KNOWLEDGE GRAPH IDENTIFICATION

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Overview

Problem: Build a Knowledge Graph from millions of noisy extractions

Method:

Use probabilistic soft logic to easily specify models and efficiently optimize them Approach: **Knowledge Graph Identification** reasons jointly over all facts in the knowledge graph

Results:

State-of-the-art performance on real-world datasets producing knowledge graphs with millions of facts

CHALLENGES IN KNOWLEDGE GRAPH CONSTRUCTION

Motivating Problem: New Opportunities



Motivating Problem: Real Challenges



NELL: The Never-Ending Language Learner

NELL @cmunell True or False? *kevn tv* is a #TVStation (bit.ly/18JQ8gs) Expand	1 Oct
NELL @cmunell True or False? "metro-Atlanta" is a #County (bit.ly/1hhsefi) Expand	1 Oct
NELL @cmunell True or False? "exclusive right" is an #Artery (bit.ly/1bZq2LA) Expand	1 Oct
NELL ©cmunell True or False? "Fireplace" is #SomethingFoundInOrOnBuildings (bit.ly/17E1JhW) Expand	1 Oct s • More
NELL @cmunell True or False? "will_whalen" is an #AustralianPerson (bit.ly/1fUz Expand	1 Oct zRdT)
NELL @cmunell True or False? "iron_chair" is a #HouseholdItem (bit.ly/14ZsCNI Expand	30 Sep k)
NELL @cmunell	30 Sep

True or False? "jerry gordon" is a #Chef (bit.ly/19Ry4QN) Expand

- Large-scale IE project (Carlson et al., 2010)
- Lifelong learning: aims to "read the web"
- Ontology of known labels and relations
- Knowledge base contains millions of facts

person

- monarch
- astronaut
- personbylocation
 - personnorthamerica
 - personcanada
 - personus
 - politicianus
 - personmexico
 - personeurope
 - personaustralia
- personafrica
- personsouthamerica
- personasia
- personantarctica
 visualartist
- visuala
 model
- scientist
- iournalist
- female
- actor
- professor
- director
- architect
- politician
- politicianus
- musician
- athlete
- chefmale
- writer
- ceo
- judge
- mlauthor
- coach
- celebrity
- comedian
- criminal

Examples of NELL errors

Entity co-reference errors

Kyrgyzstan has many variants:

- Kyrgystan
- Kyrgistan
- Kyrghyzstan
- Kyrgzstan
- Kyrgyz Republic

Saudi Cultural Days in the Kyrgyz Republic has concluded its activities in the capital Bishkek in the weekend in a special ceremony held on this occasion. The event was attended by Deputy Minister of Culture and Tourism of the Kyrgyz Republic Koulev Mirza; Kyrgyzstan's Ambassador to Saudi Arabia Jusupbek Sharipov; the Saudi Embassy Acting Chargé d'affaires to Kyrgyzstan, Mari bin Barakah Al-Derbas and members of the embassy staff, in the presence of a heavy turnout of Kyrgyz citizens.

The Days of Culture of Saudi Arabia in Kyrgyzstan will be held from 6 to 9 May.

Home > Holiday Destinations > Kyrghyzstan > Bishkek > Climate Profile

🧭 Fast Forecast

Holiday Weather

Refugees are often from areas where conflict is historically embedded and marked in ideology and injustice. The Tsarnaev family emigrated from the Chechen diaspora in Kyrgzstan, a region Stalin deported the Chechens to in 1943. After the fall of the Berlin Wall in 1991, Chechens engaged in a battle for independence from Russia that led to the Tsarnaevs' petition for refugee status in the early

Missing and spurious labels

Anssi Kullberg has sent along some great trip reports to unusual places, including Kyrgyzstan, Pakistan, Egypt/Jordan, and Afghanistan. I had to create a whole new country page for Afghanistan to hold that last one! Thanks so much, Anssi!

Erik Kleyheeg has just returned from Lesvos with some new bird images. Included here are: <u>Common</u> <u>Scops-Owl</u>, <u>Wood Warbler</u>, <u>Spanish Sparrow</u>, <u>Red-</u> <u>throated Pipit</u>, <u>Eurasian Chiff-chaff</u>, and <u>Cretzschmar's</u> <u>Bunting</u>. Kyrgyzstan is labeled a bird and a country

Куrgyzstan (/kȝrgɪ'stɑːn/ kur-gi-sтани;^[5] Куrgyz: Кыргызстан (IPA: [qшrвшs'stɑn]); Russian: Киргизия), officially the Kyrgyz Republic (Kyrgyz: Кыргыз Республикасы; Russian: Кыргызская Республика), is a country located in Central Asia.^[6] Landlocked and mountainous, Kyrgyzstan is bordered by Kazakhstan to the north, Uzbekistan to the west, Tajikistan to the southwest and China to the east. Its capital and largest city is Bishkek.

Missing and spurious relations

Guidance

Kazakhstan / Kyrgyzstan – Consular Fees

Organisation:Foreign & Commonwealth OfficePage history:Published 4 April 2013

Kyrgyzstan's location is ambiguous – Kazakhstan, Russia and US are included in possible locations

Kyrgyzstan U.S. Air Base Future Unclear

A Central Asian country of incredible natural beauty and proud nomadic traditions, most of Kyrgyzstan was formally annexed to Russia in 1876. The Kyrgyz staged a major revolt against the Tsarist Empire in 1916 in which almost one-sixth of the Kyrgyz population was killed. Kyrgyzstan became a Soviet republic in 1936 and

Violations of ontological knowledge

- Equivalence of co-referent entities (sameAs)
 - SameEntity(Kyrgyzstan, Kyrgyz Republic)
- Mutual exclusion (disjointWith) of labels
 - MUT(bird, country)
- Selectional preferences (domain/range) of relations
 - RNG(countryLocation, continent)

Enforcing these constraints require **jointly** considering multiple extractions

KNOWLEDGE GRAPH IDENTIFICATION

Motivating Problem (revised)



Knowledge Graph Identification



Solution: Knowledge Graph Identification (KGI)

- Performs graph identification:
 - entity resolution
 - collective classification
 - link prediction
- Enforces ontological constraints
- Incorporates multiple uncertain sources

Illustration of KGI: Extractions

Uncertain Extractions: .5: Lbl(Kyrgyzstan, bird) .7: Lbl(Kyrgyzstan, country) .9: Lbl(Kyrgyz Republic, country) .8: Rel(Kyrgyz Republic, Bishkek, hasCapital)

Illustration of KGI: Extraction Graph



Illustration of KGI: Ontology + ER



Illustration of KGI



MODELING KNOWLEDGE GRAPH IDENTIFICATION



Background: Probabilistic Soft Logic (PSL)

- Templating language for hinge-loss MRFs, very scalable!
- Model specified as a collection of logical formulas

SAMEENT $(E_1, E_2) \land \operatorname{LBL}(E_1, L) \Rightarrow \operatorname{LBL}(E_2, L)$

- Uses soft-logic formulation
 - Truth values of atoms relaxed to [0,1] interval
 - Truth values of formulas derived from Lukasiewicz t-norm

Background: PSL Rules to Distributions

- Rules are grounded by substituting literals into formulas
- $\mathbf{w_{EL}} : SAMEENT(Kyrgyzstan, Kyrygyz Republic) \tilde{\wedge} \\ LBL(Kyrgyzstan, country) \Rightarrow LBL(Kyrygyz Republic, country)$
 - Each ground rule has a weighted distance to satisfaction derived from the formula's truth value

$$P(G | E) = \frac{1}{Z} \exp\left[-\sum_{r \in R} w_r \varphi_r(G)\right]$$

 The PSL program can be interpreted as a joint probability distribution over all variables in knowledge graph, conditioned on the extractions

Background: Finding the best knowledge graph

- MPE inference solves $\max_{G} P(G)$ to find the best KG
- In PSL, inference solved by convex optimization
- Efficient: running time scales with O(|R|)

PSL Rules for the KGI Model

PSL Rules: Uncertain Extractions



PSL Rules: Entity Resolution

 $\mathbf{w_{EL}} : \mathrm{SAMEENT}(E_1, E_2) \tilde{\wedge} \mathrm{LBL}(E_1, L) \Rightarrow \mathrm{LBL}(E_2, L)$ $\mathbf{w_{ER}} : \mathrm{SAMEENT}(E_1, E_2) \tilde{\wedge} \mathrm{REL}(E_1, E, R) \Rightarrow \mathrm{REL}(E_2, E, R)$ $\mathbf{w_{ER}} : \mathrm{SAMEENT}(E_1, E_2) \tilde{\wedge} \mathrm{REL}(E, E_1, R) \Rightarrow \mathrm{REL}(E, E_2, R)$

ER predicate captures confidence that entities are co-referent

- Rules require co-referent entities to have the same labels and relations
- Creates an *equivalence class* of co-referent entities

PSL Rules: Ontology

Inverse:

 $\mathbf{w}_{\mathbf{O}}$: INV(R, S) $\tilde{\wedge}$ REL $(E_1, E_2, R) \Rightarrow$ REL (E_2, E_1, S)

Selectional Preference:

 $\mathbf{w_O}: \operatorname{DOM}(R, L) \qquad \tilde{\wedge} \operatorname{Rel}(E_1, E_2, R) \Rightarrow \operatorname{LBL}(E_1, L)$ $\mathbf{w_O}: \operatorname{RNG}(R, L) \qquad \tilde{\wedge} \operatorname{Rel}(E_1, E_2, R) \Rightarrow \operatorname{LBL}(E_2, L)$

Subsumption:

 $\mathbf{w_O}: \operatorname{SUB}(L, P) \qquad \tilde{\wedge} \operatorname{LBL}(E, L) \qquad \Rightarrow \operatorname{LBL}(E, P) \\ \mathbf{w_O}: \operatorname{RSUB}(R, S) \qquad \tilde{\wedge} \operatorname{REL}(E_1, E_2, R) \qquad \Rightarrow \operatorname{REL}(E_1, E_2, S)$

Mutual Exclusion:

 $\mathbf{w}_{\mathbf{O}}: \operatorname{MUT}(L_{1}, L_{2}) \quad \tilde{\wedge} \operatorname{LBL}(E, L_{1}) \quad \Rightarrow \quad \tilde{\neg} \operatorname{LBL}(E, L_{2})$ $\mathbf{w}_{\mathbf{O}}: \operatorname{RMUT}(R, S) \quad \tilde{\wedge} \operatorname{REL}(E_{1}, E_{2}, R) \quad \Rightarrow \quad \tilde{\neg} \operatorname{REL}(E_{1}, E_{2}, S)$

Adapted from Jiang et al., ICDM 2012

EVALUATION

Two Evaluation Datasets

	LinkedBrainz	NELL	
Description	Community-supplied data about musical artists, labels, and creative works	Real-world IE system extracting general facts from the WWW	
Noise	Realistic synthetic noise	Imperfect extractors and ambiguous web pages	
Candidate Facts	810K	I.3M	
Unique Labels and Relations	27	456	
Ontological Constraints	49	67.9K	

LinkedBrainz dataset for KGI



Mapping to FRBR/FOAF ontology			
DOM	rdfs:domain		
RNG	rdfs:range		
INV	owl:inverseOf		
SUB	rdfs:subClassOf		
RSUB	rdfs:subPropertyOf		
MUT	owl:disjointWith		

Adding noise to LinkedBrainz

Add realistic noise to LinkedBrainz data:

Error Type	Erroneous Data
Co-reference	User misspells artist
Label	User swaps artist and album fields
Relation	User omits or adds spurious albums for artist
Reliability	Gaussian noise on truth value of information

LinkedBrainz experiments

Comparisons:

BaselineUse noisy truth values as fact scoresPSL-ERONIYOnly apply rules for Entity ResolutionPSL-OntOnlyOnly apply rules for Ontological reasoningPSL-KGIApply Knowledge Graph Identification model

	AUC	Precision	Recall	FI at .5	Max FI
Baseline	0.672	0.946	0.477	0.634	0.788
PSL-EROnly	0.797	0.953	0.558	0.703	0.831
PSL-OntOnly	0.753	0.964	0.605	0.743	0.832
PSL-KGI	0.901	0.970	0.714	0.823	0.919

NELL Evaluation: two settings

Target Set: restrict to a subset of KG (jiang, ICDM12)

- Closed-world model
- Uses a target set: subset of KG
- Derived from 2-hop neighborhood
- Excludes trivially satisfied variables

Complete: Infer full knowledge graph



- Open-world model
- All possible entities, relations, labels
- Inference assigns truth value to each variable

NELL experiments:

Target Set

Task: Compute truth values of a target set derived from the evaluation data

Comparisons:

Baseline Average confidences of extractors for each fact in the NELL candidates

NELL Evaluate NELL's promotions (on the full knowledge graph)

MLN Method of (Jiang, ICDM12) – estimates marginal probabilities with MC-SAT

PSL-KGI Apply full Knowledge Graph Identification model

Running Time: Inference completes in 10 seconds, values for 25K facts

	AUC	FI
Baseline	.873	.828
NELL	.765	.673
MLN (Jiang, 12)	.899	.836
PSL-KGI	.904	.853

NELL experiments: Complete knowledge graph

Task: Compute a full knowledge graph from uncertain extractions

Comparisons:

NELL's strategy: ensure ontological consistency with existing KB

PSL-KGI Apply full Knowledge Graph Identification model

Running Time: Inference completes in 130 minutes, producing 4.3M facts

	AUC	Precision	Recall	FI
NELL	0.765	0.801	0.477	0.634
PSL-KGI	0.892	0.826	0.871	0.848

Conclusion

- Knowledge Graph Identification is a powerful technique for producing knowledge graphs from noisy IE system output
- Using PSL we are able to enforce global ontological constraints and capture uncertainty in our model
- Unlike previous work, our approach infers complete knowledge graphs for datasets with millions of extractions

Code available on GitHub:

https://github.com/lings/KnowledgeGraphIdentification

