Towards Nonmonotonic Relational Learning from Knowledge Graphs

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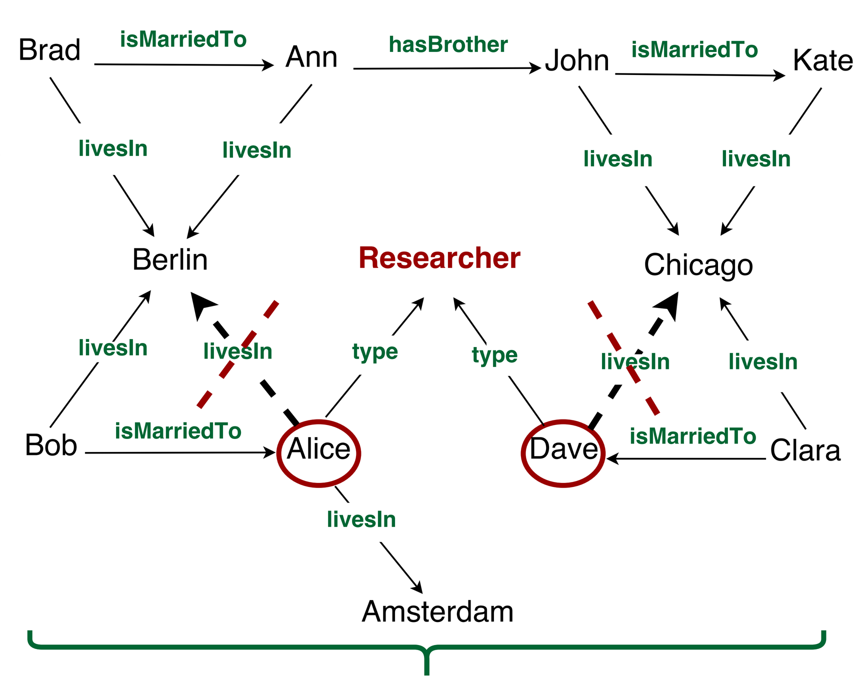
1. Motivation

- **Knowledge Graphs**: huge collections of triples encoding un(bin-)ary facts under **O**pen **W**orld **A**ssumption
  $\underbrace{\langle alice\ isMarriedTo\ bob\rangle}_{isMarriedTo(alice,bob)}, \underbrace{\langle mat\ type\ researcher\rangle}_{researcher(mat)}$
- Automatically constructed, thus **incomplete** / **inaccurate**
- Horn rule mining to **complete** / **clean** KGs e.g., [Galaraga, *et al.*, 2015]
- **But**: exceptions are not captured by Horn rules, thus erroneous predictions
- **Aim of this work:** methods for nonmonotonic rule learning from KGs under OWA
- **Challenges: OWA**, **huge size** of KGs



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

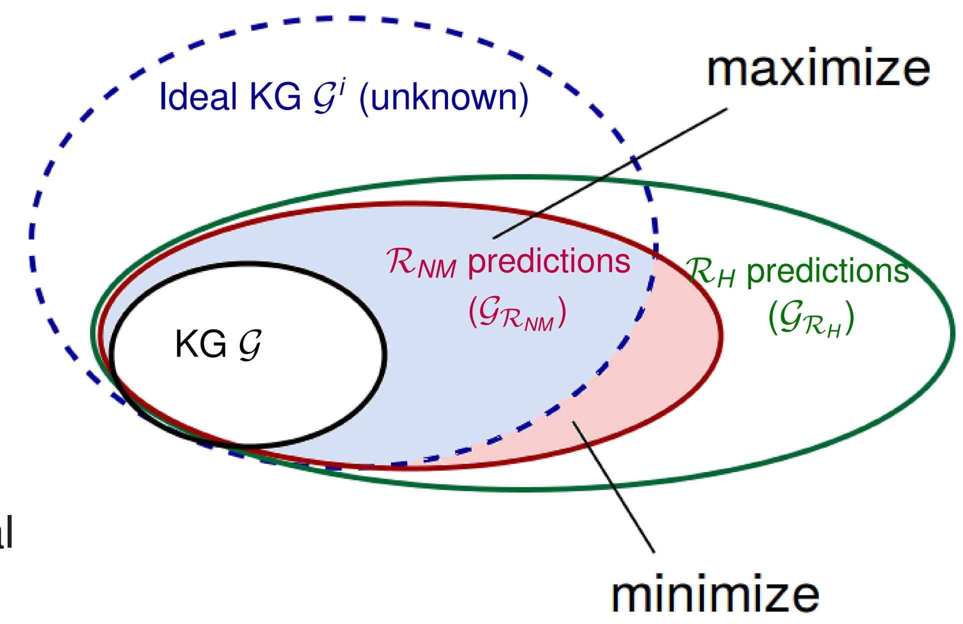
- **Contributions:**
  - Quality-based Horn theory revision framework
  - Exception ranking method based on cross-talk among the rules
  - Preliminary experiments on a real-world KG

2. Problem Statement

Quality-based Horn Theory Revision (QHTR)

Given:
- Knowledge Graph $\mathcal{G}$
- Set of Horn rules $\mathcal{R}_H$

Find:
- Nonmonotonic revision $\mathcal{R}_{NM}$, s.t.
  - **conflicting predictions** made by $\mathcal{R}_{NM}^{aux}$ are minimal
  - **average conviction** is maximal
    $conv(r,\mathcal{G}) = \dfrac{1 - supp(r,\mathcal{G})}{1 - conf(r,\mathcal{G})}$



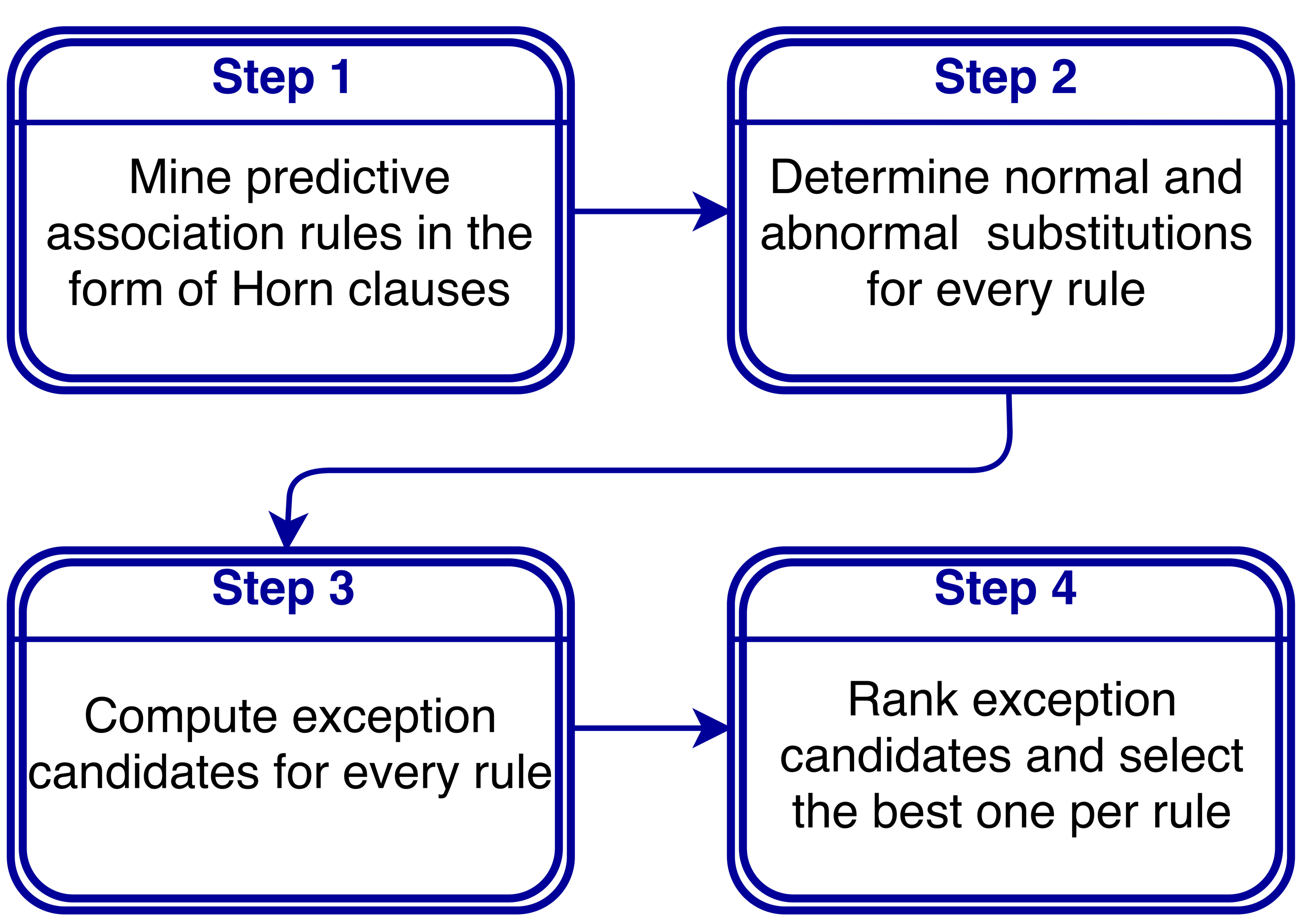
Conflicting predictions:

$$\mathcal{R}_{NM}^{aux} = \left\{\begin{array}{l} r_1: livesIn(X,Z) \leftarrow isMarriedTo(Y,X), livesIn(Y,Z), not\ res(X) \\ r_1^{aux}: not\_livesIn(X,Z) \leftarrow isMarriedTo(Y,X), livesIn(Y,Z), res(X) \\ r_2: livesIn(X,Z) \leftarrow bornIn(X,Z), not\ emmigrant(X) \\ r_2^{aux}: not\_livesIn(X,Z) \leftarrow bornIn(X,Z), emmigrant(X) \end{array}\right\}$$

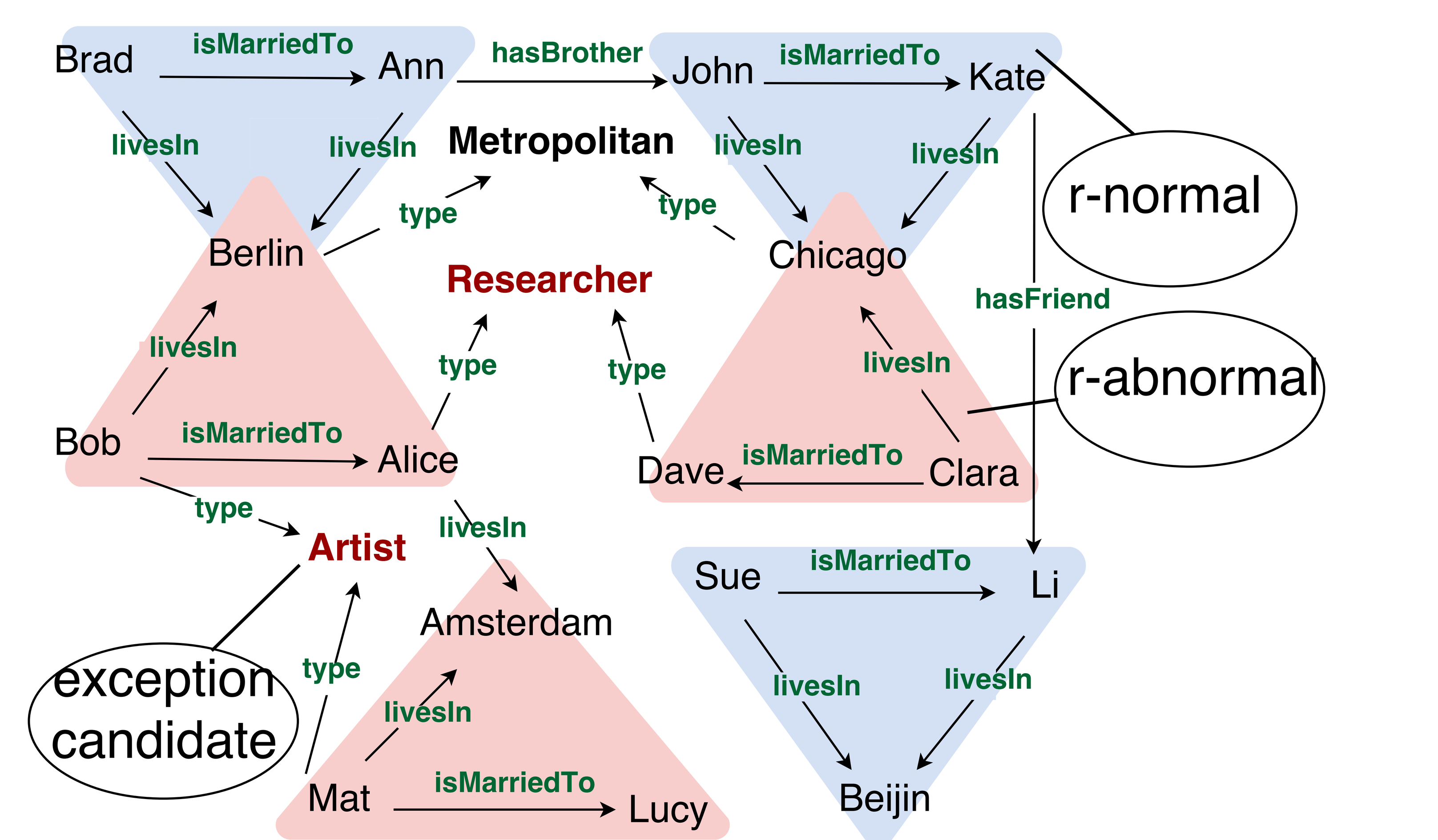
$\{livesIn(c,d), not\_livesIn(c,d)\} \in \mathcal{G}_{\mathcal{R}_{NM}^{aux}}$ are conflicting predictions

Intuition: researcher might be a strong exception for r_1, but application of r_2 to the KG could weaken it; less conflicts less weak exceptions

3. Approach Overview



4. (Ab)normal Substitutions and Exception Candidates



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

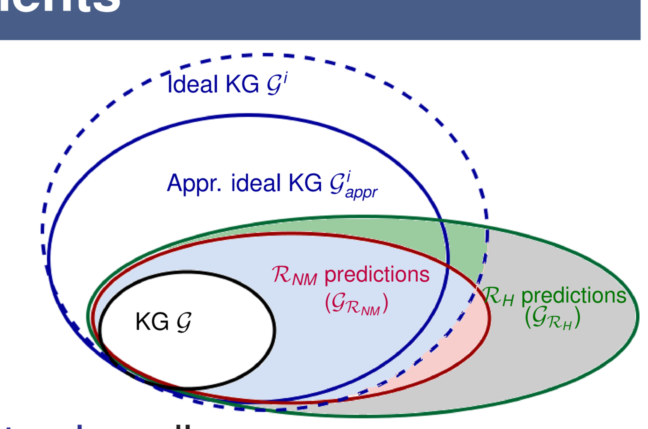
5. Exception Ranking

$$\begin{array}{l} r_1 \ldots\ldots\ldots \{e_1|e_2|e_3|\ldots\} \\ r_2 \ldots\ldots\ldots \{e_1|e_2|e_3|\ldots\} \\ r_3 \ldots\ldots\ldots \{e_1|e_2|e_3|\ldots\} \end{array}$$

- **Naive:** pick for $r \in \mathcal{R}_H$ a revision r' with the highest $conv(r',\mathcal{G})$
- **Partial materialization:** first cautiously materialize all rules with all of their exception candidates from $\mathcal{R}_H \backslash r$, get a KG $\mathcal{G}'$, and then pick a revision r' for r with the highest $\dfrac{conv(r',\mathcal{G}') + conv(r'^{aux},\mathcal{G}')}{2}$
- **Ordered partial materialization:** same as partial materialization, but materialize only rules ordered higher than r based on $conv$

6. Preliminary Experiments

- $\mathcal{G}^i_{appr}$: IMDB (movie) ≈600.000 facts, ≈40 relations
- $\mathcal{G}$: random. rem. 20% from $\mathcal{G}^i_{appr}$ for every relation
- $\mathcal{R}_H$: $h(X,Y) \leftarrow p(X,Z), q(Z,Y)$ mined from $\mathcal{G}$
- Exception types: $e_1(X), e_2(Y), e_3(X,Y)$
- OPM ranker, predictions are computed by answer set solver dlv



k	avg. conv.		confl.	number of predictions					
				$\mathcal{R}_H$		$\mathcal{R}_{NM}$		$\mathcal{R}_H$ not $\mathcal{R}_{NM}$	
	$\mathcal{R}_H$	$\mathcal{R}_{NM}$	$\mathcal{R}_{NM}$	all	in $\mathcal{G}^i_{appr}$	all	in $\mathcal{G}^i_{appr}$	false ✓	in $\mathcal{G}^i_{appr}$
5	4.08	6.16	0.28	345	161	331	156	0	14
10	2.91	4.21	0.08	2178	456	2118	450	27	33
15	2.5	3.42	0.09	3482	629	3348	622	86	48
20	2.29	3.0	0.13	5278	848	5046	835	157	75

Table : Top k rule revision results

Examples of mined rules:

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

7. References

- Fast Rule Mining in Ontological Knowledge Bases with AMIE+ *VLBD journal*, 2015.
- S. Wrobel. First Order Theory Refinement In proc. *Advances in Inductive Logic Programming*, 1996.
- M. Gad-elrab,D.Stepanova,J.Urbani,G.Weikum. Exception-enriched Rule Learning from Knowledge Graphs In proc. *ISWC*, 2016.