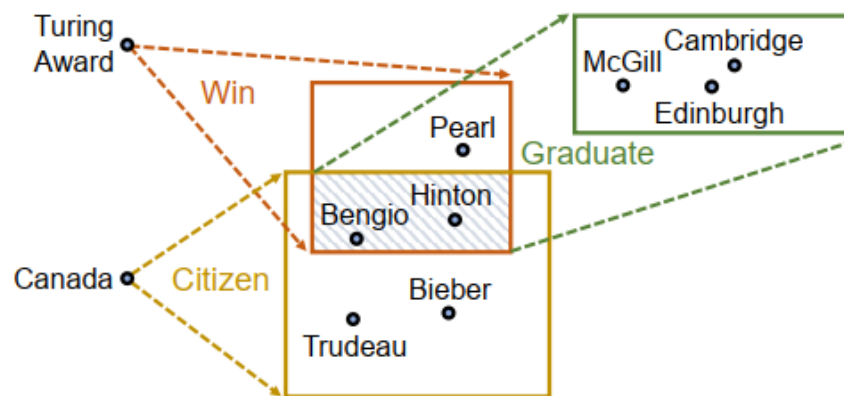
(B) Computation Graph

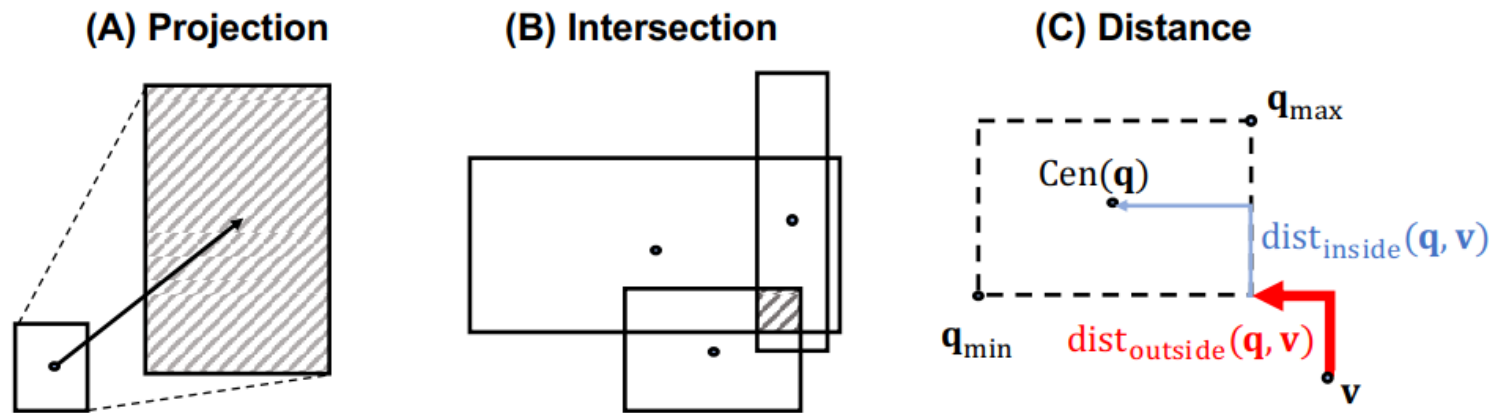


(C) Knowledge Graph Space



(D) Vector Space





define a box in \mathbb{R}^d by $\mathbf{p} = (\text{Cen}(\mathbf{p}), \text{Off}(\mathbf{p})) \in \mathbb{R}^{2d}$

$$\text{Box}_{\mathbf{p}} \equiv \{\mathbf{v} \in \mathbb{R}^d : \text{Cen}(\mathbf{p}) - \text{Off}(\mathbf{p}) \preceq \mathbf{v} \preceq \text{Cen}(\mathbf{p}) + \text{Off}(\mathbf{p})\}$$

- **Geometric projection operator:**

$$\mathbf{p} + \mathbf{r} \quad (\text{Cen}(\mathbf{r}), \text{Off}(\mathbf{r})) \in \mathbb{R}^{2d} \text{ with } \text{Off}(\mathbf{r}) \succeq \mathbf{0}$$

- **Geometric intersection operator:**

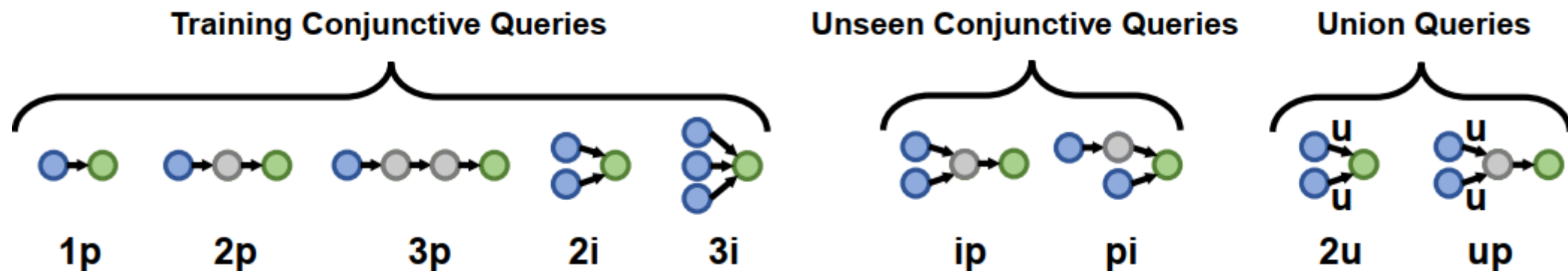
中心上attention, sigmoid函数缩小偏移量

$$\text{Cen}(\mathbf{p}_{\text{inter}}) = \sum_i \mathbf{a}_i \odot \text{Cen}(\mathbf{p}_i), \quad \mathbf{a}_i = \frac{\exp(\text{MLP}(\mathbf{p}_i))}{\sum_j \exp(\text{MLP}(\mathbf{p}_j))},$$

$$\{\mathbf{p}_1, \dots, \mathbf{p}_n\} \text{ as } \mathbf{p}_{\text{inter}} = (\text{Cen}(\mathbf{p}_{\text{inter}}), \text{Off}(\mathbf{p}_{\text{inter}})) \quad \text{Off}(\mathbf{p}_{\text{inter}}) = \text{Min}(\{\text{Off}(\mathbf{p}_1), \dots, \text{Off}(\mathbf{p}_n)\}) \odot \sigma(\text{DeepSets}(\{\mathbf{p}_1, \dots, \mathbf{p}_n\})),$$

- **Entity-to-box distance:** 实体到query box中心的曼哈顿距离

- **Disjunction** (DNF下总在最后一步进行): $\text{dist}_{\text{agg}}(\mathbf{v}; q) = \text{Min}(\{\text{dist}_{\text{box}}(\mathbf{v}; \mathbf{q}^{(1)}), \dots, \text{dist}_{\text{box}}(\mathbf{v}; \mathbf{q}^{(N)})\})$



Method	Avg	1p	2p	3p	2i	3i	ip	pi	2u	up
FB15k										
Q2B	0.484	0.786	0.413	0.303	0.593	0.712	0.211	0.397	0.608	0.33
GQE	0.386	0.636	0.345	0.248	0.515	0.624	0.151	0.310	0.376	0.273
GQE-DOUBLE	0.384	0.630	0.346	0.250	0.515	0.611	0.153	0.320	0.362	0.271
FB15k-237										
Q2B	0.268	0.467	0.24	0.186	0.324	0.453	0.108	0.205	0.239	0.193
GQE	0.228	0.402	0.213	0.155	0.292	0.406	0.083	0.17	0.169	0.163
GQE-DOUBLE	0.23	0.405	0.213	0.153	0.298	0.411	0.085	0.182	0.167	0.16
NELL995										
Q2B	0.306	0.555	0.266	0.233	0.343	0.48	0.132	0.212	0.369	0.163
GQE	0.247	0.418	0.228	0.205	0.316	0.447	0.081	0.186	0.199	0.139
GQE-DOUBLE	0.248	0.417	0.231	0.203	0.318	0.454	0.081	0.188	0.2	0.139

在不能直接得到答案的复杂QA上实验，此处指标为Hits@3

SCALABLE NEURAL METHODS FOR REASONING WITH A SYMBOLIC KNOWLEDGE BASE - ICLR2020

➤ 背景/动机

- learning neural semantic parsers from denotations, 使用神经方法将自然语言问题翻译成结构化查询, 使用符号KB查询引擎执行。问题: 难以获得数据; 一个答案可能与许多可能的结构化查询相关联, 从而引入噪声
- learning semantic parsers from denotations, 训练数据由成对(Q,A), 其中Q是一个自然语言的问题, A是期望的答案。问题: 要学习的端到端过程包括一个不可微的操作——即使用包含答案的符号知识库进行推理。一些系统也“神经化”了知识库推理, 但到目前为止涉及小的知识库

➤ 主要贡献

- 可扩展性: 可以分布在多个gpu上, 扩展到数千万个实体和事实
- 完全端到端的神经解析器
- 新的方法架构, 可以扩展到其他任务上, 在两类任务上用简单的端到端架构取得了有竞争力的表现 (KB completion & learning semantic parsers from denotations)

SCALABLE NEURAL METHODS FOR REASONING WITH A SYMBOLIC KNOWLEDGE BASE - ICLR2020

- weighted set as k-hot, 用一个向量表示一个集合，元素=0表示不在集合里，<1表示概率，>1表示多重集
- 关系矩阵使用稀疏的矩阵数据结构来实现，COO（sparse coordinate pair）编码

$$R\text{-neighbors}(X) \equiv \{x_j : \exists r \in R, x_i \in X \text{ so that } (x_i, x_j) \in r\}$$

$$follow(\mathbf{x}, \mathbf{r}) \equiv \mathbf{xM}_R = \mathbf{x}(\sum_{k=1}^{N_R} \mathbf{r}[k] \cdot \mathbf{M}_{r_k})$$

$$follow(\mathbf{x}, \mathbf{r}) = \sum_{k=1}^{N_R} (\mathbf{r}[k] \cdot \mathbf{xM}_{r_k})$$

$$follow(\mathbf{x}, \mathbf{r}) = (\mathbf{xM}_{subj}^T \odot \mathbf{rM}_{rel}^T) \mathbf{M}_{obj}$$

subject是x的三元组 关系是r的三元组

Strategy	Definition	Batch?	Space complexity
naive mixing	Eq 1-2	no	$O(N_T + N_E + N_R)$
late mixing	Eq 3	yes	$O(N_T + bN_E + bN_R)$
reified KB	Eq 4	yes	$O(bN_T + bN_E)$

N_T, N_E, N_R 分别是三元组、实体、关系数量

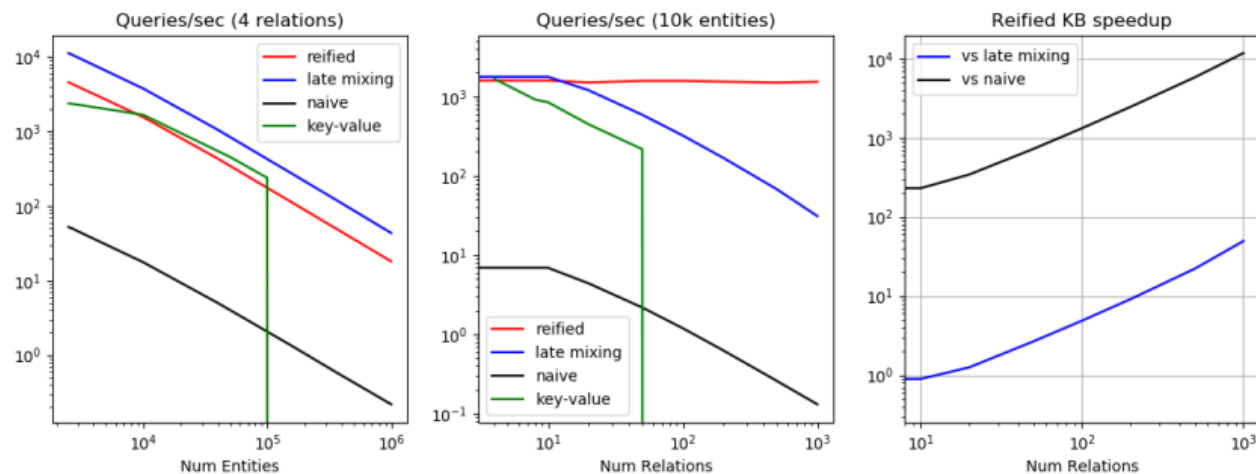


Figure 1: Left and middle: inference time in queries/sec on a synthetic KB as size and number of relations is varied. Queries/sec is given as zero when GPU memory of 12Gb is exceeded. Right: speedups of reified KBs over the baseline implementations.

	ReifKB (ours)	ReifKB + mask	KV-Mem (baseline)	VRN	GRAFT- Net	PullNet	non-differentiable components of architectures	
WebQSP	52.7	—	46.7	—	67.8	68.1	KV-Mem	initial memory
MetaQA								retrieval
1-hop	96.2	—	95.8	97.5	97.0	97.0		
2-hop	81.1	95.4	25.1	89.9	94.8	99.9	VRN	question-specific
3-hop	72.3	79.7	10.1	62.5	77.2	91.4	GRAFTNet	subgraph retrieval
Grid							PullNet	all iterative retrievals
5-hop	98.4	—	—	—	—	—		
10-hop	89.7	—	—	—	—	—	ReifKB(ours)	<i>none</i>

The reified KB representation is quite compact, using only six integers and three floats for each KB triple.

只能产生单个实体作为回答

NELL-995			ReifKB (Ours)	MINERVA
	H@1	H@10		
ReifKB (Ours)	64.1	82.4	64.1	66.3
DistMult*	61.0	79.5	98.9	99.3
ComplEx*	61.2	82.7	73.6	34.4
ConvE*	67.2	86.4	72.3	41.7

NELL-995	ReifKB (Ours)	MINERVA
Grid with seed entity	64.1	66.3
10-hop NSEW	98.9	99.3
10-hop NSEW-VH	73.6	34.4
MetaQA 3-hop	72.3	41.7

Table 4: Left: Hits@1 and Hits@10 for KB completion on NELL 995. Starred KB completion methods are transductive, and do not generalize to entities not seen in training. Right: Comparison to MINERVA on several tasks for Hits@1.

	NELL-995	MetaQA-3hop	WebQuestionsSP
# Facts	154,213	196,453	43,724,175
# Entities	75,492	43,230	12,942,798
# Relations	200	9	616
Time (seconds)	44.3	72.6	1820

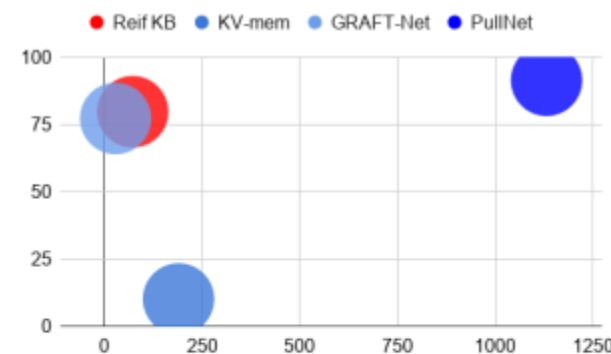
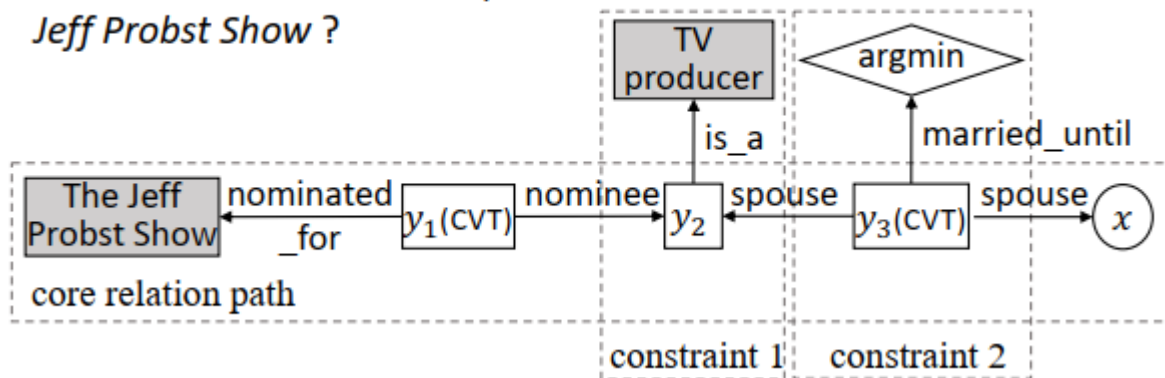


Table 5: Left, time to run 10K examples for KBs of different size. Right, time for 10k examples vs Hits@1 performance for ReifKB compared to three baselines on MetaQA-3hop questions.

Query Graph Generation for Answering Multi-hop Complex Questions from Knowledge Bases - ACL2020

- 任务
复杂KBQA，带限制多跳推理。(自然语言查询Q,实体答案A)
- 背景/动机：
之前复杂KBQA的工作分为带限制的单跳推理（谁是美国第一任总统？）和多跳推理（谁是Facebook创始人的妻子？）
- 主要贡献
处理了一种新型的更加复杂的推理任务

Who is the first wife of TV producer that was nominated for *The Jeff Probst Show* ?



- 查询图生成：利用约束和beam search减少搜索空间
- 查询图排序：利用查询图涉及的实体类型数量、grounded entities的数量等特征，输入全连接层后softmax算概率

CWQ 训练、验证、测试集合问题数量：27623, 3518, 3531

QType	CWQ	WQSP	Method	CWQ Prec@1/F1	WQSP F1	CQ F1	Method	CWQ Prec@1/F1
1-hop w/o CONS	0.1%	71.3%	Yih et al. (2015)	—/—	69.0	—	SOTA	40.8/36.5
1-hop w/ CONS	35.9%	28.2%	Bao et al. (2016)	—/—	—	40.9	w/ BERT	44.1/40.4
2-hop w/o CONS	33.5%	0.0%	Luo et al. (2018)	—/—	—	42.8	w/ LSTM	42.1/38.7
2-hop w/ CONS	30.5%	0.5%	Lan et al. (2019a)	39.3/36.5	67.9	—	w/o extend	25.2/22.8
			Chen et al. (2019) [†]	30.5/29.8	68.5	35.3	w/o connect	33.2/31.3
			Bhutani et al. (2019)	40.8/33.9	60.3	—	w/o aggregate	42.4/39.6
			Ansari et al. (2019)	—/—	72.6	—		
			Our Method	44.1/40.4	74.0	43.3		

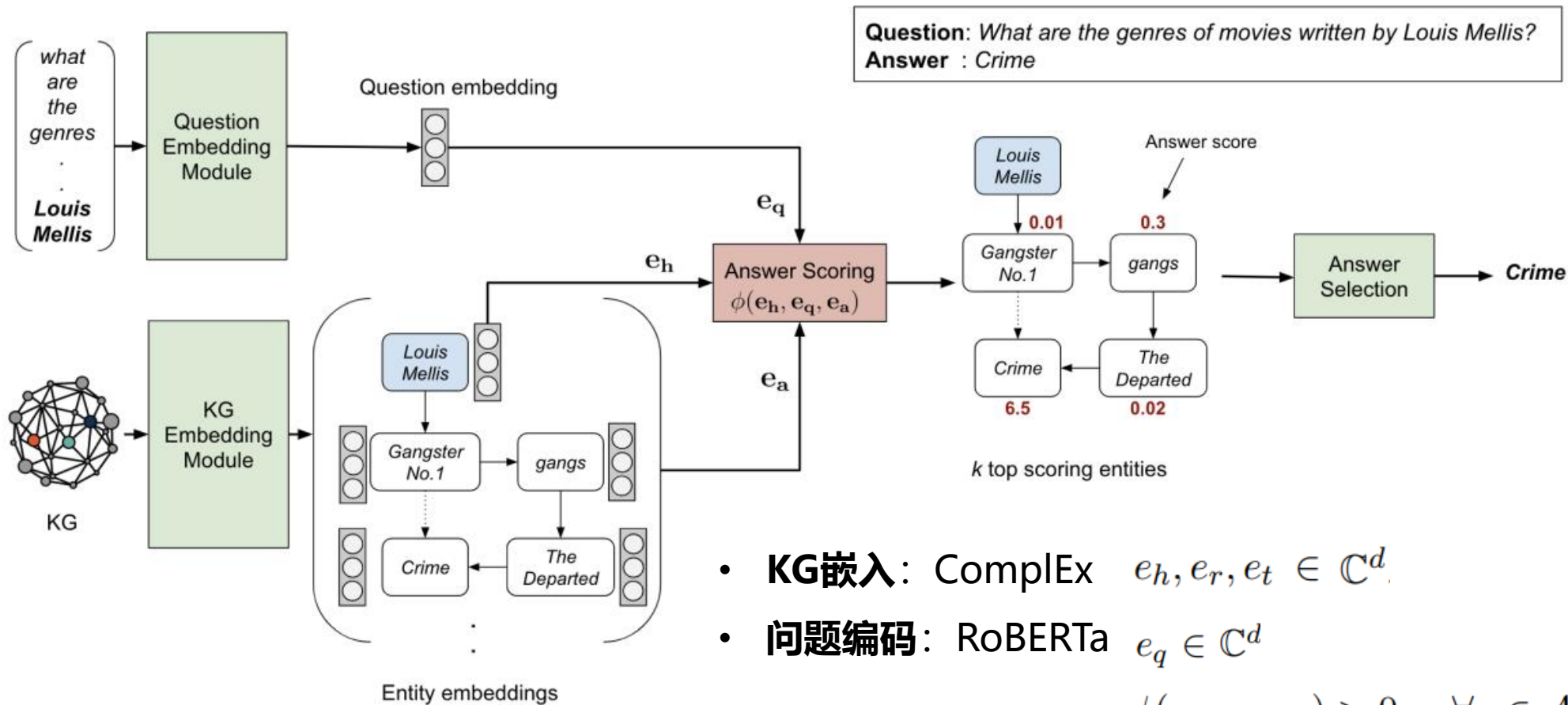
(a)

(b)

(c)

Improving Multi-hop Question Answering over Knowledge Graphs using Knowledge Base Embeddings - ACL2020

- 任务：KGQA（自然语言询问Q&关键实体 e_h ，答案实体A）
- 动机
 - 最近关于多跳KGQA的研究试图使用相关的外部文本来处理KG稀疏性，但相关文本语料库的可用性和识别本身就是一个挑战
 - KG嵌入方法虽然相关性很高，但对于多跳KGQA，目前还没有研究
- 主要贡献
 - 稀疏KGs上有效处理多跳KGQA
 - 由于**EmbedKGQA**将所有实体都视为候选答案，答案范围不像之前限定k-hop的工作一样受限



• **KG嵌入**: ComplEx $e_h, e_r, e_t \in \mathbb{C}^d$

• **问题编码**: RoBERTa $e_q \in \mathbb{C}^d$

$\phi(e_h, e_q, e_a) > 0 \quad \forall a \in \mathcal{A} \quad \leftarrow$ 如果a是答案

$\phi(e_h, e_q, e_{\bar{a}}) < 0 \quad \forall \bar{a} \notin \mathcal{A} \quad \leftarrow$ 如果a不是答案

ComplEx的打分函数, a是是实体集中的实体

答案选择:

对于小的KGs简单地选择得分最高的实体 $e_{ans} = \arg \max_{a' \in \mathcal{E}} \phi(e_h, e_q, e_{a'})$

对于大的KG加了剪枝 $e_{ans} = \arg \max_{a' \in \mathcal{N}_h} \phi(e_h, e_q, e_{a'}) + \gamma * \text{RelScore}_{a'}$

$$h_q = \text{RoBERTa}(q')$$

$$S(r, q) = \text{sigmoid}(h_q^T h_r) \quad \text{RelScore}_{a'} = |\mathcal{R}_a \cap \mathcal{R}_{a'}|$$

\mathcal{R}_a 是所有 $S(r, q) > 0.5$ 的关系集合, $\mathcal{R}_{a'}$ 是候选答案到 e_h 路径上的r

DIFFERENTIABLE REASONING OVER A VIRTUAL KNOWLEDGE BASE - ICLR2020

处理基于文本的**QA**问题中的多跳推理

谢谢！

汇报人：凌静

2021/4/2