Making knowledge bases more complete

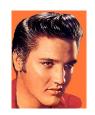
Wikimedia Showcase 2019-12-18

Fabian M. Suchanek Télécom Paris University, France

I am an Elvis Fan!



We visited Elvis in New Zealand





Elvis' lodge in Murchison



Apple Siri



Apple Siri

What is the capital of New Zealand? "Wellington"

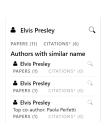


Amazon Echo

Discovered 6 kineasis proteins that relate to cancer



IBM Watson





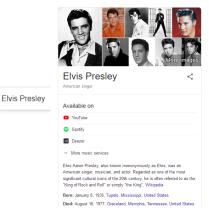


Microsoft Academic

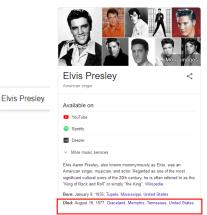
Ebay Knowledge Graph

Ebay Shopbot on Facebook Messenger

Google



Google Knowledge Graph



Google

Google Knowledge Graph

???

Knowledge Bases



For us, a knowledge base (KB) is a graph, where the nodes are entities and the edges are relations.

(We do not distinguish T-Box and A-Box.)

This talk

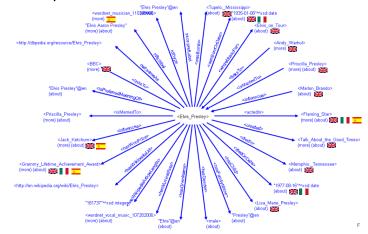


- 1. Constructing Knowledge Bases
- 2. Completing Knowledge Bases

Extracting from Wikipedia



Example: YAGO about Elvis



YAGO: a large knowledge base



http://yago-knowledge.org open code and open data

Wikipedia + WordNet time and space 10 languages 100 relations

100m facts

10m entities

95% accuracy used by DBpedia and TBM Watson

New version in preparation!







[WWW'07, JWS'08, WWW'11 demo, AII'13, WWW'13 demo, CIDR'15, ISWC'16]









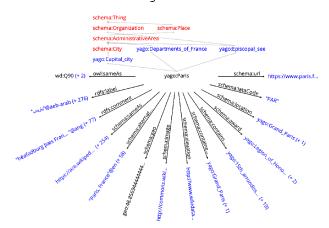






YAGO 4: A "reason-able" KB

YAGO 4 combines schema.org + Wikidata + constraints

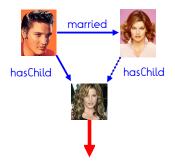


This talk



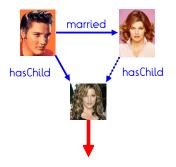
- 1. Constructing Knowledge Bases ✓
- 2. Completing Knowledge Bases

Incompleteness: Concrete facts



 $married(x,y) \land hasChild(x,z) \Rightarrow hasChild(y,z)$

Incompleteness: Concrete facts



 $married(x,y) \land hasChild(x,z) \Rightarrow hasChild(y,z)$

But: Rule mining needs counter examples and RDF ontologies are positive only

Partial Completeness Assumption



Assumption: If we know $r(x,y_1),..., r(x,y_n)$, then all other r(x,z) are false.

Partial Completeness Assumption



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If we know $r(x,y_1),..., r(x,y_n)$, then all other r(x,z) are false.

Partial Completeness Assumption



Assumption:

If we know $r(x,y_1),..., r(x,y_n)$, then all other r(x,z) are false.

AMIE finds rules in knowledge bases



AMIE is based on an efficient in-memory database implementation.

Caveat: rules cannot predict the unknown with high precision

AMIE finds rules in knowledge bases





New version in preparation!













the quality of YAGO w ls a precision of 95%, as iks to our brilliant algori

© Girl Happy 23





the quality of YAGO w ls a precision of 95%, as iks to our brilliant algori



© Girl Happy 24



the quality of YAGO w ls a precision of 95%, as iks to our brilliant algori



Given a subject s and a relation r, do we know all o with r(s,o) ?

© Girl Happy

Signals for Incompleteness



Closed World Assumption Partial Completeness Assumption Popularity oracle No-change oracle Star-pattern oracle Class-oracle

AMIE oracle: Learn rules such as $moreThan_1(x, hasParent) \Rightarrow complete(x, hasParent)$



Signals for Incompleteness (F1)

Relation	CWA	PCA	$card_2$	Popularity	No change	Star	Class	AMIE	
diedIn	60%	22%		4%	15%	50%	99%	96%	-
directed	40%	96%	19%	7%	71%	0%	0%	100%	
graduatedFrom	89%	4%	2%	2%	10%	89%	92%	87%	
hasChild	71%	1%	1%	2%	13%	40%	78%	78%	
hasGender	78%	100%	_	2%	_	86%	95%	100%	١.
hasParent*	1%	54%	100%	_	_	0%	0%	100%	У
isCitizenOf*	4%	98%	11%	1%	4%	10%	5%	100%	
isConnectedTo	87%	34%	19%			68%	88%	89%	
isMarriedTo*	55%	7%	0%	3%	12%	37%	57%	46%	
wasBornIn	28%	100%		5%	8%	0%	0%	100%	



Relation	CWA	PCA	\mathbf{card}_2	Popularity	Star	Class	AMIE
alma_mater	90%	14%	5%	1%	87%	87%	87%
brother	93%	1%	_	1%	94%	96%	96%
child	70%	1%	_	1%	79%	72%	73%
country_of_citizenship*	42%	97%	10%	3%	0%	0%	98%
director	81%	100%	_	3%	94%	89%	100%
father*	5%	100%	6%	9%	89%	8%	100%
mother*	3%	100%	3%	10%	67%*	5%	100%
place_of_birth	53%	100%	7%	5%	55%	0%	100%
place_of_death	89%	35%	1%	2%	81%	81%	96%
sex_or_gender	81%	100%	6%	3%	92%	91%	100%
spouse*	57%	7%	_	1%	54%	54%	55%



• = biased training sample



AMIE can predict incompleteness

•born In: 100% F1-measure

•diedIn: 96%

•directed: 100%

• graduatedFrom: 87%

hasChild: 78%isMarriedTo: 46%

... and more.



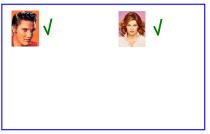




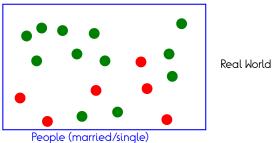


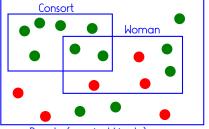
[WSDM 2017]

>rep&married >married



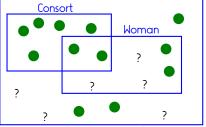






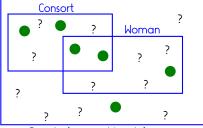
Real World

People (married/single)



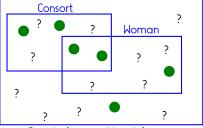
People (married/single)

Knowledge base under the Open World Assumption



People (married/single)

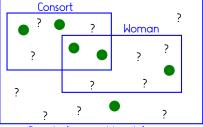
Knowledge base under the Open World Assumption and incompleteness



People (married/single)

Knowledge base under the Open World Assumption and incompleteness

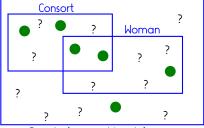
Baseline 1: Obligatory if all instances have it



Knowledge base under the Open World Assumption and incompleteness

People (married/single)

Baseline 1: Obligatory if all instances have it X
Baseline 2: Obligatory if at least n% of instances have it

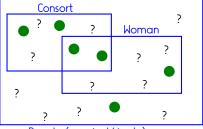


Knowledge base under the Open World Assumption and incompleteness

People (married/single)

Baseline 1: Obligatory if all instances have it X
Baseline 2: Obligatory if at least n% of instances have it =>Woman
Baseline 3: Obligatory if all instances that have it fall in the class

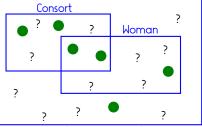




Knowledge base under the Open World Assumption and incompleteness

People (married/single)

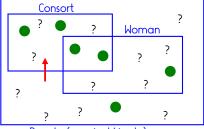
Baseline 1: Obligatory if all instances have it X
Baseline 2: Obligatory if at least n% of instances have it =>Woman
Baseline 3: Obligatory if all instances that have it fall in the class
=>Person X



Knowledge base under the Open World Assumption and incompleteness

People (married/single)

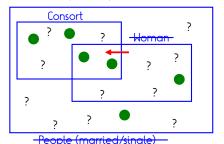
Theorem: If the KB is sampled randomly uniformly from the real world, and if the density of an attribute changes when we go into an intersecting class, then the attribute cannot be obligatory.



Knowledge base under the Open World Assumption and incompleteness

People (married/single)

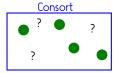
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Knowledge base under the Open World Assumption and incompleteness

Theorem: If the KB is sampled randomly uniformly from the real world, and if the density of an attribute changes when we go into an intersecting class, then the attribute cannot be obligatory.

Determining obligatory attributes



We can predict obligatory attributes of classes with up to 80% precision (at 40% recall).





Caveat: We do not actually predict, but exclude.





[WWW 2018]

≻rep

Incompleteness: Missing entities

We have the following cities in our knowledge base:



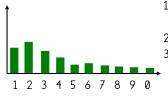
Are there any cities missing?

Incompleteness: Missing entities

We have the following cities in our knowledge base:



Are there any cities missing?



- 1) Take the number of inhabitants of each city
- 2) Take the first digit
- Plot the number of cities per first digit

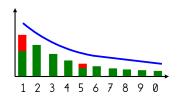
Incompleteness: Missing entities

Benford's law says that the first digit d appears with probability

$$log_{\scriptscriptstyle 10}(1+rac{1}{d})$$

=> We can give a minimum numbers of cities that are missing to make the distribution representative of the real world.

(For other classes, we can learn a parameter for a variant of the law.)











[ISWC 2018]



This talk



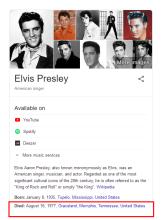
- 1. Constructing Knowledge Bases \checkmark
- 2. Completing Knowledge Bases \checkmark

Is Elvis dead?



???

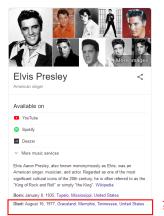
Is Elvis dead?





???

Is Elvis dead?





100m statements 95% accuracy -> 5m wrong statements

???

Knowledge Bases



- 1. Constructing Knowledge Bases \checkmark
- 2. Completing Knowledge Bases \checkmark