



知识图谱前沿动态综述

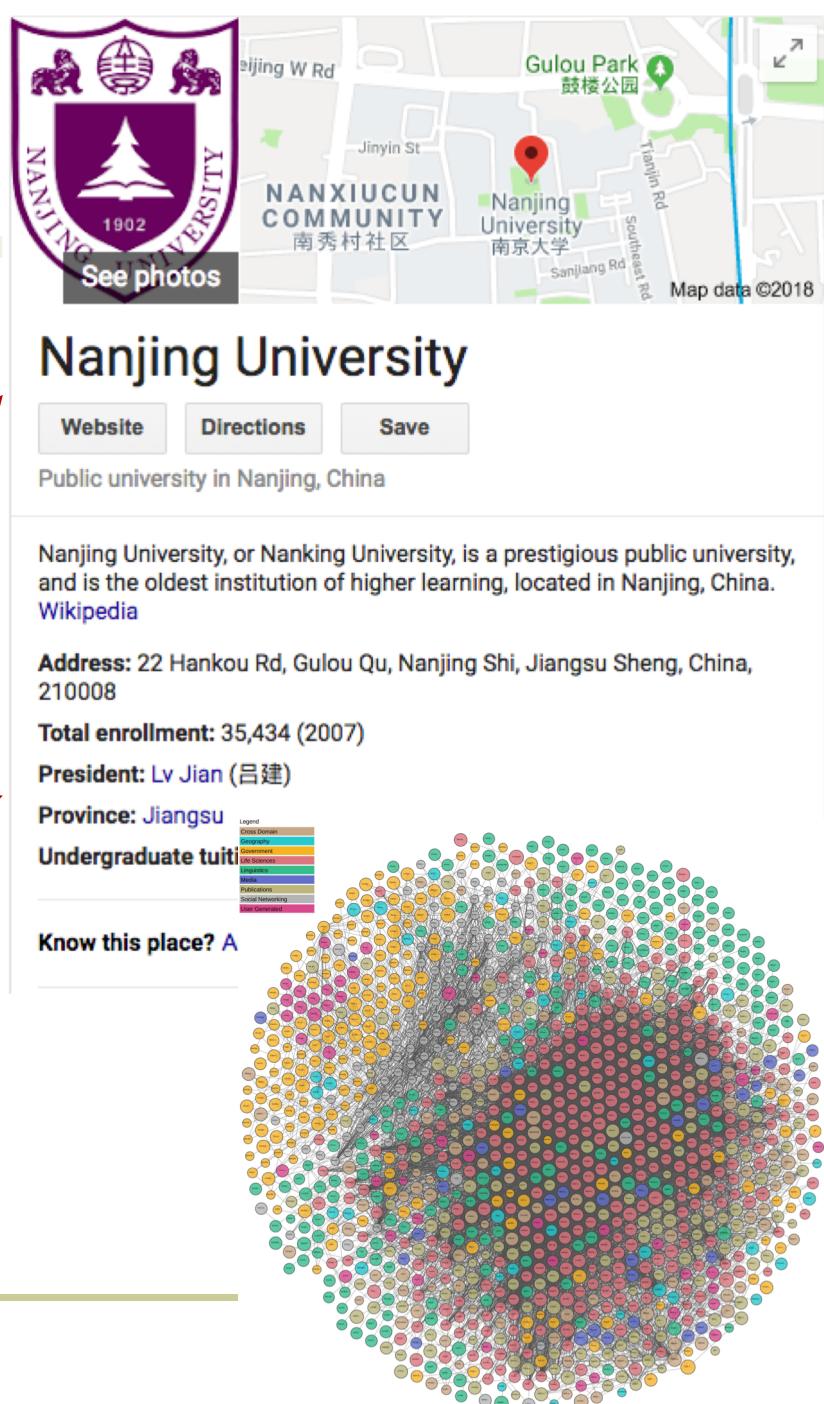
胡伟

Home: <http://ws.nju.edu.cn/~whu> E-mail: whu@nju.edu.cn

南京大学 计算机软件新技术国家重点实验室

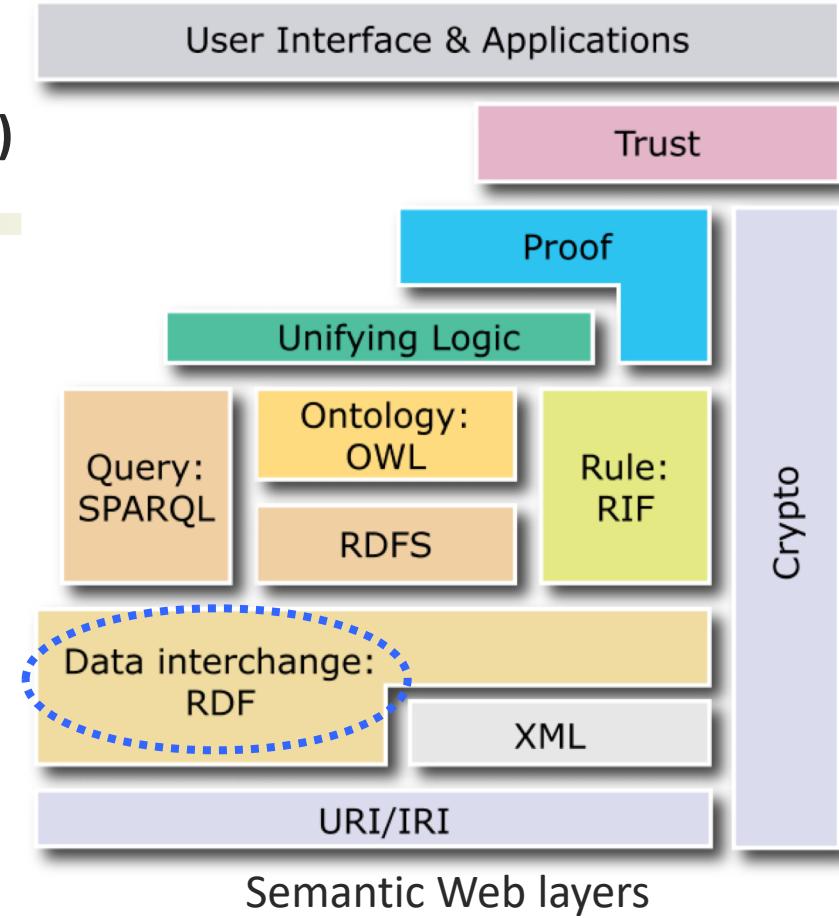
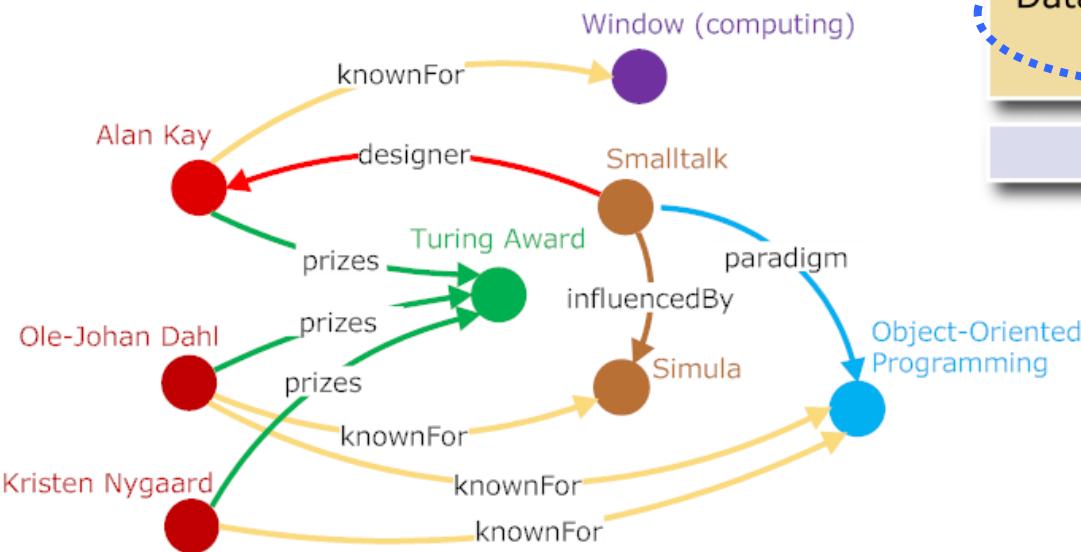
知识图谱

- 知识图谱于2012年5月由Google正式提出，其初衷是为了提高搜索引擎的能力，改善用户的搜索质量以及搜索体验
 - Node: entity / concept
 - Edge: attribute / relationship
- Other famous knowledge bases
 - DBpedia, Freebase, Wikidata, YAGO, WordNet, Probable ...
 - Linked Open Data (LOD) cloud



RDF (Resource Description Framework)

■ RDF三元组

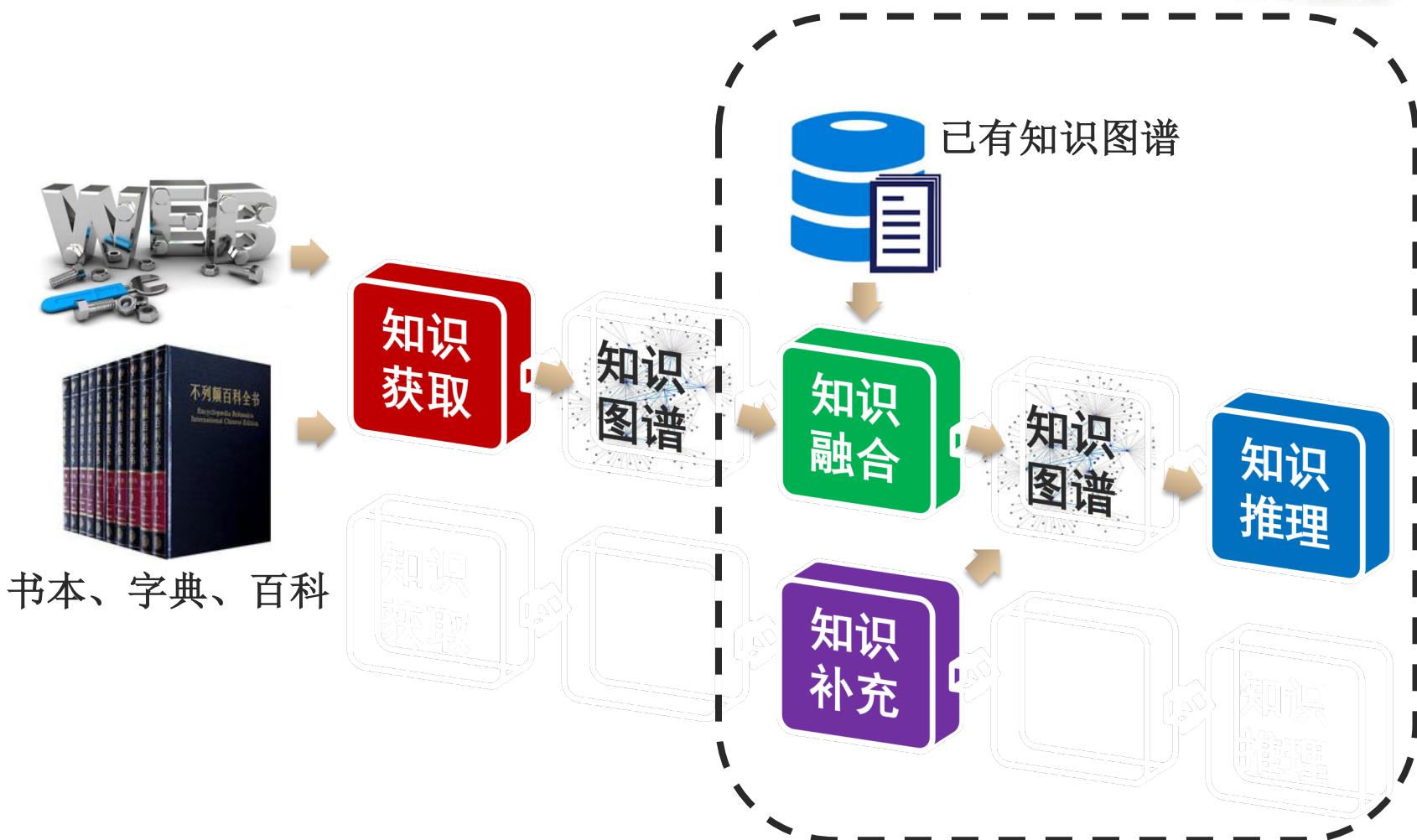


Semantic Web layers



*“The world is **not**
made of strings, but
is made of **things**”*

知识图谱研究框架



调研



■ 知识补充

1. T. Dettmers, P. Minervini, P. Stenetorp, S. Riedel. Convolutional 2D Knowledge Graph Embeddings. In: **AAAI 2018**
2. J. Lajus, F.M. Suchanek. Are All People Married? Determining Obligatory Attributes in Knowledge Bases. In: **WWW 2018**
3. P. Mirza, S. Razniewski, F. Darari, G. Weikum. Enriching Knowledge Bases with Counting Quantifiers. In: **ISWC 2018**

■ 知识融合

1. Z. Sun, W. Hu, Q. Zhang, Y. Qu. Bootstrapping Entity Alignment with Knowledge Graph Embedding. In: **IJCAI 2018**
2. P. Kolyvakis, A. Kalousis, D. Kiritidis. DeepAlignment: Unsupervised Ontology Matching with Refined Word Vectors. In: **NAACL-HLT 2018**

■ 知识推理

1. P.G. Omran, K. Wang, Z. Wang. Scalable Rule Learning via Learning Representation. In: **IJCAI 2018**

提纲

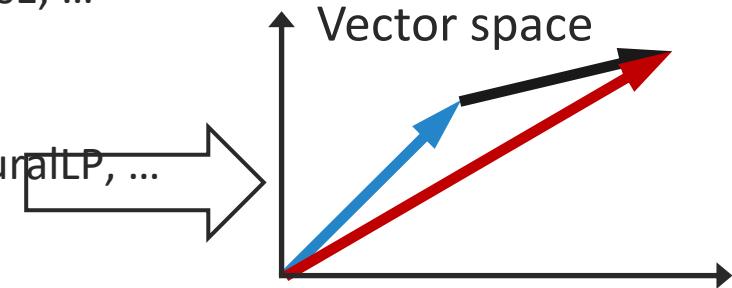


- 知识补充
- 知识融合
- 知识推理

知识补充



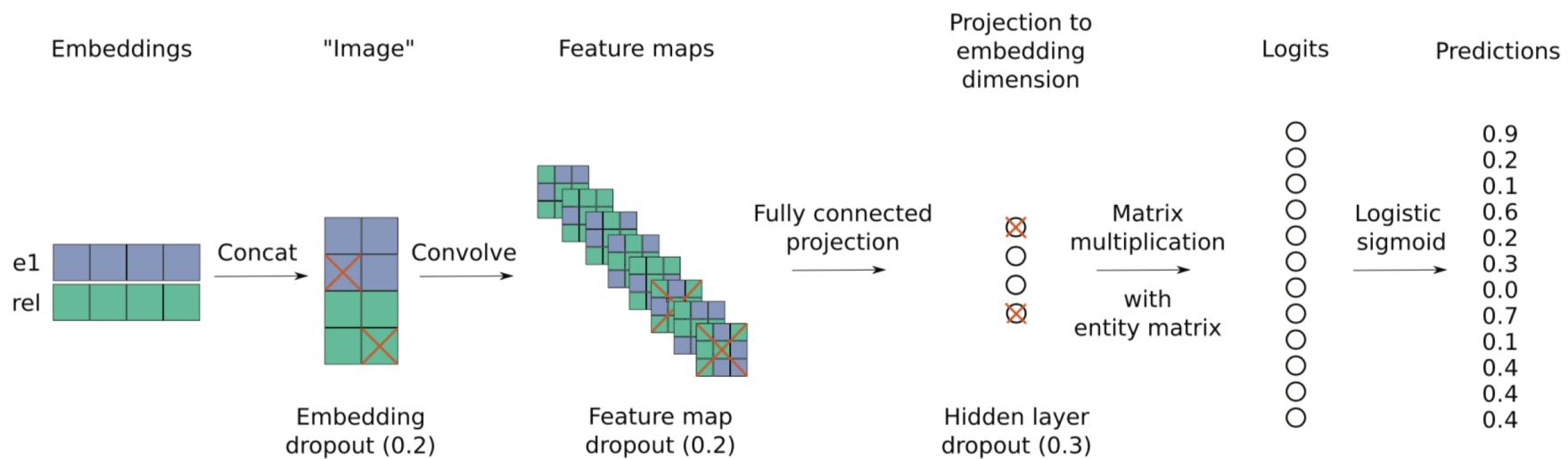
- 问题：现有知识图谱依然不完备
- 任务：**entity / link prediction**
 - given $(s, r, ?)$, complete a triple by predicting o // or s given $(?, r, o)$
- 方法：表示学习
 - 翻译模型（translational models）
 - TransE: model (s, r, o) as $s + r \approx o$
 - 后续改进: TransH, TransR, PTransE, ...
 - 语义模型
$$(\text{Washington}, \text{capitalOf}, \text{America}) \xrightarrow{\text{DISTMULT, ComplEx, NREat, NeuralTP, ...}} \bullet \bullet \bullet \bullet + \bullet \bullet \bullet \bullet \approx \bullet \bullet \bullet \bullet$$



Convolutional 2D Knowledge Graph Embeddings



- 方法: a multi-layer **convolutional** network model
 - 步骤 1 & 2: 变形并合并实体和关系embeddings
 - 步骤 3, 4 & 5: 输入卷积层, 将结果投影到一个 k 维空间, 匹配候选



- 效果: FB15K-237测试集上实验结果优异

知识补充

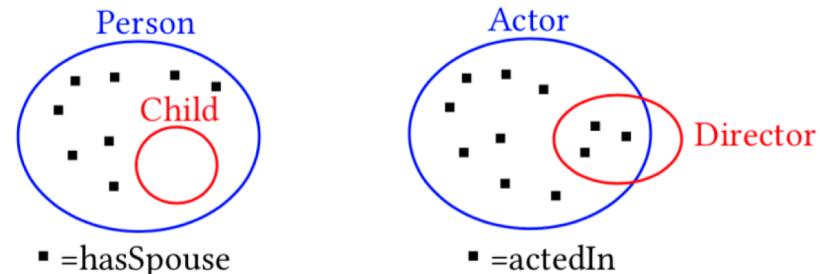


- 问题：现有知识图谱有待进一步挖掘
- 任务：**obligatory attributes (必要属性)**
 - Determine whether all instances of a given class have a given attribute in the real world – while all we have is an incomplete KB
 - *hasBirthDate* is an obligatory attribute for class *Person*, while *hasSpouse* is not
- 任务：**counting quantifiers (计数量词)**
 - Text often contains only counting information: the number of objects that stand in a specific relation with a certain entity, without mentioning the objects themselves
 - Given the sentence “*Trump has three sons and two daughters*”, the output for predicate *numberOfChildren* should be **5**.
 - Children CQ: Wikipedia 12%; name mentioned: 7%; Wikidata: 2.5%

Determining Obligatory Attributes in Knowledge Bases



- 问题：必要属性
- 挑战
 1. 数十万概念，难以人工判断；自动化处理很难，比如没有反例数据
 2. **开放世界假设：**无法判断一条没有包含在知识库中的三元组的真伪
- 方法
 - 基于概念层次结构来推断概念的必要属性
 - 基本假设
 - 假设知识库的不完全性在知识库中所有概念上都是**均匀分布**的
 - 如果一个属性在某个概念上分布较稀疏，而在其他概念上分布较稠密，则可以推断它一定不是分布较稀疏的概念的必要属性



$$s_p^K(c, c') = \frac{\text{conf}(c \setminus c' \subseteq p_K)}{\text{conf}(c \cap c' \subseteq p_K)}$$

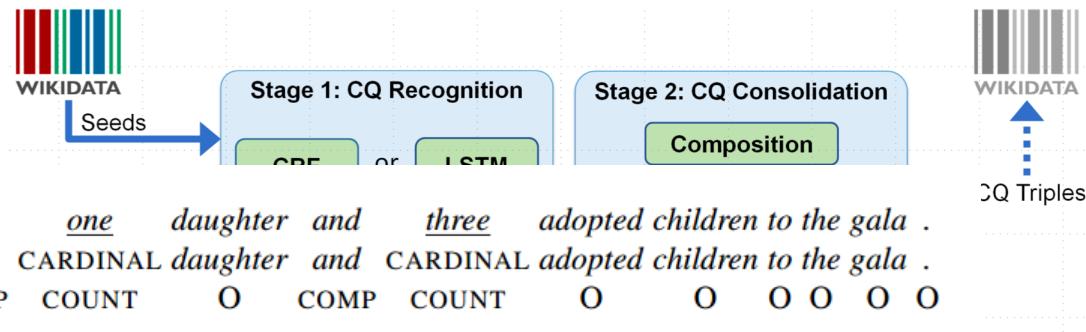
Enriching Knowledge Bases with Counting Quantifiers



- 问题: 计数量词
- 挑战: Non-maximal seeds; Sparse, skewed observations; Linguistic diversity
- 方法

○ 步骤 1: 识别CQ

sentence	Jolie brought her <u>twins</u> , <u>one</u> daughter and <u>three</u> adopted children to the gala .
pre-processed	Jolie brought her NUMTERM , CARDINAL daughter and CARDINAL adopted children to the gala .
output tags	O O O COUNT COMP COUNT O COMP COUNT O O O O O O



○ 步骤 2: 合并CQ

- l_1 : Angelina has a grand total of six_{0.4} children together: three_{0.3} biological [and]_{0.6} three_{0.5} adopted.
- l_2 : The arrival of the first_{0.5} biological child of Jolie and Pitt caused an excited flurry with fans.
- l_3 : On July 12, 2008, she gave birth to twins_{0.8}: a_{0.1} son, Knox Léon, [and]_{0.5} a_{0.2} daughter, Vivienne Marcheline.

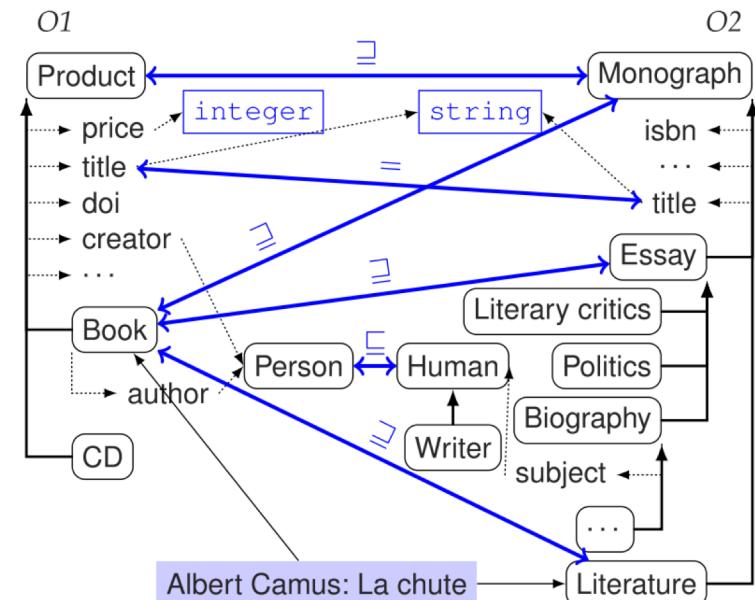
知识融合



- 问题：相似领域存在多个异构的知识图谱
- 任务：**实体对齐 & 本体匹配**
 - 实体对齐侧重发现指称真实世界相同对象的不同实例
 - 本体匹配侧重发现（模式层）等价或相似的类、属性或关系
- 流程
 - KB₁
 - Prior Alignment
 - KB₂
 - Alignment Process
 - Alignment Result

Parameters

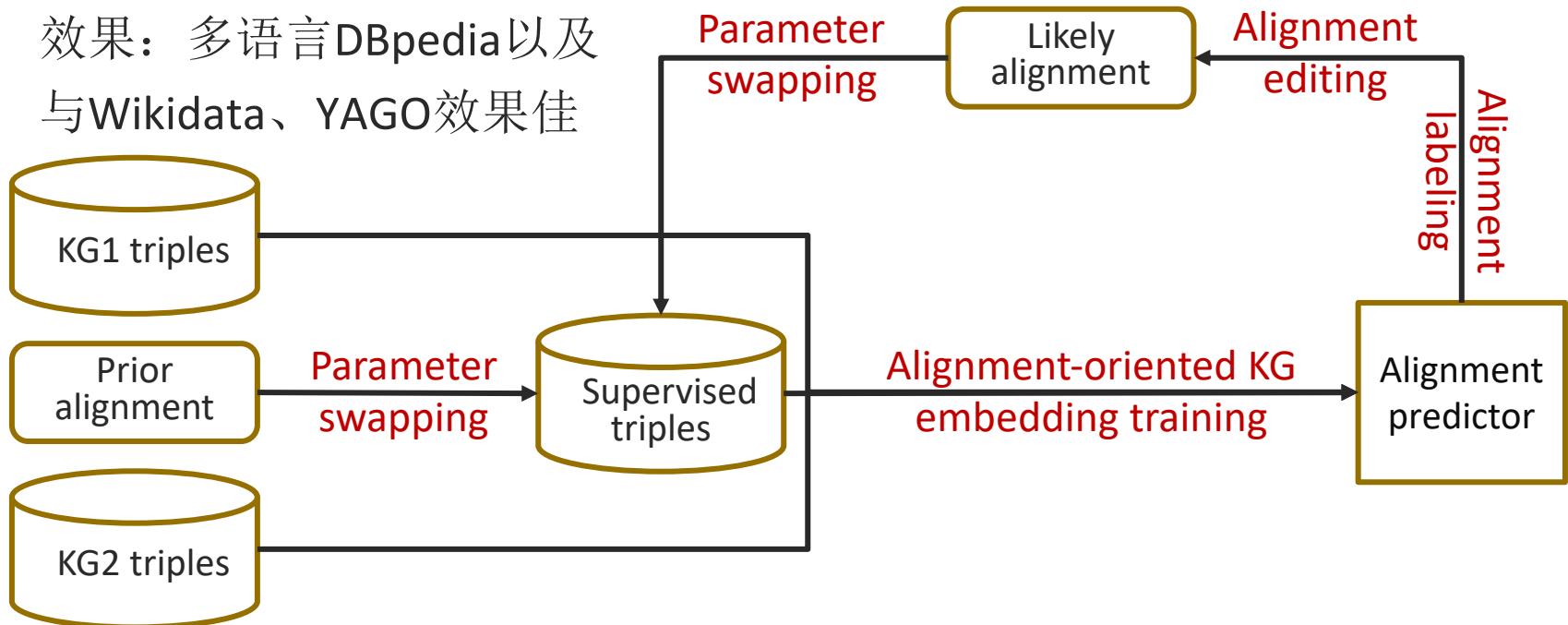
Resources
- 方法
 - 文本相似性：编辑距离、向量空间模型 ...
 - 结构相似性：子图匹配 ...



Bootstrapping Entity Alignment with KG Embedding



- 目标：通过embedding度量实体相似度
- 挑战：1) 面向对齐的知识图谱表示学习; 2) 已知的先验对齐数量少
- 方法：bootstrapping
- 效果：多语言DBpedia以及与Wikidata、YAGO效果佳



Unsupervised Ontology Matching with Refined Word Vectors



- 目标: 无监督表示学习
- 挑战: tailor word embeddings to the domains and ontologies
- 方法
 - Learn domain-specific word vectors
 - WordNet, PPDP, WikiSynonyms
 - 相似性度量: Dual embedding space model
 - Extend stable marriage algorithm
 - ε -optimal mappings: 补充少量多对多映射
- 效果
 - OAEI Conference 数据集
 - Schema.org – DBpedia alignment

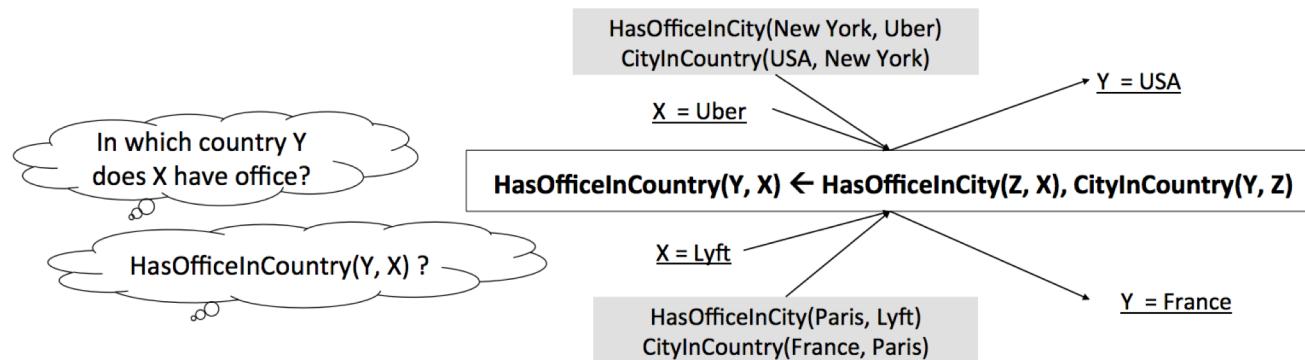
antonym repel
synonym attract
original word-vector distance

System	Precision	Recall	Micro-F1
DeepAlignment	0.71	0.80	0.75
CroMatch	0.76	0.69	0.72
AML	0.79	0.65	0.71
DeepAlignment _*	0.68	0.68	0.68
XMap	0.81	0.58	0.67
LogMap	0.79	0.58	0.66
LogMapBio	0.75	0.58	0.65
StringEquiv	0.83	0.50	0.62

知识推理



- 问题：谓词逻辑存在高效证明系统的子集包括描述逻辑和**规则系统**
- 任务：
 - 规则： $P_t(x, y) \leftarrow P_1(x, z_1) \wedge P_2(z_1, z_2) \wedge \cdots \wedge P_n(z_{n-1}, z_n)$
- 方法
 - 传统方法：归纳逻辑程序设计（*inductive logic programming*）
 - 例如，AMIE+
 - 统计预测模型：表示学习
- 应用
 - 问答
 - ...



Scalable Rule Learning via Learning Representation



- 目标：基于表示学习的规则学习
- 挑战：可伸缩性
- 方法
 - 采样：只包含和目标谓词相关的实体和事实
 - 表示学习 & 规则搜索
 - 评分函数：相似性和共现性
 - 规则评估：确信度和覆盖率
- 效果

Algorithm 1 Learn rules for a KG and a target predicate

Input: a KG K , a predicate P_t , an integer $len \geq 2$, and two real numbers $MinSC, MinHC \in [0, 1]$

Output: a set $Rules$ of CP rules

- 1: $K' := \text{Sampling}(K, P_t, len)$
- 2: $(\mathcal{P}, \mathcal{A}) := \text{Embeddings}(K')$
- 3: $Candidates := \emptyset$
- 4: **for** $2 \leq l \leq len$ **do**
- 5: Add $\text{RuleSearch}(K', P_t, \mathcal{P}, \mathcal{A}, l)$ to $Candidates$
- 6: **end for**
- 7: $Rules := \text{Evaluate}(Candidates, K)$
- 8: $Rules := \text{Filter}(Candidates, MinSC, MinHC)$
- 9: **return** $Rules$

KG	RLvLR			AMIE+		
	#R	#QR	Time	#R	#QR	Time
YAGO2s	6.3	1.8	0.96	5.65	0.5	10.00
DBpedia 3.8	42.7	9.2	3.88	9.05	0.5	4.59
Wikidata	56.8	25.6	2.41	0.95	0.3	10.00

Table 2: Rule mining comparison between RLvLR and AMIE+

KG	RLvLR		AMIE+	
	#Facts	#QFacts	#Facts	#QFacts
YAGO2s	1.1M	7K	0.27M	1
DBpedia 3.8	16.6M	162K	1.6M	1.8K
Wikidata	2.1M	99K	0.17M	4.6K

Table 3: The numbers of new facts predicted by RLvLR and AMIE+

总结



- 报告从知识补充、知识融合、知识推理三个方面介绍了知识图谱的前沿技术动态
- 报告还有很多未尽之处
 - 人机协作：众包、摘要
 - 机器学习：强化学习、生成对抗网络
 - 知识图谱应用：问答、推荐
 -

其他进展



- L. Cai, W.Y. Wang. [KBGAN: Adversarial learning for knowledge graph embeddings](#). In: **NAACL-HLT 2018**
- M. Chen, Y. Tian, M. Yang, C. Zaniolo. [MTransE: Multilingual knowledge graph embeddings for cross-lingual knowledge alignment](#). In: **IJCAI 2017**
- S. Guo, Q. Wang, L. Wang, B. Wang, L. Guo. [Knowledge graph embedding with iterative guidance from soft rules](#). In: **AAAI 2018**
- J. Huang, W. Hu, H. Li, Y. Qu. [Automated comparative table generation for facilitating human intervention in multi-entity resolution](#). In: **SIGIR 2018**
- Z. Wang, Q. Lv, X. Lan, Y. Zhang. [Cross-lingual knowledge graph alignment via graph convolutional networks](#). In: **EMNLP 2018**
- W. Xiong, T. Hoang, W.Y. Wang. [DeepPath: A reinforcement learning method for knowledge graph reasoning](#). In: **EMNLP 2017**
- H. Zhu, R. Xie, Z. Liu, M. Sun. [IPTransE: Iterative entity alignment via joint knowledge embeddings](#). In: **IJCAI 2017**
- Y. Zhuang, G. Li, Z. Zhong, J. Feng. [Hike: A hybrid human-machine method for entity alignment in large-scale knowledge bases](#). In: **CIKM 2017**



谢谢！

致谢

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