Nonmonotonic Rule Learning from Knowledge Graphs

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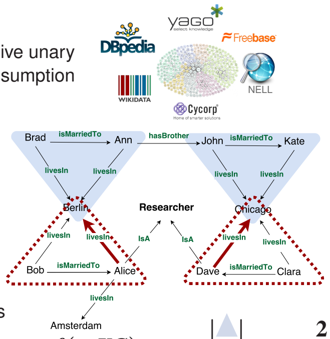
1. Motivation

- **Knowledge Graphs**: huge collections of positive unary and binary facts treated under **O**pen **W**orld **A**ssumption
  $isMarriedTo(alice, bob), researcher(mat)$
- Automatically constructed, thus **incomplete** / **inaccurate**
- Horn rule mining to **complete** / **clean** KGs e.g., [Galárraga, *et al.*, 2015]
- **But**: exceptions are not captured by Horn rules, thus erroneous predictions



- **Our aim:** mine rules with exceptions from KGs
- **Challenges:** **OWA**, **huge size** of KGs

$$conf(r, KG) = \frac{|\triangle|}{|\triangle| + |\triangle|} = \frac{2}{4}$$

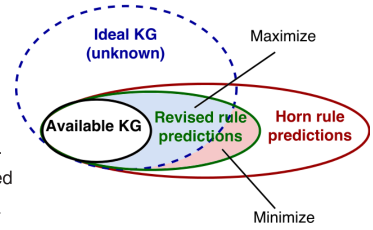
$$r: \ livesIn(X,Z) \leftarrow isMarriedTo(Y,X), livesIn(Y,Z)$$

- **Contributions:**
  - Quality-based Horn theory revision framework
  - Exception ranking method based on cross-talk among the rules
  - Experiments on real-world Knowledge Graphs

2. Quality-based Horn Theory Revision

Given:
- **Knowledge Graph**
- **Set of Horn rules**

Find:
- **Nonmonotonic rules revision**, s.t.
  - **average conviction** is maximized
    $$conv(r, KG) = \frac{1 - supp(r, KG)}{1 - conf(r, KG)}$$
  - number of **conflicting predictions** is minimized



$$livesIn(X,Z) \leftarrow isMarriedTo(Y,X), livesIn(Y,Z), not\ researcher(X)$$
$$not\_livesIn(X,Z) \leftarrow isMarriedTo(Y,X), livesIn(Y,Z), researcher(X)$$

$$livesIn(X,Z) \leftarrow bornIn(X,Z), not\ moved(X)$$
$$not\_livesIn(X,Z) \leftarrow bornIn(X,Z), moved(X)$$

$$\underbrace{\{livesIn(c,d), not\_livesIn(c,d)\}}_{\text{conflicting predictions}}$$

3. Approach Overview

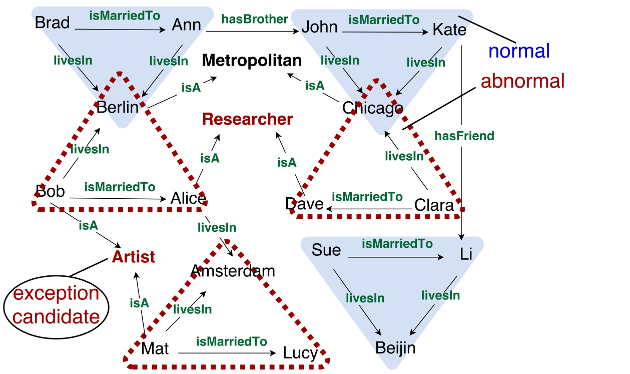
Step 1: Mine predictive association rules in the form of Horn clauses

Step 2: Determine normal and abnormal substitutions for every rule

Step 3: Compute exception candidates for every rule

Step 4: Rank exception candidates and select the best one per rule

4. (Ab)normal Substitutions and Exception Candidates



$$r: \ livesIn(X,Z) \leftarrow isMarriedTo(Y,X), livesIn(Y,Z) \ \{\underbrace{not\ researcher(X) | not\ artist(Y)}_{\text{exception candidates}}$$

5. Exception Ranking

$$rule1 \ldots\ldots\ldots \{e1 \mid e2 \mid e3 \mid \ldots\}$$
$$rule2 \ldots\ldots\ldots \{e1 \mid e2 \mid e3 \mid \ldots\}$$
$$rule3 \ldots\ldots\ldots \{e1 \mid e2 \mid e3 \mid \ldots\}$$

Globally best revision is infeasible: exponentially many candidates!

- **Naive:** pick a rule exception that results in the highest conviction
- **Partial materialization (PM):** apply all rules apart from a given one with their exceptions to KG, then pick an exception for the given rule that results in the highest average conviction of it and its rewriting
- **Ordered partial materialization (OPM):** same as **PM**, but apply only rules ordered higher than a given one
- **Weighted ordered partial materialization (WOPM):** same as **OPM**, but takes weights of predicted facts into account

References

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- M. Gad-elrab, D.Stepanova, J.Urbani, G.Weikum. Exception-enriched Rule Learning from Knowledge Graphs. In proc. *International Semantic Web Conference*, 2016.
- L. Galárraga, C. Teflioudi, K. Hose, F. M. Suchanek. Fast Rule Mining in Ontological Knowledge Bases with AMIE+. *VLBD journal*, 2015.
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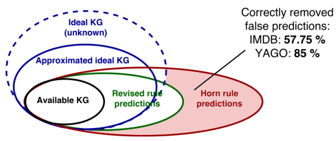
6. Experiments

- Approximated ideal KG: original
- Available KG: randomly remove 20% of facts for every relation from available KG
- Rules: $h(X,Y) \leftarrow p(X,Z), q(Z,Y)$
- Exceptions: $e_1(X), e_2(Y), e_3(X,Y)$
- OPM ranker, predictions computed by an answer set solver

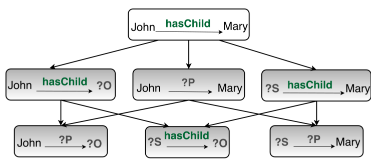


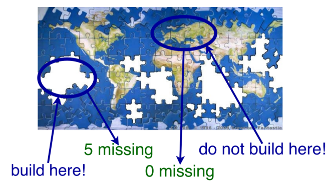
Examples of mined rules:

$$r_1: writtenBy(X,Z) \leftarrow hasPredecessor(X,Y), writtenBy(Y,Z), not\ american\_film(X)$$
$$r_2: actedIn(X,Z) \leftarrow isMarriedTo(X,Y), directed(Y,Z), not\ silent\_film\_actor(X)$$

7. Further Work

- **Cardinality** meta-data in **rule learning**: John has **5** children, **3** people won award





- Learn **cardinality rules**: "If X has $\leq$ 2 siblings, then his parents have $\leq$ 3 children"

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