知识库问答的问题与挑战

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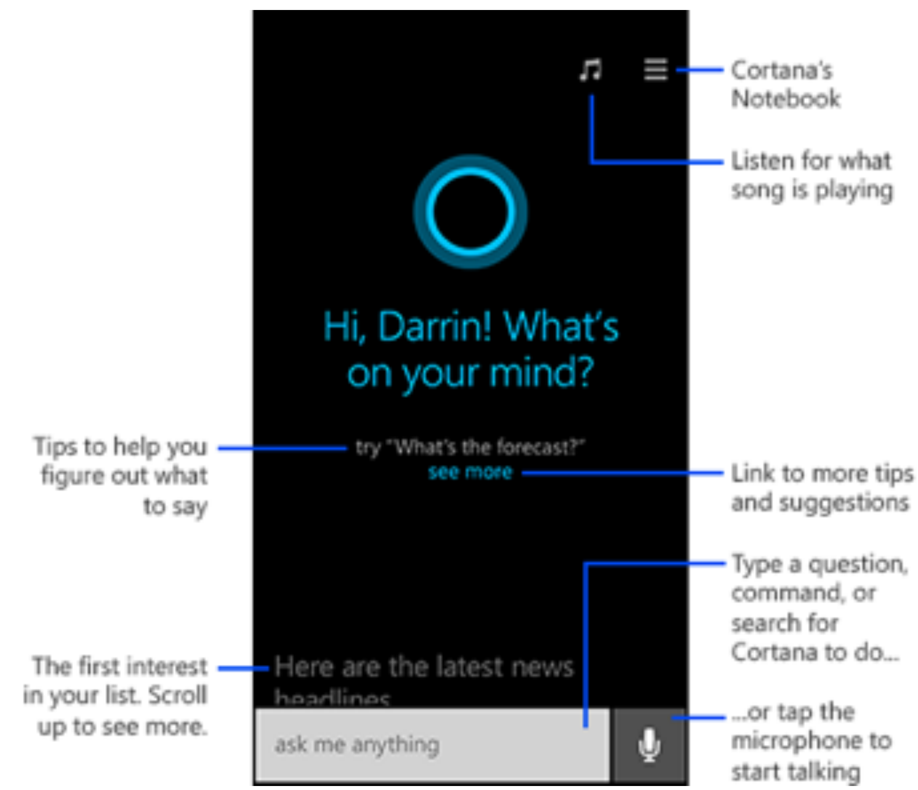
问答系统是下一代搜索引擎的基本形态



问答系统分类

IR-based QA

基于关键词匹配＋信息抽取，仍然是基于浅层语义分析

Community QA

依赖于网民贡献，问答过程仍然依赖于关键词检索技术

KB-based QA

Knowledge Base

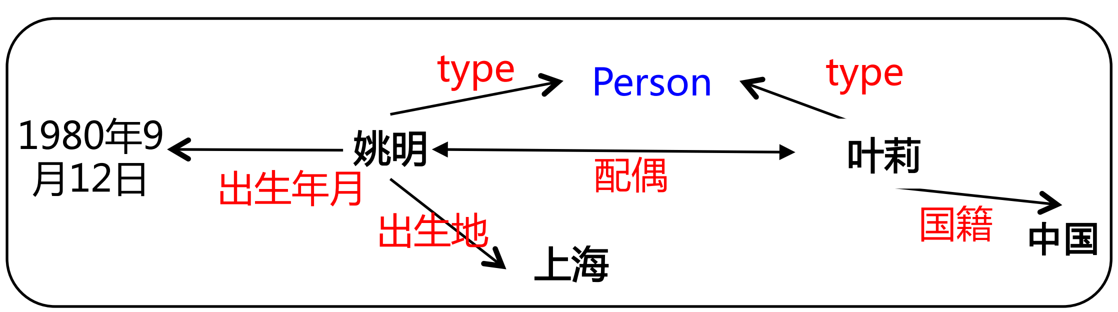
知识库

- 关系数据库

人物表				
ID	姓名	出生地	出生年月	国籍
10001	姚明	上海	1980年9月12日	中国
10002	叶莉	上海	1981年11月20日	中国

婚姻表		
配偶	配偶	结婚时间
10001	10002	2007年8月6日

- 知识图谱



超过5.7亿实体
超过18亿条事实（关系）

ProBase

2,653,873概念

百度知心

搜狗知立方

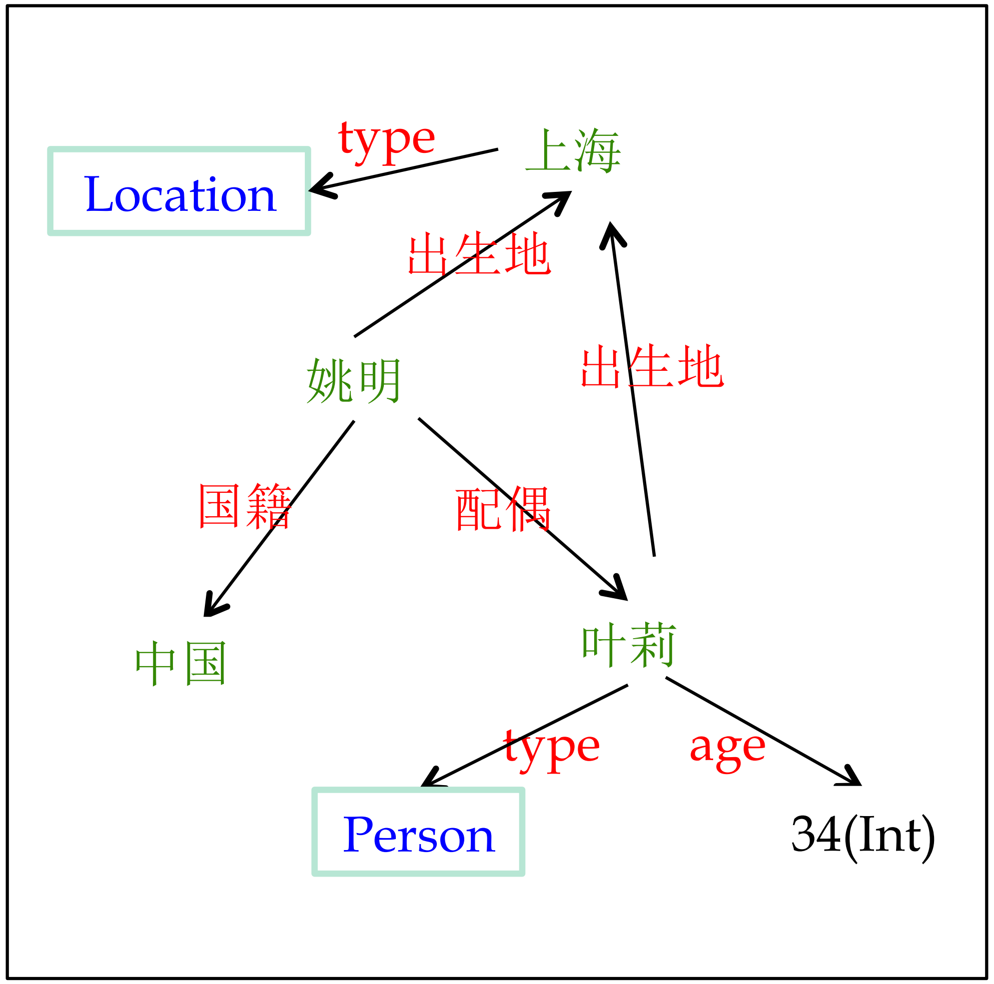
知识库问答关键问题

姚明的老婆出生在哪里?

语义解析

查询

```
SELECT DISTINCT ?x
WHERE {
      ?y 出生地 ?x.
      res:姚明 配偶 ?y.
}
```



知识库问答关键问题

- 如何形式化表示问句语义?
- 如何解析问句语义，将自然语言问句转为化形式化查询?
- 如何扩展到大规模知识库?
- 如何扩展到多知识库?

如何形式化表示问句语义

如何形式化表示

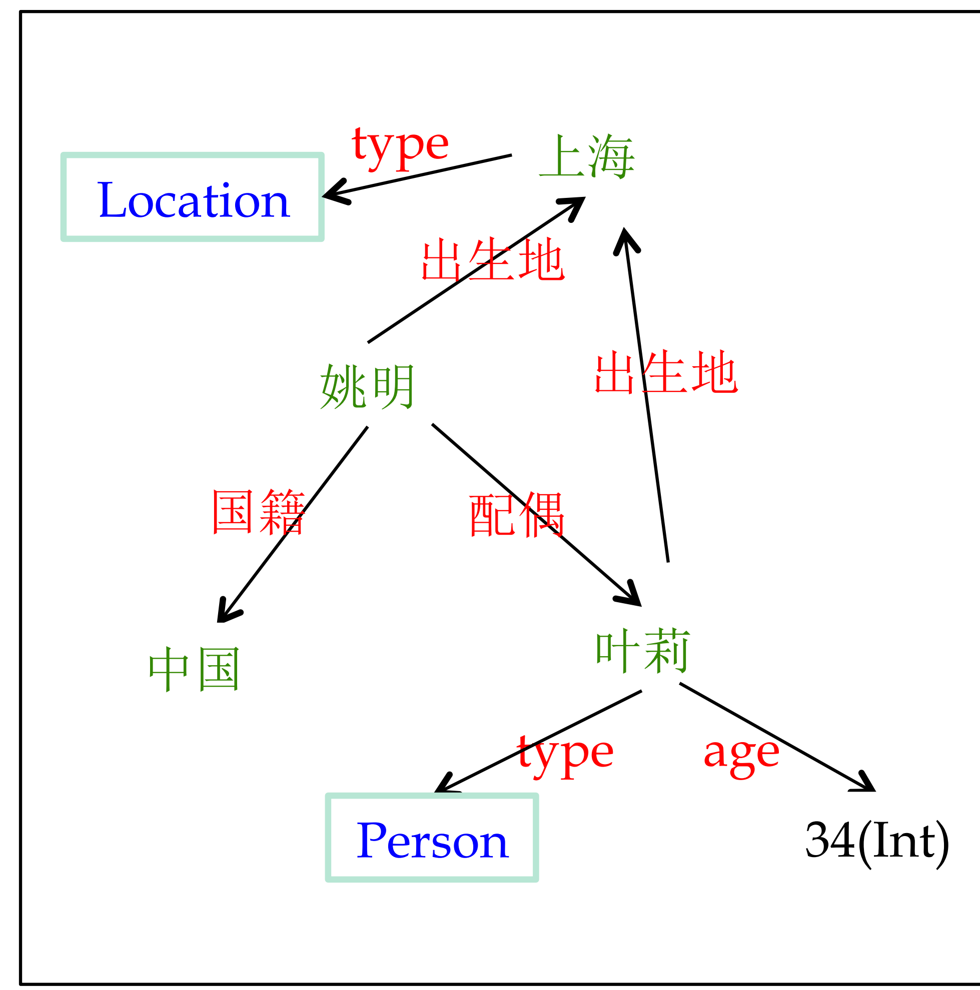
姚明的老婆出生在哪里?

λx . 配偶(姚明，y) Λ 出生地(y, x)

逻辑表达式
Lambda演算
DCS-Tree
…

```
SELECT DISTINCT ?x
WHERE {
      ?y 出生地 ?x.
      res:姚明 配偶 ?y.
}
```

SQL
SPARQL
Prolog
FunQL
…



Lambda演算

- 用于函数定义、函数应用和递归的一种形式表示
  - Constants
    - entities, numbers, functions
  - Logical connectors:
    - $\wedge, \vee, \rightarrow, \neg$
  - Quantification
    - $\exists, \forall$
  - Additional quantifiers
    - Count, argmax ....

Lambda演算

a) What states border Texas

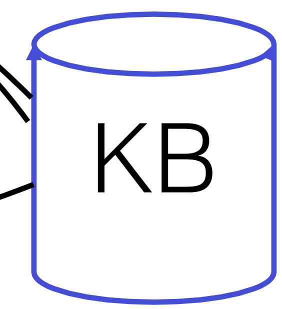
$$\lambda x.state(x) \wedge borders(x, texas)$$

b) What is the largest state

$$\arg\max(\lambda x.state(x), \lambda x.size(x))$$

c) What states border the state that borders the most states

$$\lambda x.state(x) \wedge borders(x, \arg\max(\lambda y.state(y), \lambda y.count(\lambda z.state(z) \wedge borders(y, z))))$$



核心：实体、关系三元组
（实体1，关系，实体2）

如何解析问句语义，将自然语言问句转化为结构化查询语句

如何扩展到大规模知识库

如何语义解析

Which software has been developed by organizations founded in California, USA?

短语检测: software | developed by | organizations | founded in | California

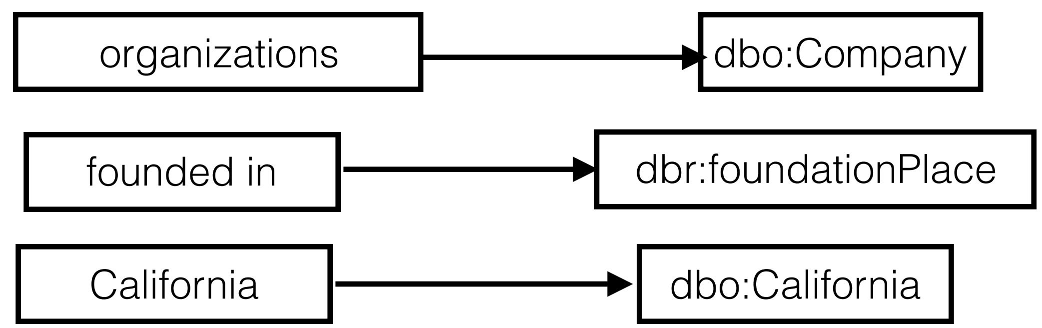
资源映射: dbo:Software | dbr:developer | dbo:Company | dbr:foundationPlace | dbo:California

语义组合: <dbo:Software, dbr:developer, dbo:Company> | <dbo:Company, dbr:foundationPlace, dbo:California

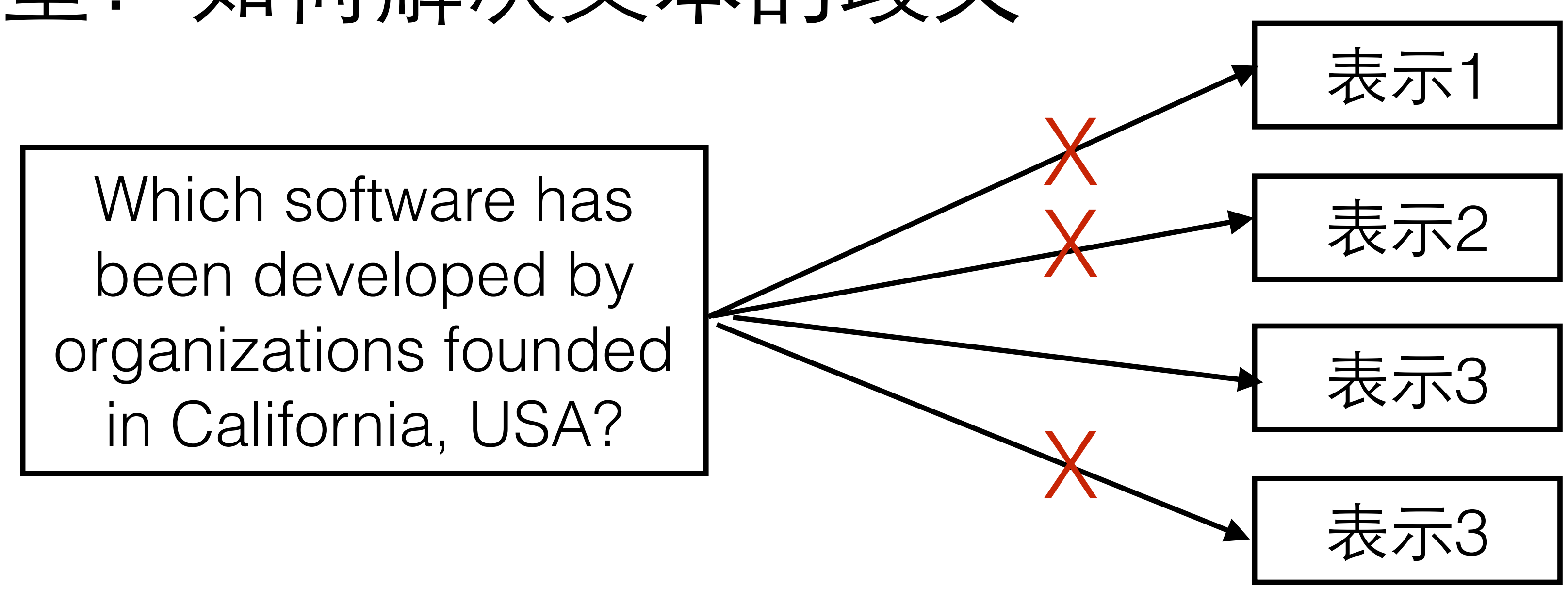
逻辑表达式

两个核心

- 词典：获得短语到资源的映射



- 模型：如何解决文本的歧义



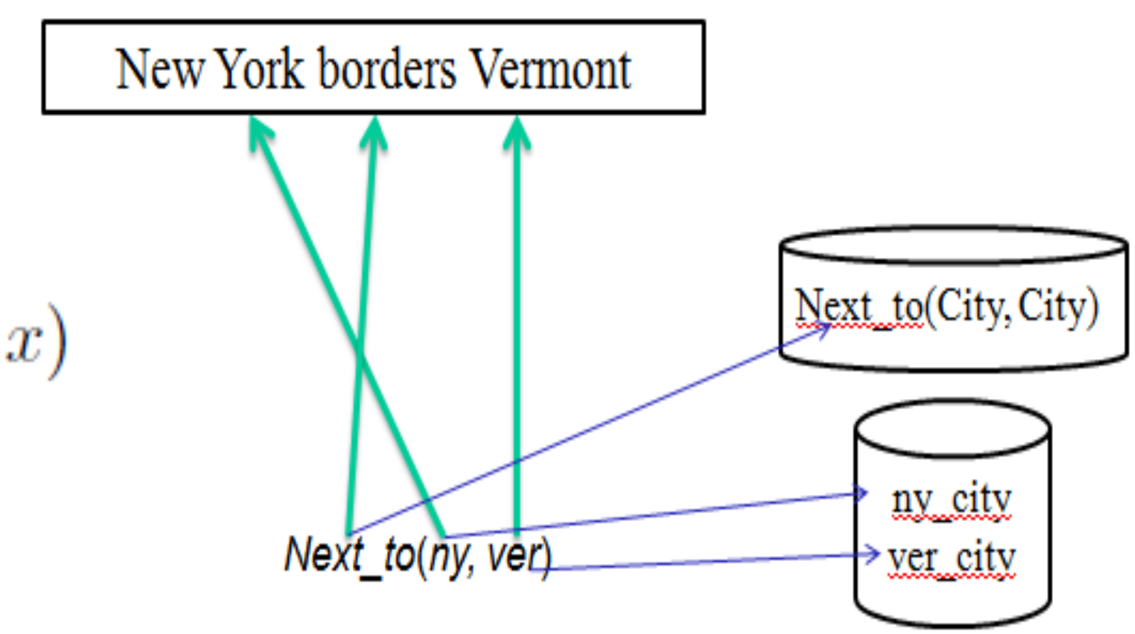
已有语义解析方法

- 语义解析（Semantic Parsing）
  - 组合范畴语法（Combinatory Categorical Grammars）[Zettlemoyer, 1995]
  - “移位-规约”推导（Shift-reduce Derivations）[Zelle, 1995]
  - 同步语法（Synchronous Grammars）[Wong, 2007]
  - 混合树（Hybrid Tree）[Lu, 2008]
  - 类CFG语法（CFG-like Grammars）[Clarke, 2010]
  - 类CYK方法（CYK-like Grammars）[Liang, 2011]

CCG（词典+组合规则）

- 词典（三部分）
  - 自然语言词语（短语）：New York
  - 词语所对应的句法范畴：NP
  - 词语所对应的知识库语义单元：ny

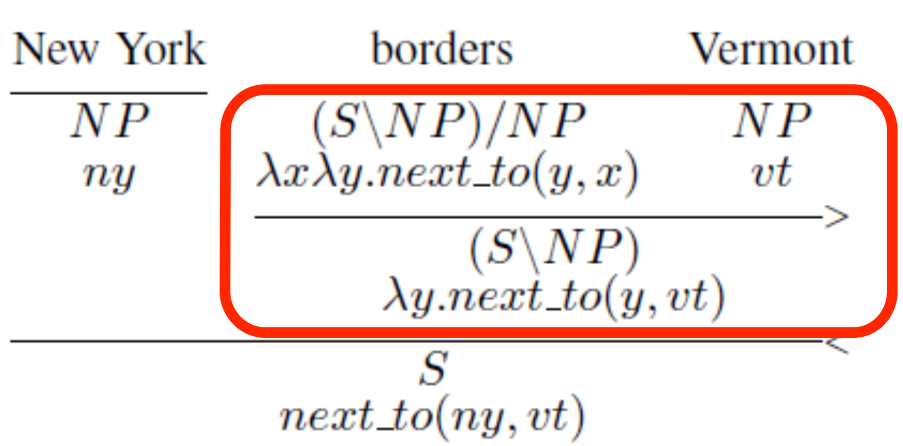
$$\text{New York} \vdash NP : ny$$
$$\text{borders} \vdash S\backslash NP/NP : \lambda x \lambda y.next\_to(y, x)$$
$$\text{Vermont} \vdash NP : vt$$

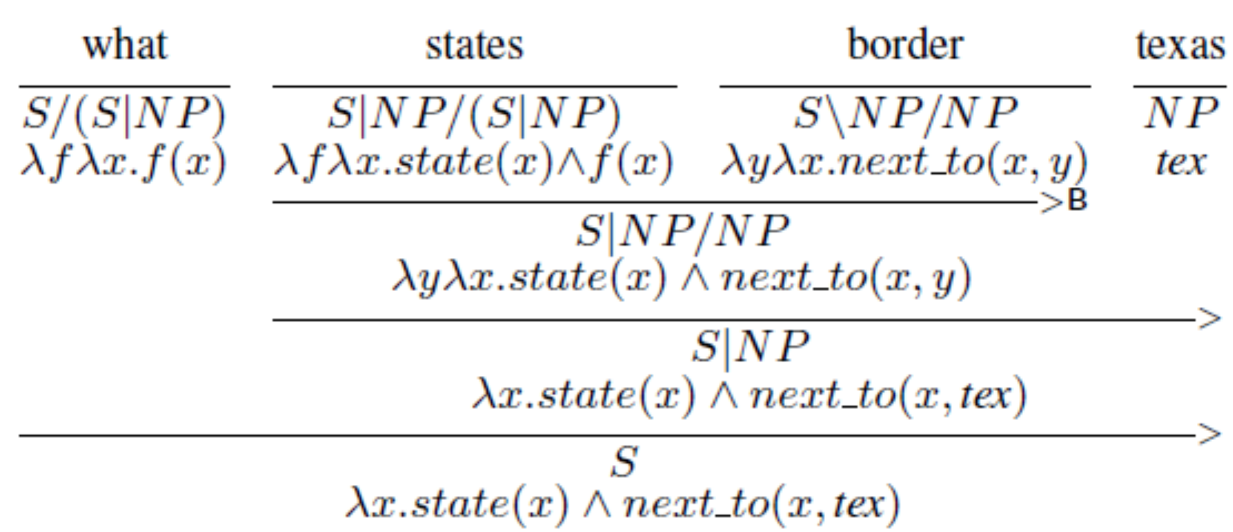


CCG（词典+组合规则）

- 组合规则

$$
\begin{array}{llll}
X/Y : f & Y : g & \Rightarrow & X : f(g) \quad (>) \\
Y : g & X\backslash Y : f & \Rightarrow & X : f(g) \quad (<) \\
\\
X/Y : f & Y/Z : g & \Rightarrow & X/Z : \lambda x.f(g(x)) \quad (> \mathbf{B}) \\
Y\backslash Z : g & X\backslash Y : f & \Rightarrow & X\backslash Z : \lambda x.f(g(x)) \quad (< \mathbf{B})
\end{array}
$$





词典学习

1) What states border Texas?

$\lambda x.state(x) \wedge borders(x, texas)$

2) What is the largest state?

$\arg\max(\lambda x.state(x), \lambda x.size(x))$

3) What states border the state that borders the most states?

$$\lambda x.state(x) \wedge borders(x, \arg\max(\lambda y.state(y), \lambda y.count(\lambda z.state(z) \wedge borders(y,z))))$$

4) Utah borders Idaho.

$borders(utah, idaho)$

Utah	:=	$NP : utah$
Idaho	:=	$NP : idaho$
borders	:=	$(S\backslash NP)/NP : \lambda x.\lambda y.borders(y,x)$
states	:=	$N : \lambda x.state(x)$
major	:=	$N/N : \lambda f.\lambda x.major(x) \wedge f(x)$
population	:=	$N : \lambda x.population(x)$
cities	:=	$N : \lambda x.city(x)$
rivers	:=	$N : \lambda x.river(x)$
run through	:=	$(S\backslash NP)/NP : \lambda x.\lambda y.traverse(y,x)$
the largest	:=	$NP/N : \lambda f.\arg\max(f, \lambda x.size(x))$
river	:=	$N : \lambda x.river(x)$
the highest	:=	$NP/N : \lambda f.\arg\max(f, \lambda x.elev(x))$
the longest	:=	$NP/N : \lambda f.\arg\max(f, \lambda x.len(x))$

句子-形式化语句对

语义单元词典

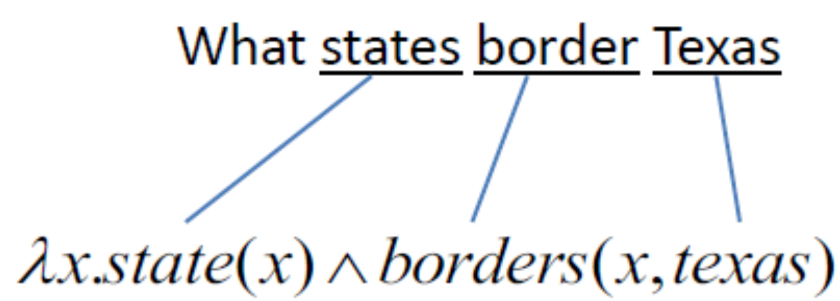
词典学习：人工模板

Rules		Categories produced from logical form
Input Trigger	Output Category	$\arg\max(\lambda x.state(x) \wedge borders(x, texas), \lambda x.size(x))$
constant c	$NP : c$	$NP : texas$
arity one predicate p_1	$N : \lambda x.p_1(x)$	$N : \lambda x.state(x)$
arity one predicate p_1	$S\backslash NP : \lambda x.p_1(x)$	$S\backslash NP : \lambda x.state(x)$
arity two predicate p_2	$(S\backslash NP)/NP : \lambda x.\lambda y.p_2(y, x)$	$(S\backslash NP)/NP : \lambda x.\lambda y.borders(y, x)$
arity two predicate p_2	$(S\backslash NP)/NP : \lambda x.\lambda y.p_2(x, y)$	$(S\backslash NP)/NP : \lambda x.\lambda y.borders(x, y)$
arity one predicate p_1	$N/N : \lambda g.\lambda x.p_1(x) \wedge g(x)$	$N/N : \lambda g.\lambda x.state(x) \wedge g(x)$
literal with arity two predicate p_2 and constant second argument c	$N/N : \lambda g.\lambda x.p_2(x, c) \wedge g(x)$	$N/N : \lambda g.\lambda x.borders(x, texas) \wedge g(x)$
arity two predicate p_2	$(N\backslash N)/NP : \lambda x.\lambda g.\lambda y.p_2(x, y) \wedge g(x)$	$(N\backslash N)/NP : \lambda g.\lambda x.\lambda y.borders(x, y) \wedge g(x)$
an arg max / min with second argument arity one function f	$NP/N : \lambda g.\arg\max / \min(g, \lambda x.f(x))$	$NP/N : \lambda g.\arg\max(g, \lambda x.size(x))$
an arity one numeric-ranged function f	$S/NP : \lambda x.f(x)$	$S/NP : \lambda x.size(x)$

人工规则：覆盖度有限，不具扩展

词典学习：统计对齐

- 自然语言和逻辑表达式看作为两种不同语言，利用机器翻译中的统计对齐学习词语（短语）和符号之间的对齐关系



面对大规模知识库如何进行词典学习?

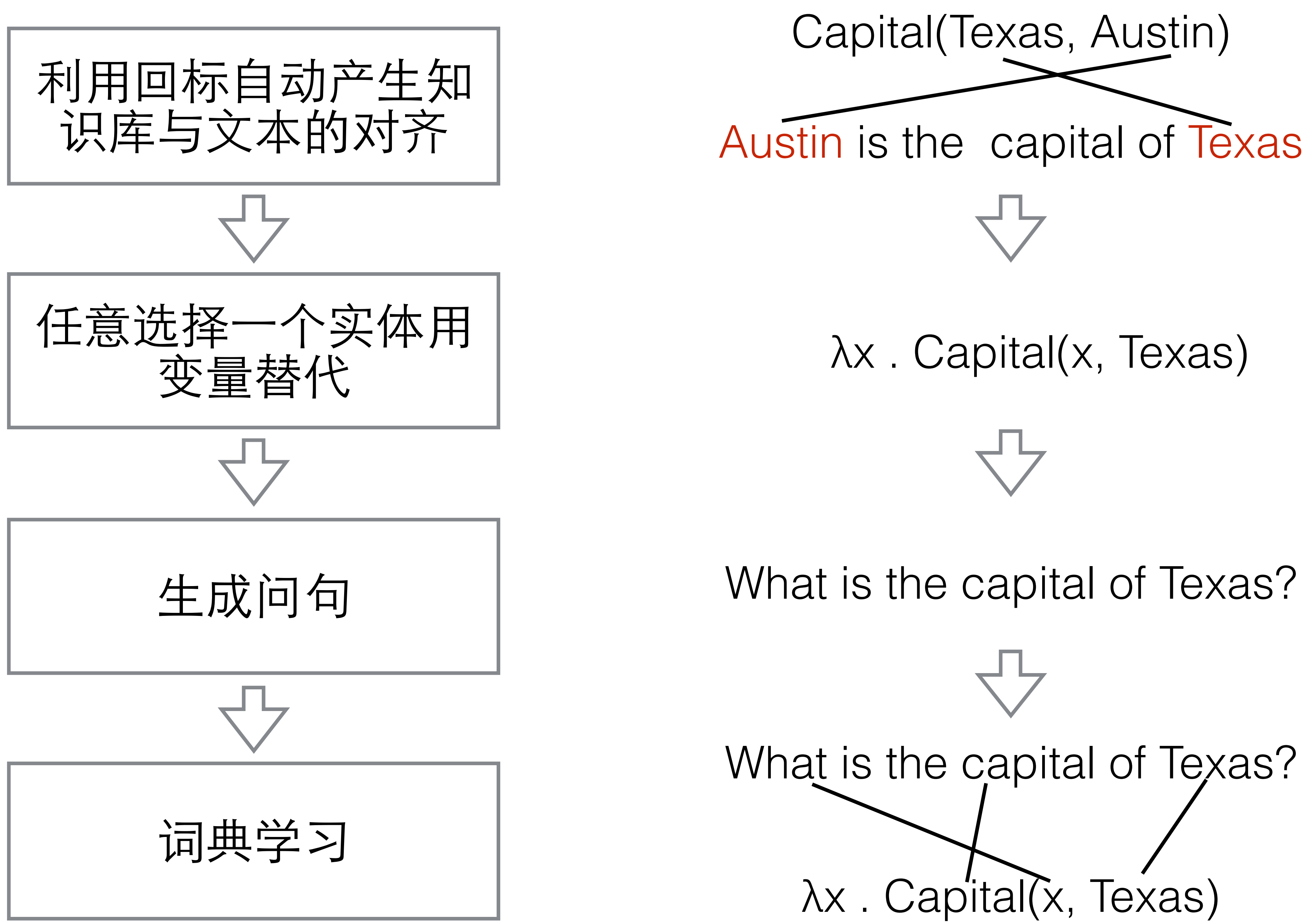
- 无法获得标注的逻辑表达式

姚明的老婆出生在哪里?

λx . 配偶(姚明， y) ∧ 出生地(y, x)

- Solution
  - 回标自动产生逻辑表达式
  - 复述自动产生逻辑表达式
  - 利用“问题-答案”自动产生逻辑表达式

回标自动生成逻辑表达式
[Krishnamurthy, 2012] [Reddy, 2014]



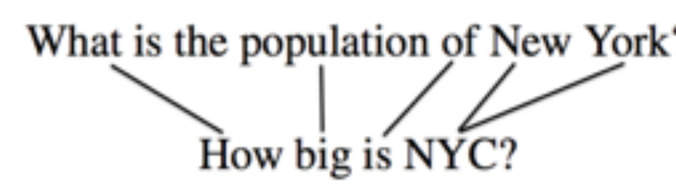
复述自动生成逻辑表达式 [Fader, 2013]

- 假设：给定句子的复述与当前句子具有相同的逻辑表达式

What is the population of New York

λx. population(x, new-york)

what is the r *of* e	=	r(?, e)
population	=	population
new york	=	new-york



How big is NYC

λx. population(x, new-york)

how r *is* e	=	r(?, e)
big	=	population
nyc	=	new-york

利用答案产生逻辑表达式[Clarke; Liang et al., 2011]

- 将逻辑表达式看做是潜在变量
- 所生成的逻辑表达式若能查询出正确结果，则为正例

What is the most populous city in California?

→ argmax(λ x. city(x) ^ loc(x; CA); λ x. pop (x))

How many states border Oregon?

→ count(λ x. state(x) ^ border(x; OR))

What is the most populous city in California?

→ Los Angeles

How many states border Oregon?

→ 3

$$\max_\theta \sum_z \underbrace{p(y \mid z, w)}_{\text{Interpretation}} \underbrace{p(z \mid x, \theta)}_{\text{Semantic parsing}}$$

Learning: EM algorithm

不借助逻辑表达式直接获取语义关系的模板

- Entity Mention（实体同义词）
  - Query Log
  - 网页锚文本
  - …
- Pattern Relation（关系模板）
  - [subj married to obj] —> spouse(subj, obj)
  - 开放域关系抽取

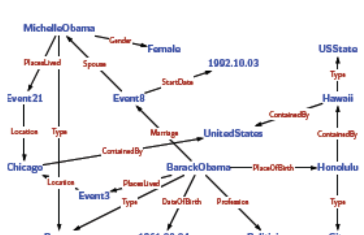
开放域关系抽取

- 利用开放域信息抽取（OpenIE）技术获取文本表达和知识库中关系实例的对应[Berant, 2013]

文本的开放域信息抽取

(*Barack Obama*, *was born in*, *Honolulu*)
(*Albert Einstein*, *was born in*, *Ulm*)
(*Barack Obama*, *lived in*, *Chicago*)
... 15M triples ...

经过实体链接后从知识库中抽取的三元组



(BarackObama, PlaceOfBirth, Honolulu)
(Albert Einstein, PlaceOfBirth, Ulm)
(BarackObama, PlacesLived.Location, Chicago)
... 600M triples ...

was born in
⇕
PlaceOfBirth

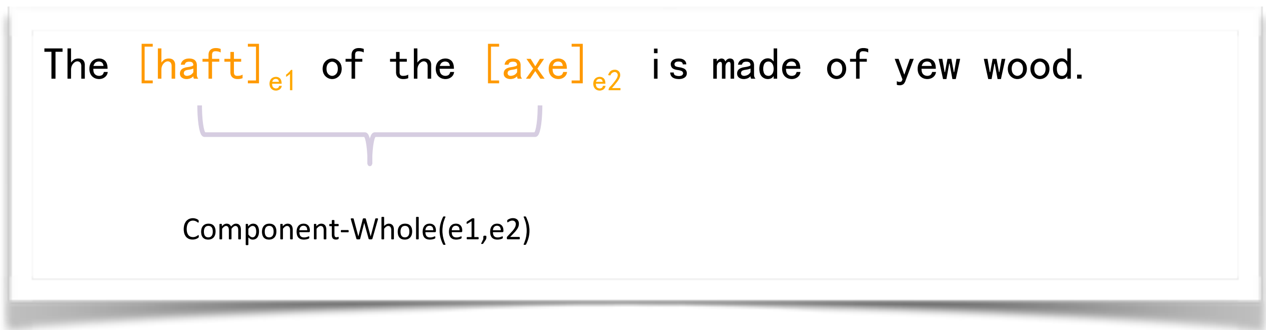
语义关系分类

- Pattern Relation（关系模板）
  - [subj married to obj] —> spouse(subj, obj)
  - 看做一个分类问题

It is said that **Jane** has married **Mr Smith** ? spouse(x,y)

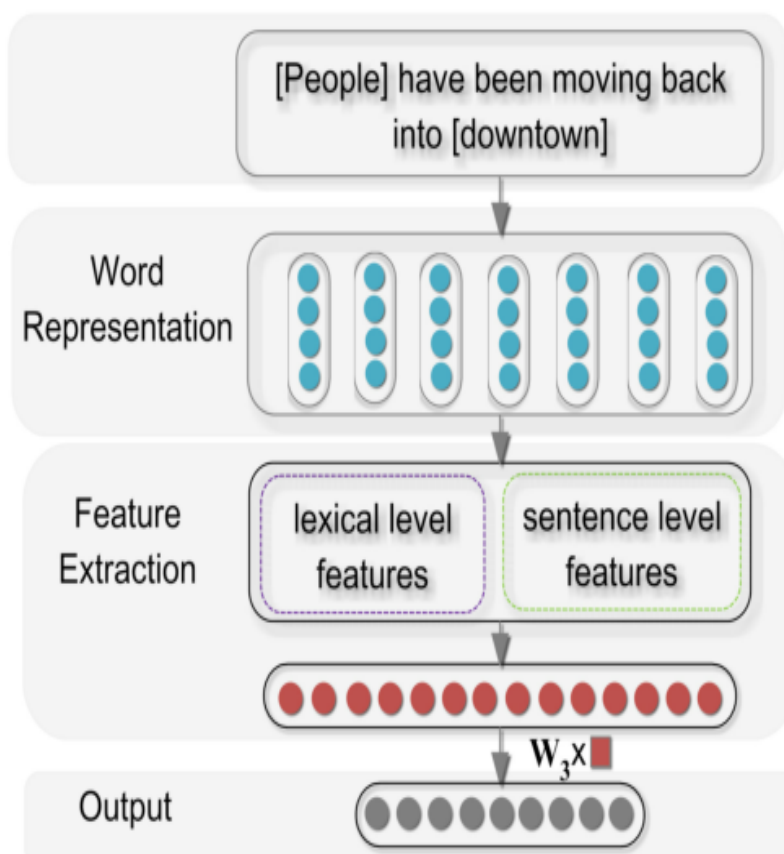
- 难点：
  - 需要NLP工具分析词性、句法等
    - 错误累积、语言依赖
  - 需要标注数据
    - 大规模开放域知识库下难以获得充足标注

Relation Identification based on Deep Convolutional Neural Network



Lexical Level Features:
捕捉词本身的语义信息

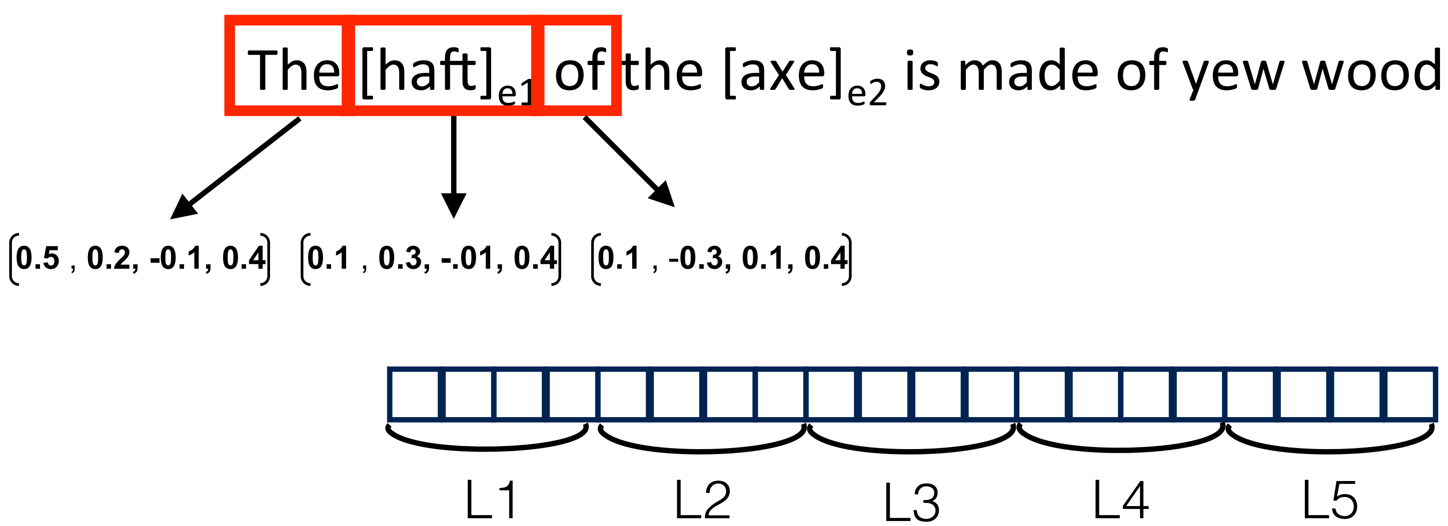
Sentence Level Features:
捕捉所在句子的上下文信息



Daojian Zeng, Kang Liu, Siwei Lai, Guangyou Zhou and Jun Zhao. **Relation Classification via Convolutional Deep Neural Network**, in *Proceedings of COLING 2014*, Dublin, Ireland, August, 23-29 (Best Paper Award)

Lexical Level Features

Features	Remark
L1	Noun 1
L2	Noun 2
L3	Left and right tokens of noun 1
L4	Left and right tokens of noun 2
L5	WordNet hypernyms of nouns



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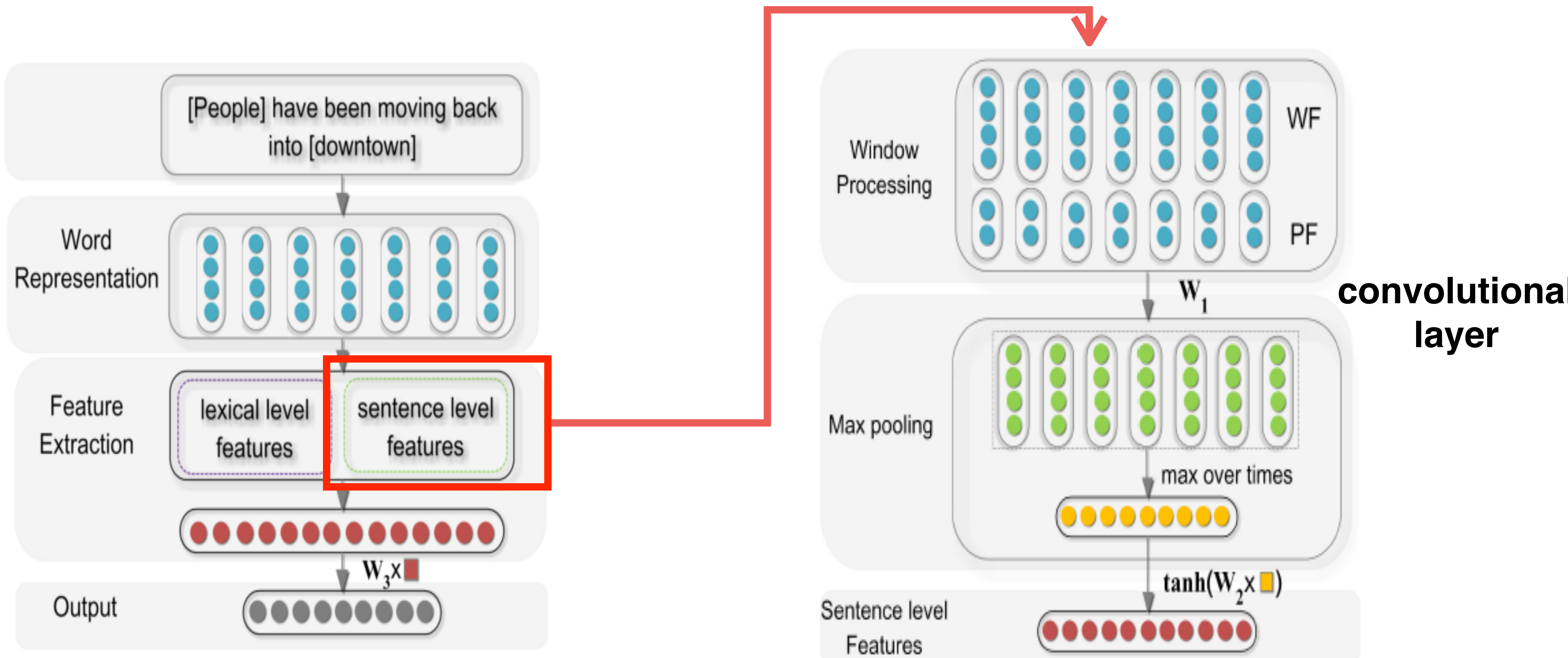
Sentence Level Features



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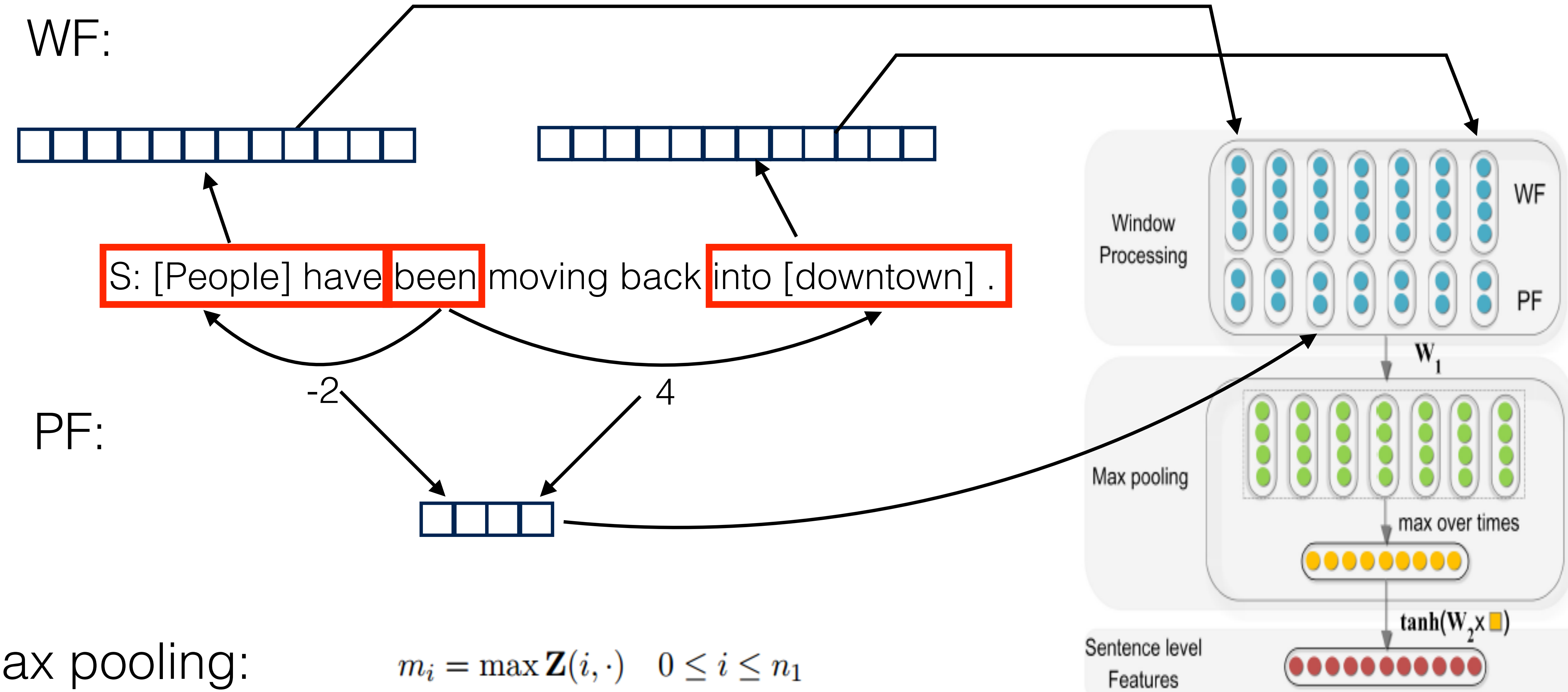
Sentence Level Features



max pooling: $m_i = \max \mathbf{Z}(i, \cdot) \quad 0 \leq i \leq n_1$

output: $\mathbf{g} = \tanh(\mathbf{W}_2 \mathbf{m})$

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实验结果

- SemEval-2010 Task 8

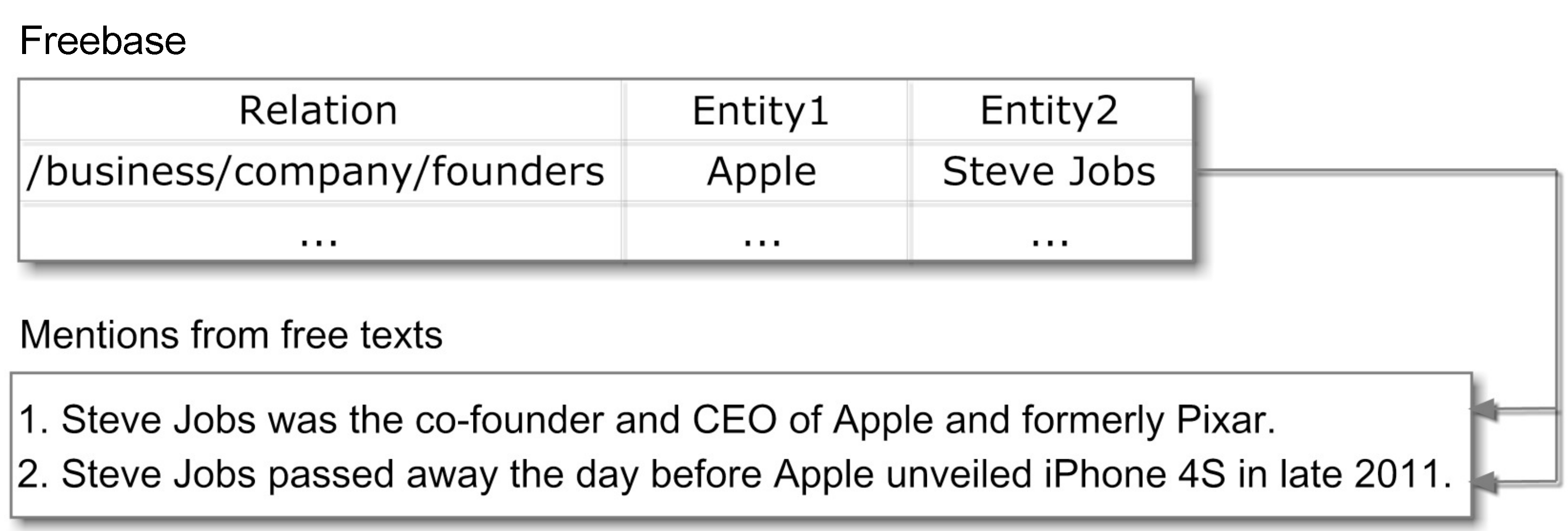
Classifier	Feature Sets	F1
SVM	POS, stemming, syntactic patterns	60.1
SVM	word pair, words in between	72.5
SVM	POS, stemming, syntactic patterns, WordNet	74.8
MaxEnt	POS, morphological, noun compound, thesauri, Google n-grams, WordNet	77.6
SVM	POS, prefixes, morphological, WordNet, dependency parse, Levin classed, ProBank, FrameNet, NomLex-Plus, Google n-gram, paraphrases, TextRunner	82.2
RNN	-	74.8
	POS, NER, WordNet, syntactic tree	77.6
MVRNN	-	79.1
	POS, NER, WordNet, syntactic tree	82.4
Proposed	word pair, WordNet	**82.7**

实验表明，我们所提出方法在需要NLP预处理和人工设计复杂特征前提下，能够有效提升实体关系分类性能

Daojian Zeng, Kang Liu, Siwei Lai, Guangyou Zhou and Jun Zhao. **Relation Classification via Convolutional Deep Neural Network**, in *Proceedings of COLING 2014*, Dublin, Ireland, August, 23-29 (Best Paper Award)

自动产生训练语料

- Distant Supervision：解决大规模知识图谱下语义关系标注问题
  - 问题：标注错误

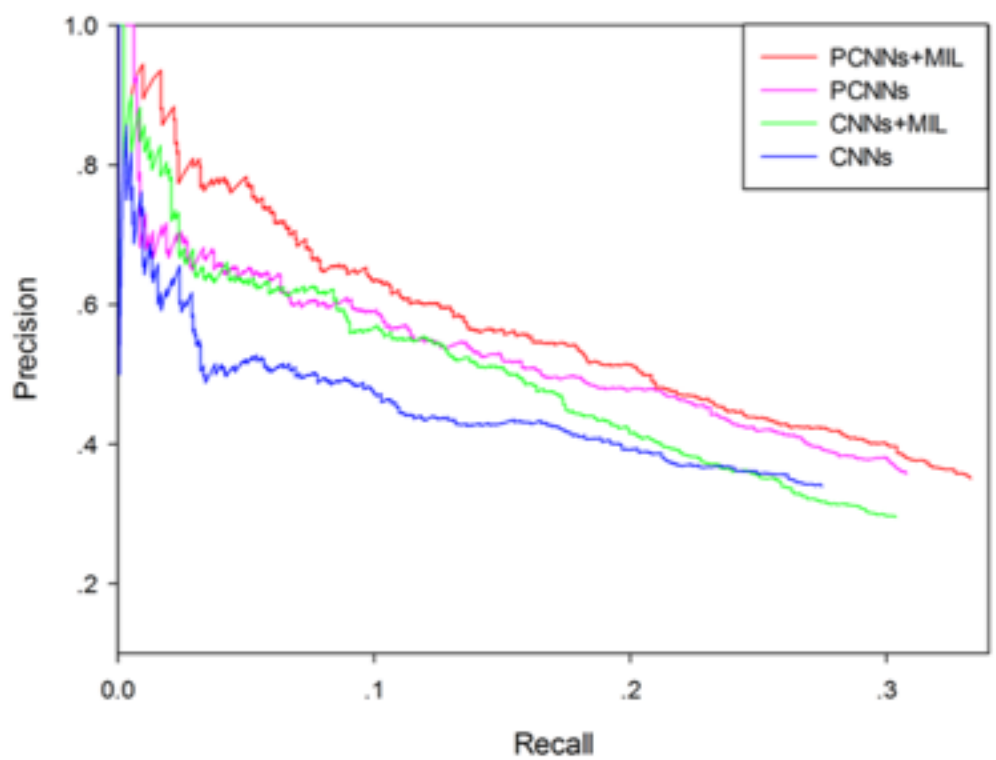


Distant Supervision for Relation Identification via Deep Convolutional Neural Network

- Multi-instance Learning

$$J(\theta) = \sum_{i=1}^{T} \log p(y_i | m_i^j; \theta)$$

$$j = \arg\max p(o_i^j | m_i^j; \theta) \quad 1 \le j \le k$$



如何处理文本歧义

- 自然语言问句表达方式复杂、关系类型多样、歧义现象严重，这一问题在面对大规模知识库时更加明显

Which software has been developed by organizations founded in California, USA?

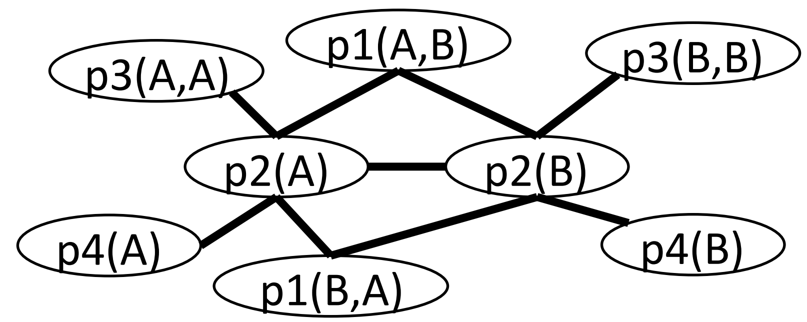
- 短语切分歧义 { California }, { California, USA }
- 资源映射
  California: {California_State}, {California_Film}
  founded: {foundationPlace},{founder}
  developed by: {developer}
- 组合歧义
  {dbo:Software, dbr:developer, dbo:Company}
  {dbo:Software, dbr:foundationPlace, dbo:Company}

各种歧义间相互影响，如何建立高效的消歧模型?

Joint Disambiguation using Markov Logic Network

- 联合学习

$$p(y)=\frac{1}{Z}\exp\Big(\sum_{(\phi_i,w_i)\in L} w_i \sum_{c\in C^{n_{\phi_i}}} f_c^{\phi_i}(y)\Big)$$



求解：Hidden Predicates

hasPhrase(i)	The *i*th candidate phrase has been chosen
hasResource(i, j)	The *i*th phrase is mapped to the *j*th semantic item
hasRelation (ri, rj, rr)	The semantic item *ri* and *rj* can be grouped together with the relation type *rr*

特征：Observed Predicates

Describing the attributes of phrases and relation between two phrases	
phraseIndex(p, i, j)	The start and end position of phrase *p* in question.
phrasePosTag(p, pt)	The POS tag of head word in phrase *p*.
phraseDepTag(p, q, dt)	The dependency path tags between phrase *p* and *q*.
phraseDepOne (p, q)	If there is only one tag in the dependency path, the predicate is true.
hasMeanWord (p, q)	If there is any one meaning word in the dependency path of two phrases, the predicate is true.
Describing the attributes of semantic item and the mapping between phrase and semantic item	
resourceType(r, rt)	The type of semantic item r. Types of semantic items include *Entity*, *Class* and *Property*
priorMatchScore(p, r, s)	The prior score of phrase *p* mapping to semantic item *r*.
Describing the attributes of relation between two semantic items in knowledge base	
hasRelatedness(p, q, s)	The semantic coherence of semantic items.
isTypeCompatible(p, q, rr)	If semantic items *p* is type-compatible with semantic items *q*, the predicate is true.
hasQueryResult(s, p, o, rr1, rr2)	If the triple pattern consisting of semantic items *s*, *p*, *o* and relation types *rr1*, *rr2* have query results, the predicate is true.

Shizhu He, Kang Liu, Yuanzhe Zhang, Liheng Xu and Jun Zhao. **Questioning Answering over Linked Data Using Markov First-order Logic**, *in Proceedings of EMNLP 2014*, Doha, Qatar, October, 25-29

Joint Disambiguation using Markov Logic Network

Benchmark	PD			PM			MG			QA					
	P	R	F1	P	R	F1	P	R	F1	#T	#Q	#A	P	R	F1
QALD-1(Joint)	0.93	0.981	**0.955**	0.895	0.944	**0.919**	0.703	0.813	**0.754**	50	37	20	0.54	0.4	**0.46**
QALD-1(Pipeine)	0.921	0.972	0.946	0.868	0.917	0.892	0.585	0.859	0.696	50	34	17	0.5	0.34	0.41
QALD-3(Joint)	0.941	0.941	**0.941**	0.878	0.918	**0.898**	0.636	0.798	0.708	99	75	45	0.6	0.46	**0.52**
QALD-3(Pipeline)	0.912	0.912	0.912	0.829	0.867	0.848	0.677	0.789	**0.729**	99	75	42	0.56	0.42	0.48
QALD-4(Joint)	0.947	0.978	**0.963**	0.937	0.967	**0.952**	0.776	0.865	**0.817**	50	26	15	0.58	0.3	**0.4**
QALD-4(Pipeline)	0.937	0.967	0.952	0.905	0.935	0.920	0.683	0.827	0.748	50	24	13	0.54	0.26	0.35

Test set	System	#T	#Q	#A	P	R	F1
QALD-3	CASIA (He et al., 2013)	99	52	29	0.56	0.3	0.38
	Scalewelis (Joris and Ferré, 2013)	99	70	32	0.46	0.32	0.38
	RTV (Cristina et al., 2013)	99	55	30	0.55	0.3	0.39
	Intui2 (Corina, 2013)	99	99	28	0.28	28	0.28
	SWIP (Pradel et al., 2013)	99	21	15	0.71	0.15	0.25
	Ours	99	75	45	0.6	0.46	0.52
QALD-4[20]	gAnswer	50	25	16	0.64	0.32	0.43
	Intui3	50	33	10	0.30	0.2	0.24
	ISOFT	50	50	10	0.2	0.2	0.2
	RO FII	50	50	6	0.12	0.12	0.12
	Ours	50	26	15	0.58	0.3	0.4

Shizhu He, Kang Liu, Yuanzhe Zhang, Liheng Xu and Jun Zhao. **Questioning Answering over Linked Data Using Markov First-order Logic**, *in Proceedings of EMNLP 2014*, Doha, Qatar, October, 25-29

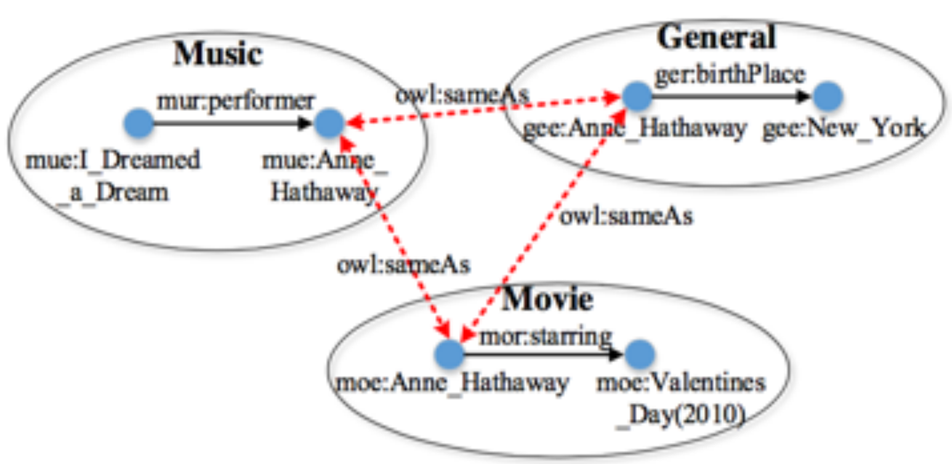
如何扩展到多知识库

如何处理多知识库

- 开放域环境下，用户的问题复杂多样，很多场景下，单单只用一个知识库的信息不能完全回答用户的问题

Which song are performed by person who was born in New York and played a role in Valentine’s Day

music KB　　people KB　　movie KB

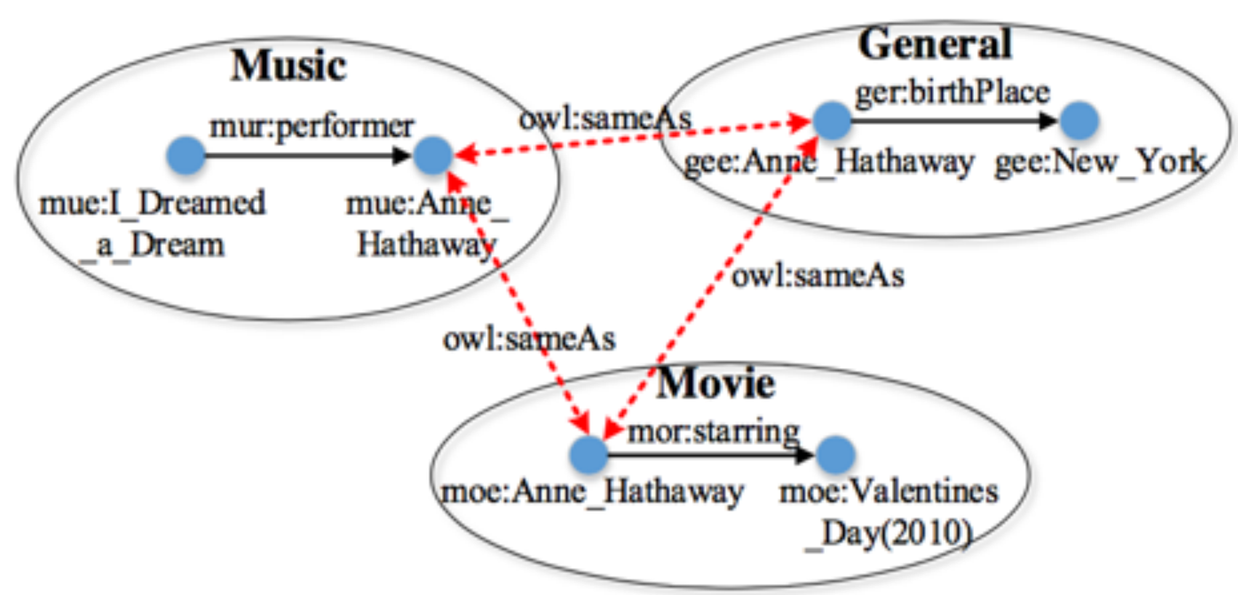


SELECT ?v1 WHERE {
⟨?v1, mur:perfomer[1], ?v2⟩
⟨?v2, owl:sameAs, ?v3⟩
⟨?v3, mor:starring, moe:Valentines_Day(2010)⟩
⟨?v3, owl:sameAs, ?v4⟩
⟨?v4, ger:birthPlace, gee:New_York⟩ }

- 多知识库间冗余、异构
- 需要对齐

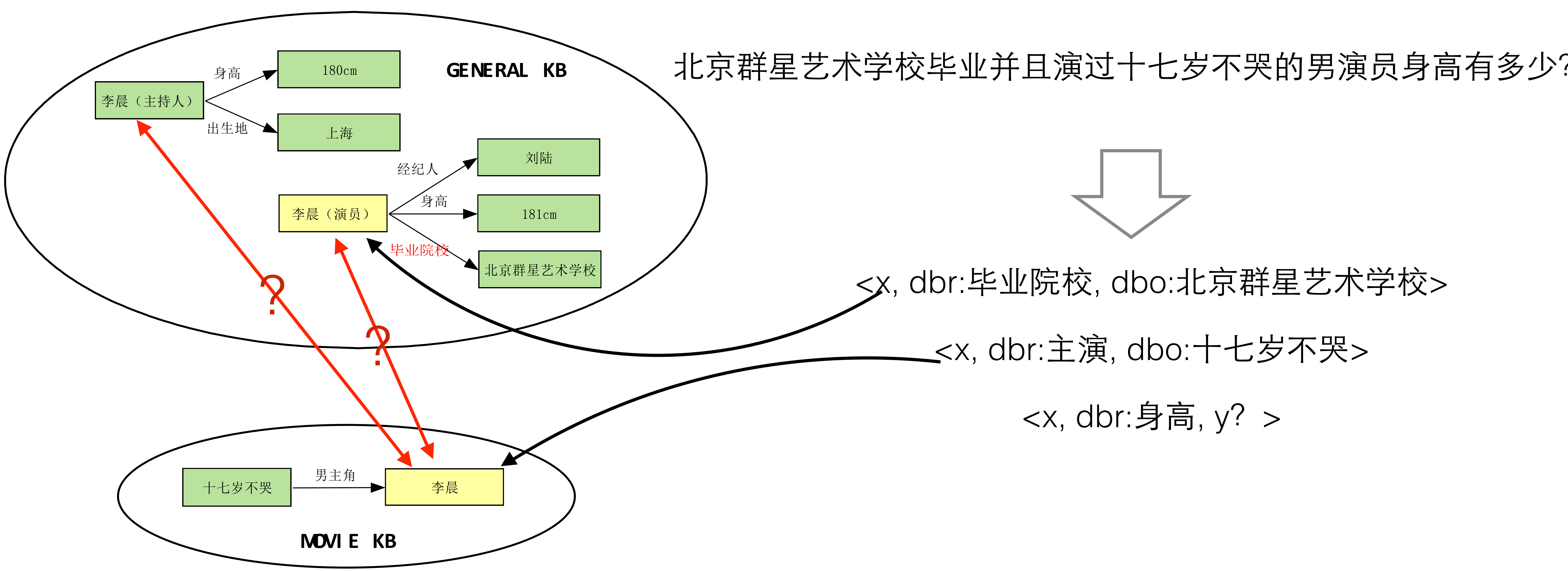
如何处理多知识库

- Pipeline: 先对齐、再问答
  - 问题：
    - 对齐有错误，错误会积累传递
    - 知识库是快速迭代更新的，对于问题的回答并不需要知识库中所有节点的对齐，只需要触发一个子图



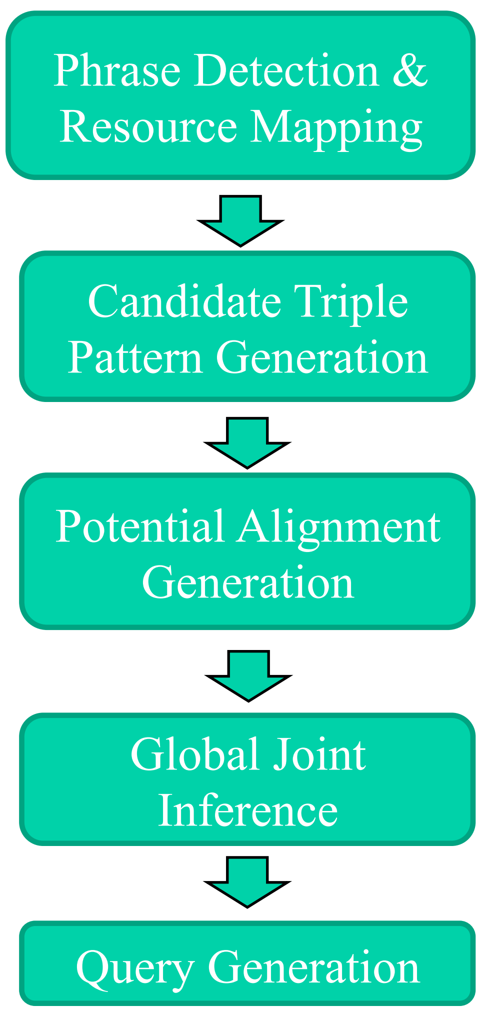
Motivation

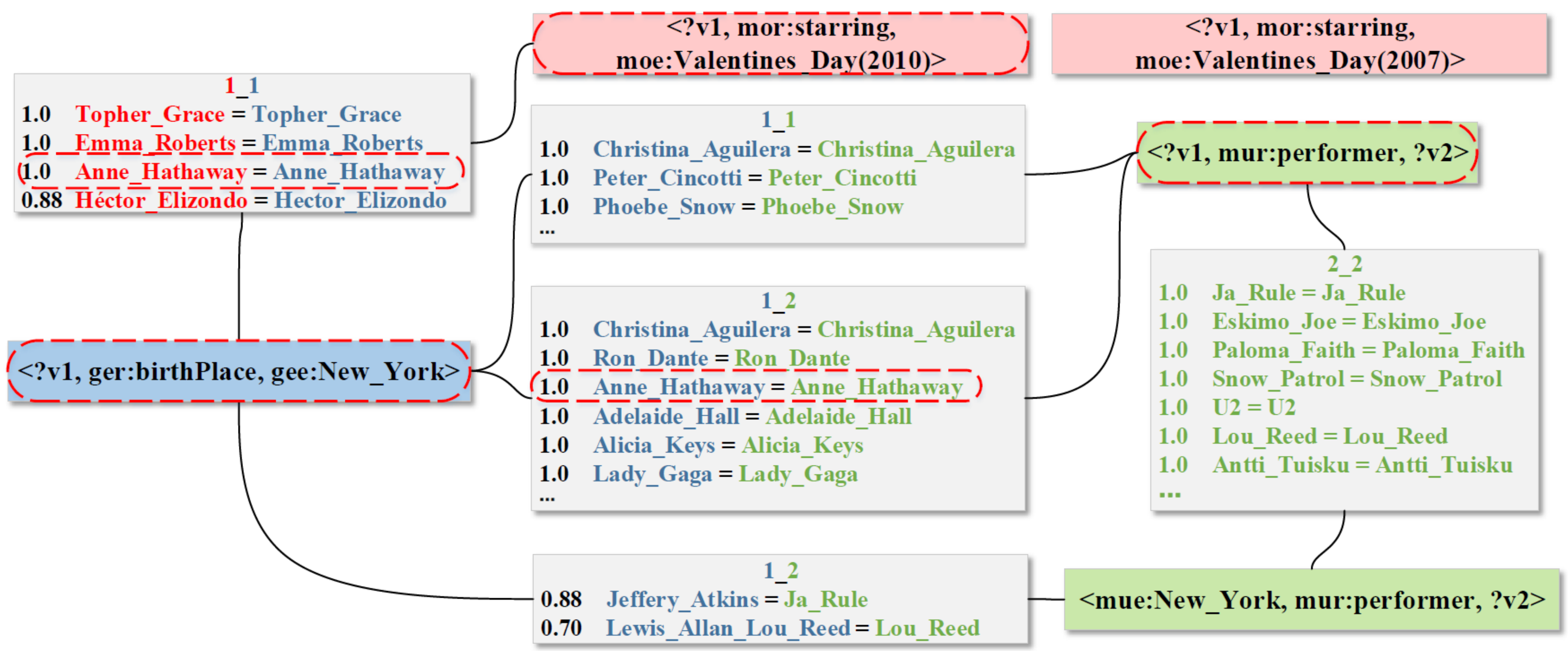
- 联合模型
  - 知识库对齐的结果影响问句分析
  - 问句的分析结果对于知识库对齐有影响



Joint Model

- 问句语义解析 and 知识库对齐
  - Integer Linear Programming





实验结果

Datasets	**Systems**	**P**	**R**	**F**
Benchmark	SINA	0.95	0.90	0.92
	Ours	**0.96**	**0.96**	**0.96**
QALD-4 TASK2	POMELO	0.82	0.87	0.85
	RO_FII	0.16	0.16	0.16
	Ours	**0.89**	**0.88**	**0.88**
Chinese	SINA	0.64	0.63	0.63
	Ours	**0.77**	**0.78**	**0.77**

Datasets (Method)	**QC**			**AC**
	P	R	F	P
benchmar (Pipe)	0.76	0.76	0.76	0.8
benchmark (Joint)	**0.96**	**0.96**	**0.96**	**0.92**
QALD-4 TASK2 (Pipe)	0.65	0.64	0.64	0.72
QALD-4 TASK2 (Joint)	**0.89**	**0.88**	**0.88**	**0.92**
Chinese (Pipe)	0.72	0.72	0.72	0.84
Chinese (Joint)	**0.77**	**0.78**	**0.77**	**0.94**

总结与展望

- 面向知识库问答的问答系统
- 知识表示：lambda演算、Prolog、…
- 面向大规模知识库的语义分析：
  - 词典学习
  - 消歧
  - 大规模：开放域信息抽取、联合语义消歧
- 面向多领域知识库的问答系统：
  - 联合学习：多知识库对齐+语义解析
- 知识库是非完备的
  - 需要知识推理

知识库不完备

- 不完备

Items	Baidu Baike		Hudong Baike		Chinese Wikipedia	
Resources	**3,234,950**		2,765,833		559,402	
~ that have abstracts	393,094	12.2%	469,009	17.0%	324,627	**58.0%**
~ that have categories	2,396,570	74.1%	912,627	33.0%	314,354	56.2%
~ that have infoboxes	56,762	1.8%	197,224	**7.1%**	24,398	4.4%
Categories	[illegible]		[illegible]		[illegible]	
Properties	**13,226**		474		2,304	
		per res.		per res.		per res.
Article Categories	6,774,442	**2.09**	2,067,349	0.75	796,679	1.42
External Links	2,529,364	0.78	827,145	0.30	573,066	**1.02**
Images	2,593,856	**0.80**	1,765,592	0.64	221,171	0.40
Infobox Properties	477,957	0.14	1,908,368	**0.69**	120,509	0.22
Internal Links	15,462,699	4.78	19,141,664	6.92	9,359,108	**16.73**
Related Pages	2,397,416	0.74	17,986,888	**6.50**	—	—
Aliases	—		—		**362,495**	
Disambiguation Links	28,937		13,733		**40,015**	
Redirects	97,680		37,040		**190,714**	

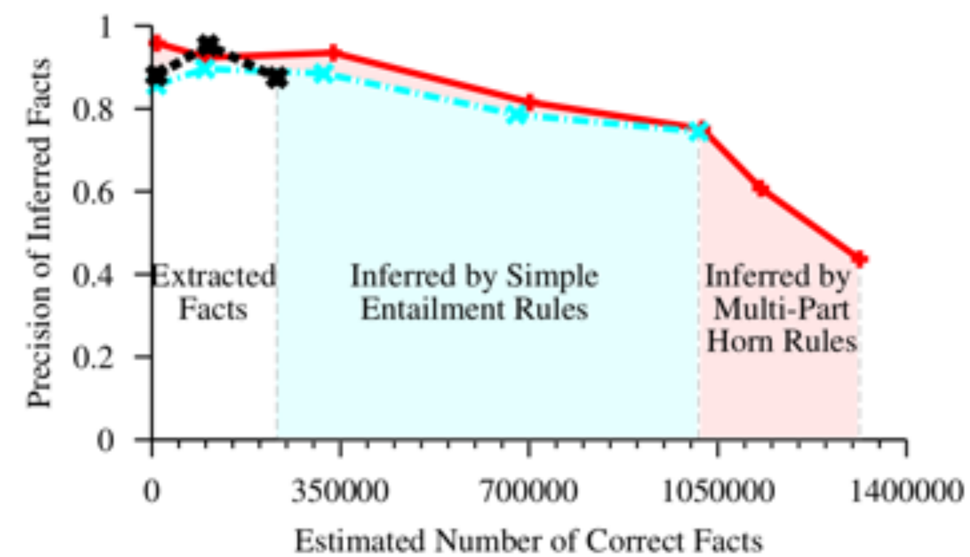
	实体数	关系数	三元组	平均实体关系数
Freebase	4千万	2万	6.37亿	15

需要知识推理技术

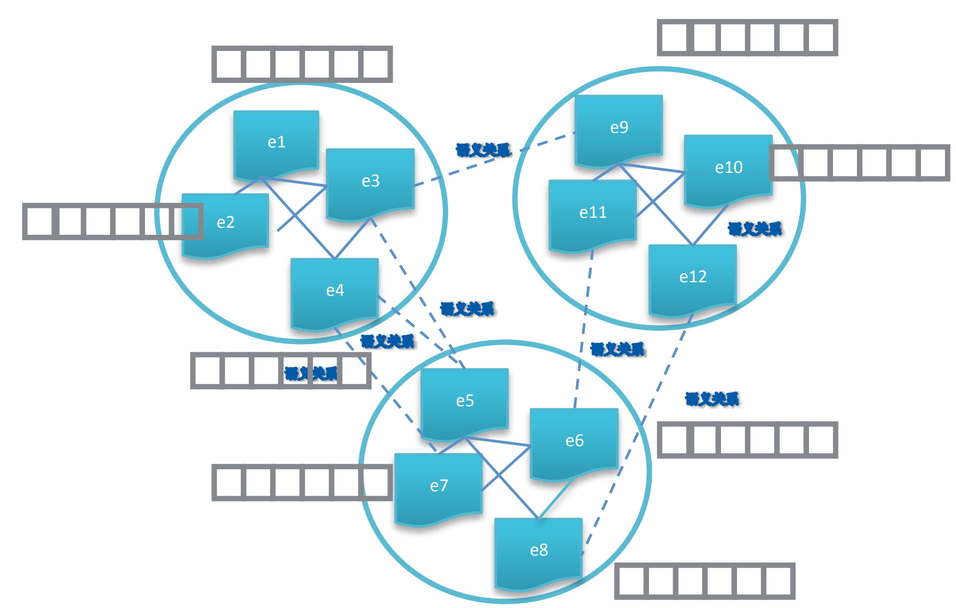
知识推理

- 逻辑推理
  - 人工规则不适用
  - 自动学习高阶规则性能差

Prevents(food,disease):IsHighIn(food,nutrient)∧Prevents(nutrient,disease)



- 基于表示学习的知识推理
  - 推理过程—>相似度计算



- 表示学习和逻辑推理相结合

Reference

[Zelle, 1995] J. M. Zelle and R. J. Mooney, “Learning to parse database queries using inductive logic programming,” in Proceedings of the National Conference on Artificial Intelligence, 1996, pp. 1050–1055.

[Wong, 2007] Y. W. Wong and R. J. Mooney, “Learning synchronous gram-mars for semantic parsing with lambda calculus,” in Proceedings of the 45th Annual Meeting-Association for computational Linguistics, 2007.

[Lu, 2008] W. Lu, H. T. Ng, W. S. Lee, and L. S. Zettlemoyer, “A generative model for parsing natural language to meaning representations,” in Proceedings of the 2008 Conference on Empirical Methods in Natural Language Processing, 2008, pp. 783–792.

[Zettlemoyer, 2005] L. S. Zettlemoyer and M. Collins, “Learning to map sentences to logical form: Structured classification with probabilistic categorial grammars,” in Proceedings of the 21st Uncertainty in Artificial Intelligence, 2005, pp. 658–666.

[Clarke, 2010] J. Clarke, D. Goldwasser, M.-W. Chang, and D. Roth, “Driving semantic parsing from the world’s response,” inProceedings of the 14th Conference on Computational Natural Language Learning, 2010, pp. 18–27

[Liang, 2011] P. Liang, M. I. Jordan, and D. Klein, “Learning dependency-based compositional semantics,” in Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies-Volume 1, 2011, pp. 590–599.

[Cai, 2013] Qingqing Cai and Alexander Yates. 2013. Large-scale semantic parsing via schema matching and lexicon extension. In ACL.

[Berant, 2013]Jonathan Berant, Andrew Chou, Roy Frostig, and Percy Liang. 2013. Semantic parsing on freebase from question-answer pairs. In EMNLP.

[Yao, 2014] Xuchen Yao and Benjamin Van Durme. 2014. Information extraction over structured data: Question answering with freebase. In ACL.

[Unger, 2012] Christina Unger, Lorenz B¨ uhmann, Jens Lehmann, Axel-Cyrille Ngonga Ngomo, Daniel Gerber, and Philipp Cimiano. 2012. Template-based question answering over rdf data. In WWW.

[Yahya, 2012]Mohamed Yahya, Klaus Berberich, Shady Elbas-suoni, Maya Ramanath, Volker Tresp, and Gerhard Weikum. 2012. Natural language questions for the web of data. In EMNLP.

[He, 2014] S. He, K. Liu, Y. Zhang, L. Xu, and J. Zhao. 2014. Question answering over linked data using first-order logic. In EMNLP.

[Artzi, 2011]Y. Artzi and L. Zettlemoyer. 2011. Bootstrap-ping semantic parsers from conversations. In Empirical Methods in Natural Language Processing (EMNLP), pages 421–432. Dan Goldwasser, Roi Reichart, James Clarke and Dan Roth. Confidence Driven Unsupervised Semantic Parsing. Proceedings of ACL (2011)

[Krishnamurthy, 2012] Jayant Krishnamurthy and Tom M. Mitchell. Weakly Supervised Training of Semantic Parsers. In Proceedings of the 2012 Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning (EMNLP-CoNLL), 2012

[Reddy, 2014] S. Reddy, M. Lapata, and M. Steedman. 2014. Large-scale semantic parsing without question-answer pairs. Transactions of the Association for Compu-tational Linguistics (TACL), 2(10):377–392.

[Fader, 2013] A. Fader, L. S. Zettlemoyer, and O. Etzioni, “Paraphrase-driven learning for open question answering.” in Proceedings of the 51th Annual Meeting-Association for computational Linguistics, 2013, pp. 1608–1618.

[Borders, 2014] Antoine Bordes, Sumit Chopra, and Jason Weston. 2014. Question answering with subgraph embed-dings. InProceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 615–620. Association for Computational Linguistics.

[Zeng, 2014] Daojian Zeng, Kang Liu, Siwei Lai, Guangyou Zhou and Jun Zhao. Relation Classification via Convolutional Deep Neural Network, in *Proceedings of COLING 2014*, Dublin, Ireland, August, 23-29 (Best Paper Award)

谢谢! Q&A!