Mining Knowledge Graphs from Text

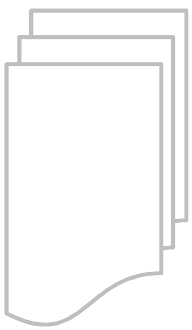
WSDM 2018

JAY PUJARA, SAMEER SINGH

Tutorial Overview

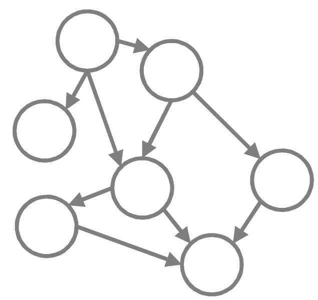
https://kgtutorial.github.io

Part 1: Knowledge Graphs



Part 2: Knowledge Extraction

Part 3: Graph Construction



Part 4: Critical Analysis

Tutorial Outline

1. Knowledge Graph Primer [Jay] 
2. Knowledge Extraction Primer [Jay] 
3. Knowledge Graph Construction
    a. **Probabilistic Models** **[Jay]** 

Coffee Break 

    b. Embedding Techniques [Sameer] 

4. Critical Overview and Conclusion [Sameer] 

Tutorial Outline

1. Knowledge Graph Primer [Jay] 
2. Knowledge Extraction from Text
    a. NLP Fundamentals [Sameer] 
    b. Information Extraction [Bhavana] 

Coffee Break 

3. **Knowledge Graph Construction**
    a. **Probabilistic Models** **[Jay]** 
    b. **Embedding Techniques** **[Sameer]** 
4. Critical Overview and Conclusion [Bhavana] 

Knowledge Graph Construction

TOPICS:

- PROBLEM SETTING
- PROBABILISTIC MODELS
- EMBEDDING TECHNIQUES

Knowledge Graph Construction

TOPICS:

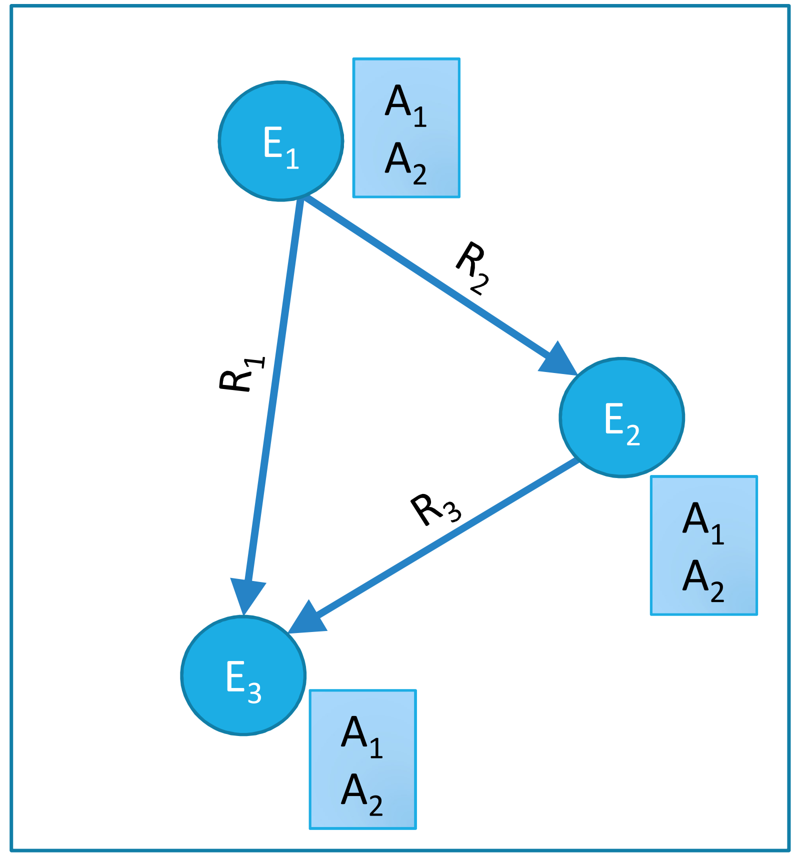
PROBLEM SETTING

PROBABILISTIC MODELS

EMBEDDING TECHNIQUES

Reminder: Basic problems

- **Who** are the entities (nodes) in the graph?
- **What** are their attributes and types (labels)?
- **How** are they related (edges)?



Graph Construction Issues

Extracted knowledge is:

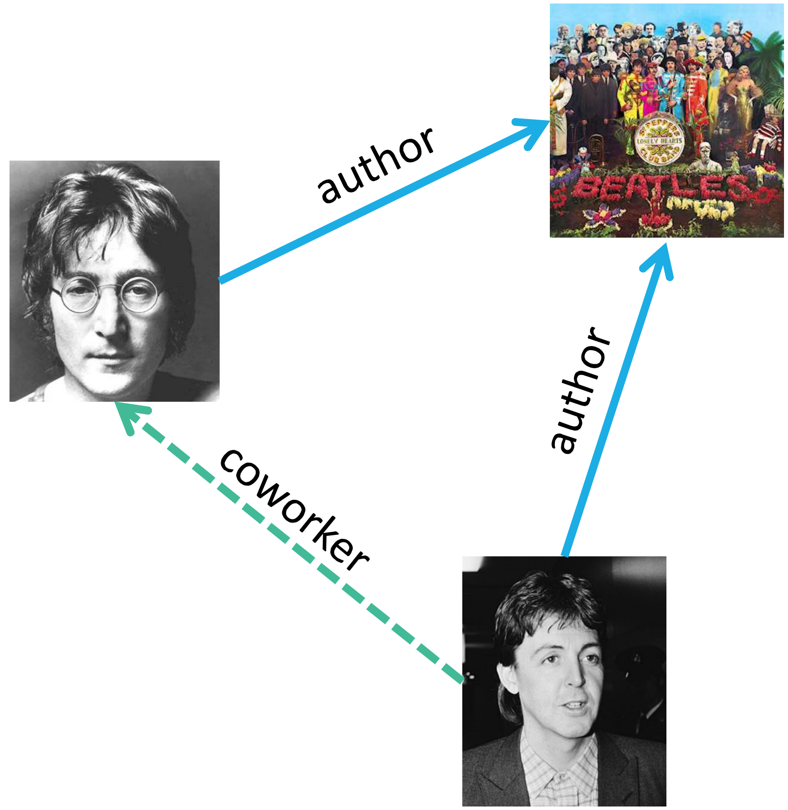
- ambiguous:
  - Ex: Beetles, beetles, Beatles
  - Ex: citizenOf, livedIn, bornIn

Graph Construction Issues

Extracted knowledge is:

- ambiguous

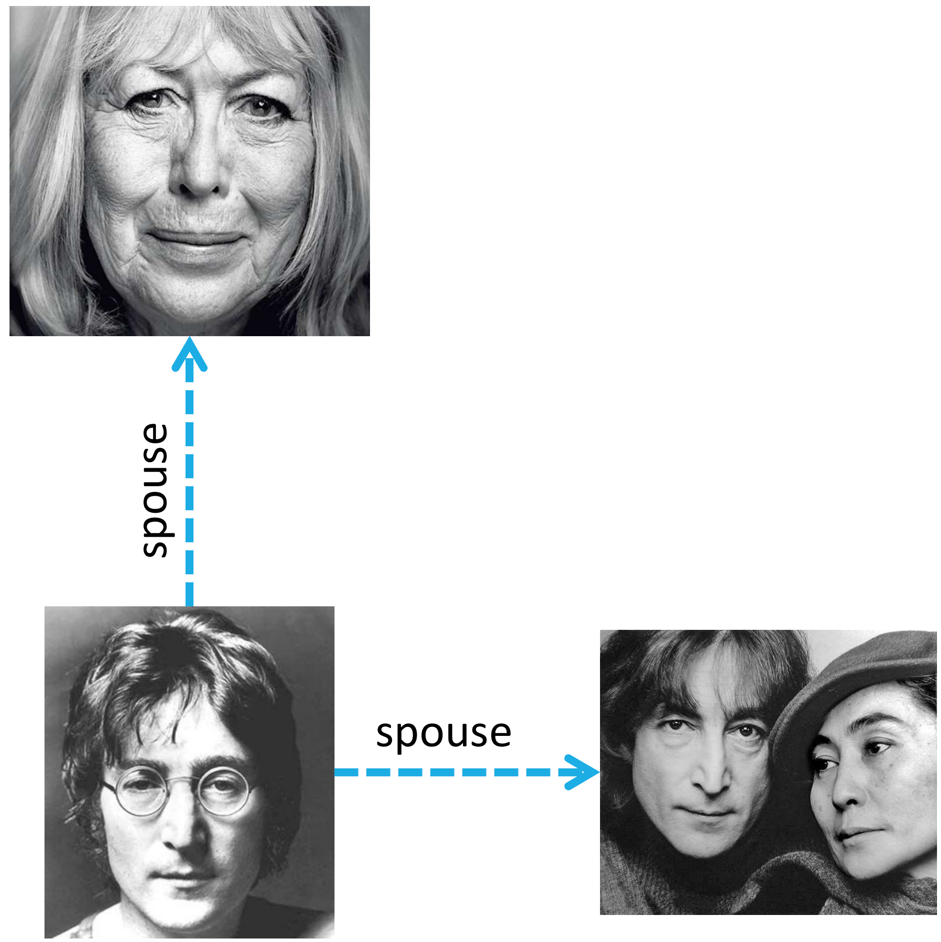
- incomplete
  - Ex: missing relationships
  - Ex: missing labels
  - Ex: missing entities



Graph Construction Issues

Extracted knowledge is:

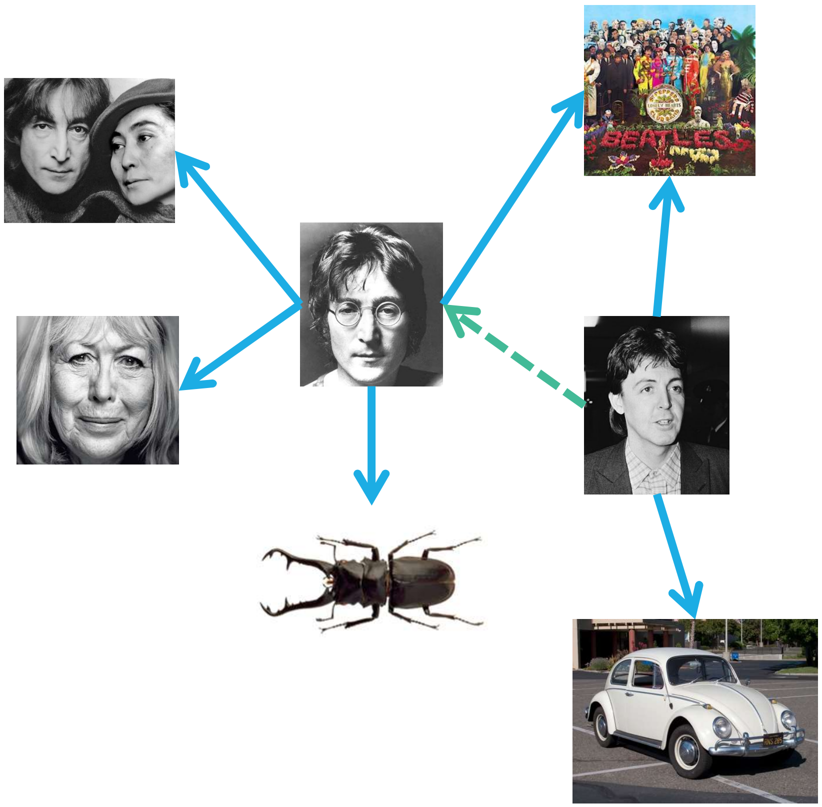
- ambiguous
- incomplete
- inconsistent
  - Ex: Cynthia Lennon, Yoko Ono
  - Ex: exclusive labels (alive, dead)
  - Ex: domain-range constraints



Graph Construction Issues

Extracted knowledge is:

- ambiguous
- incomplete
- inconsistent



Graph Construction approach

- Graph construction **cleans** and **completes** extraction graph

- Incorporate ontological constraints and relational patterns

- Discover statistical relationships within knowledge graph

Knowledge Graph Construction

TOPICS:

PROBLEM SETTING

PROBABILISTIC MODELS

EMBEDDING TECHNIQUES

Graph Construction
Probabilistic Models

TOPICS:

- Overview
- Graphical models
- Random Walk Methods

Graph Construction
Probabilistic Models

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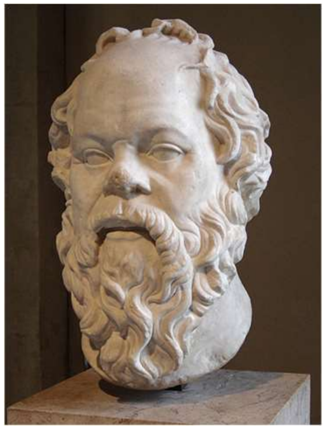
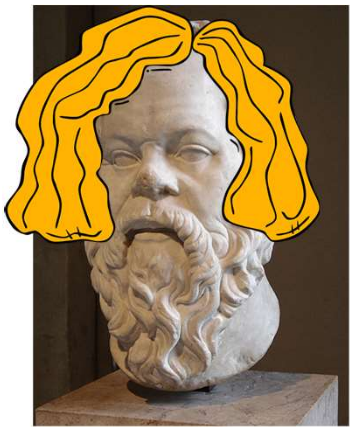
Beyond Pure Reasoning



- Classical AI approach to knowledge: reasoning

Lbl(Socrates, Man) & Sub(Man, Mortal) -> Lbl(Socrates, Mortal)

Beyond Pure Reasoning



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- Reasoning difficult when extracted knowledge has errors

Beyond Pure Reasoning

- Classical AI approach to knowledge: reasoning

Lbl(Socrates, Man) & Sub(Man, Mortal) -> Lbl(Socrates, Mortal)

- Reasoning difficult when extracted knowledge has errors
- Solution: probabilistic models

P(Lbl(Socrates, Mortal)|Lbl(Socrates,Man)=0.9)

Graph Construction
Probabilistic Models

TOPICS:

- OVERVIEW
- GRAPHICAL MODELS
- RANDOM WALK METHODS

Graphical Models: Overview

- Define **joint probability distribution** on knowledge graphs
- Each candidate fact in the knowledge graph is a **variable**
- Statistical signals, ontological knowledge and rules parameterize the **dependencies** between variables
- Find most likely knowledge graph by **optimization/sampling**

Knowledge Graph Identification

Define a graphical model to perform all three of these tasks simultaneously!

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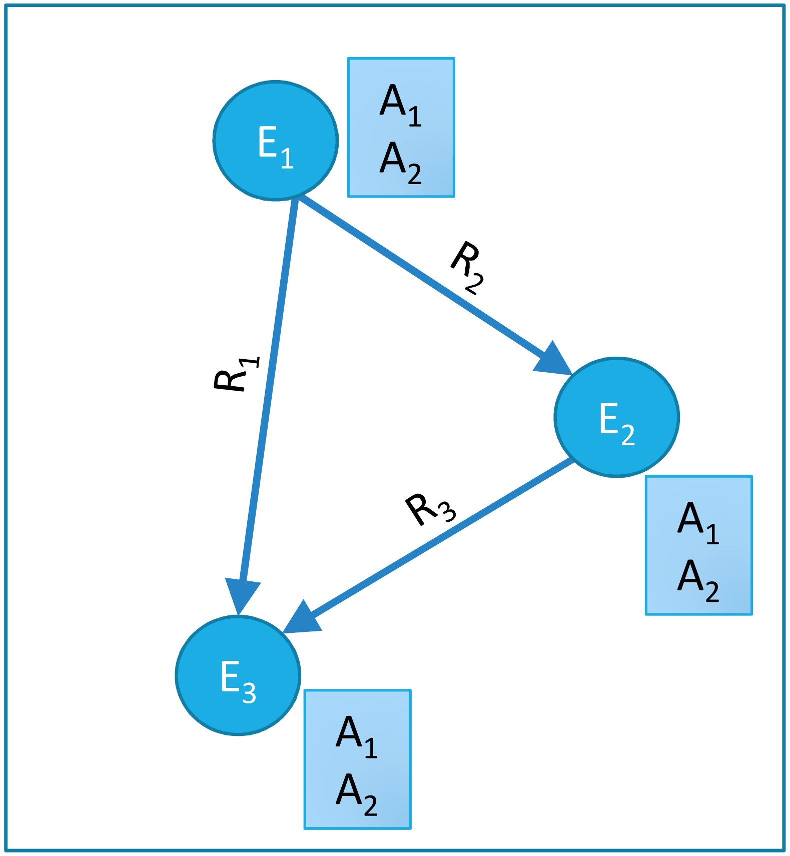
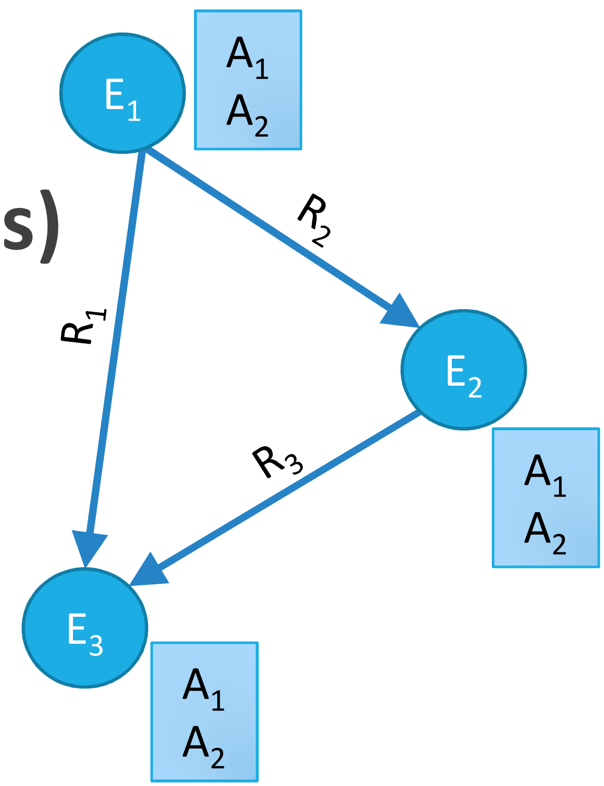


Knowledge Graph Identification

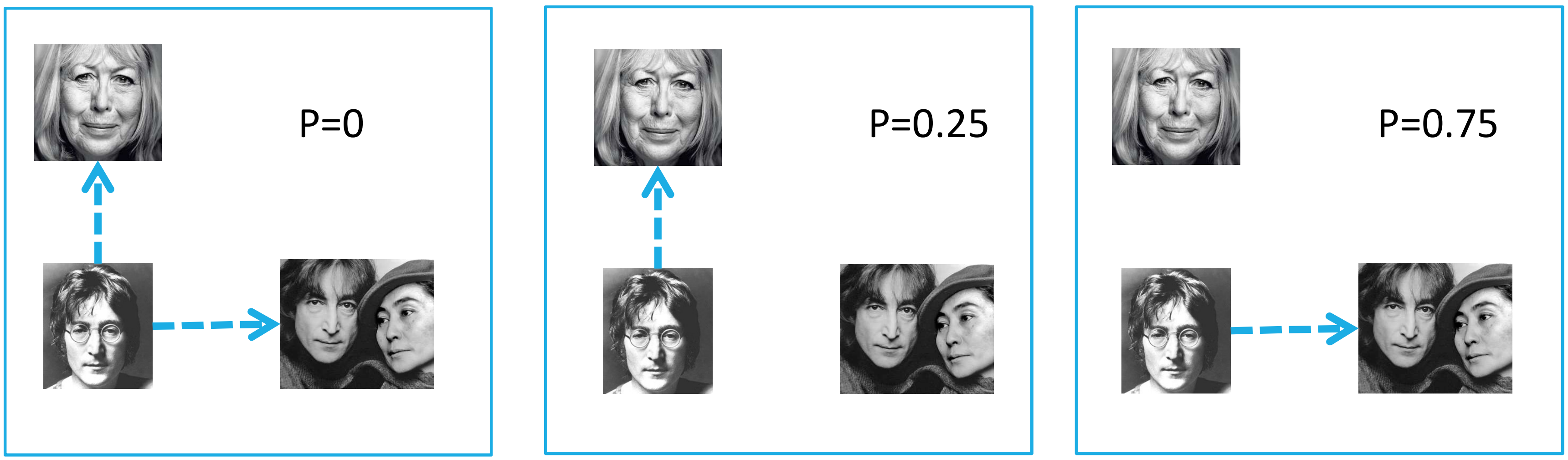
P(Who, What, How | Extractions)



Probabilistic Models

- Use dependencies between facts in KG

- Probability defined *jointly* over facts



What determines probability?

- **Statistical signals from text extractors and classifiers**

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  - P(R(John,Spouse,Yoko))=0.75; P(R(John,Spouse,Cynthia))=0.25
  - LevenshteinSimilarity(Beatles, Beetles) = 0.9

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- **Ontological knowledge about domain**

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- **Statistical signals from text extractors and classifiers**

- **Ontological knowledge about domain**
  - Functional(Spouse) & R(A,Spouse,B) -> !R(A,Spouse,C)
  - Range(Spouse, Person) & R(A,Spouse,B) -> Type(B, Person)

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- **Rules and patterns mined from data**

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  - R(A, Spouse, B) & R(A, Lives, L) -> R(B, Lives, L)
  - R(A, Spouse, B) & R(A, Child, C) -> R(B, Child, C)

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Example: The Fab Four

THE BEATLES

Illustration of KG Identification

Uncertain Extractions:
.5: Lbl(Fab Four, novel)
.7: Lbl(Fab Four, musician)
.9: Lbl(Beatles, musician)
.8: Rel(Beatles,AlbumArtist,
Abbey Road)

Illustration of KG Identification

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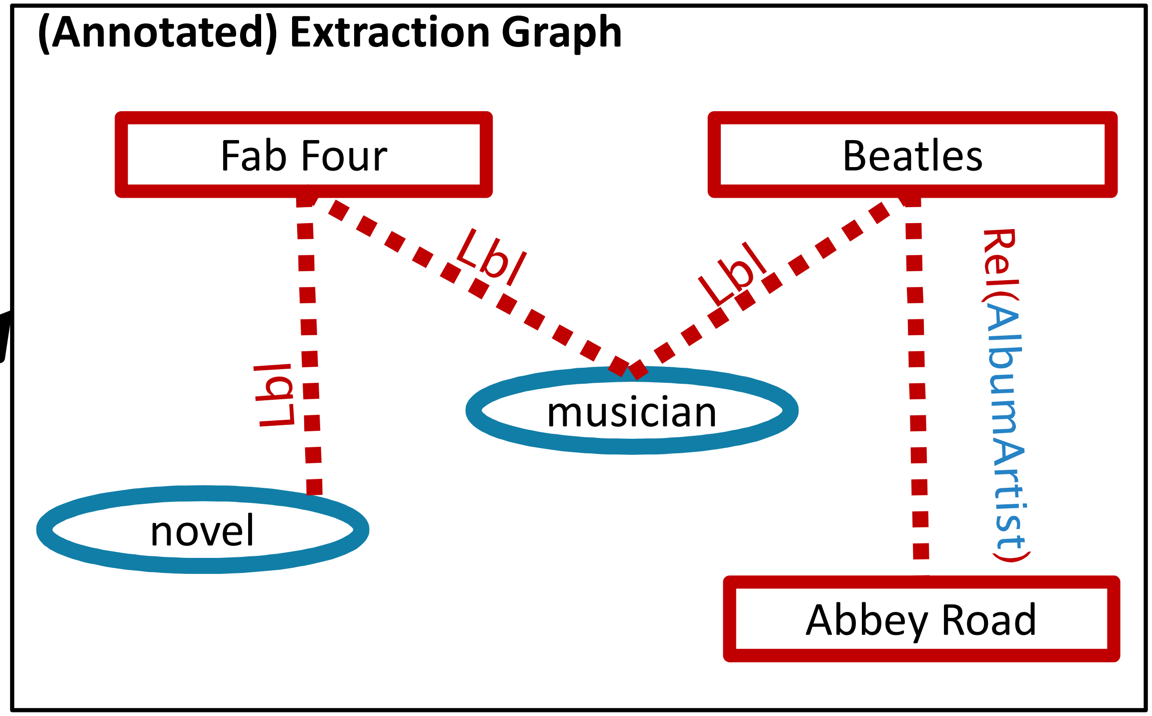

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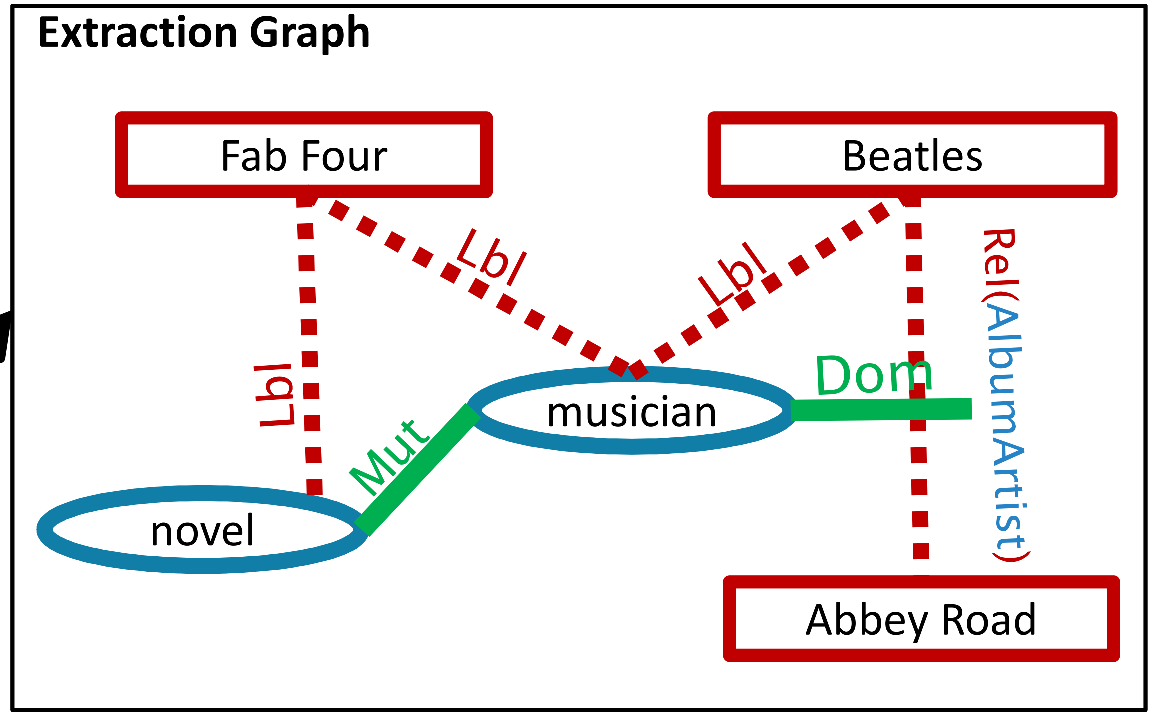

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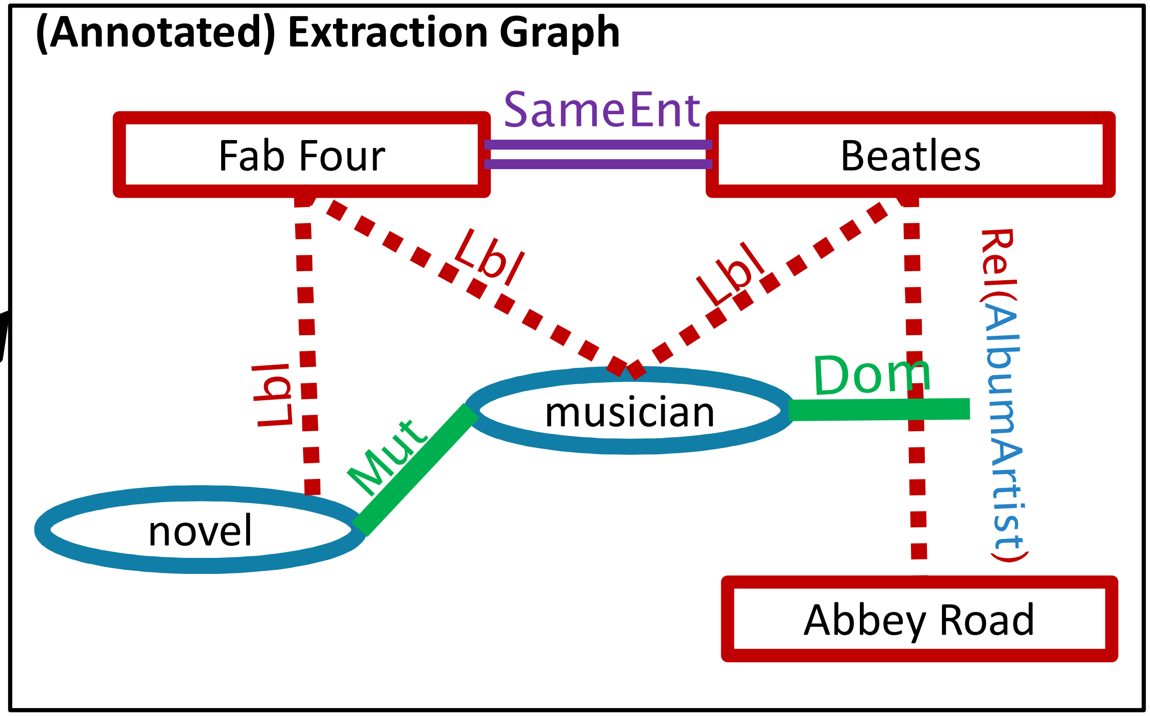
Entity Resolution:
SameEnt(Fab Four, Beatles)



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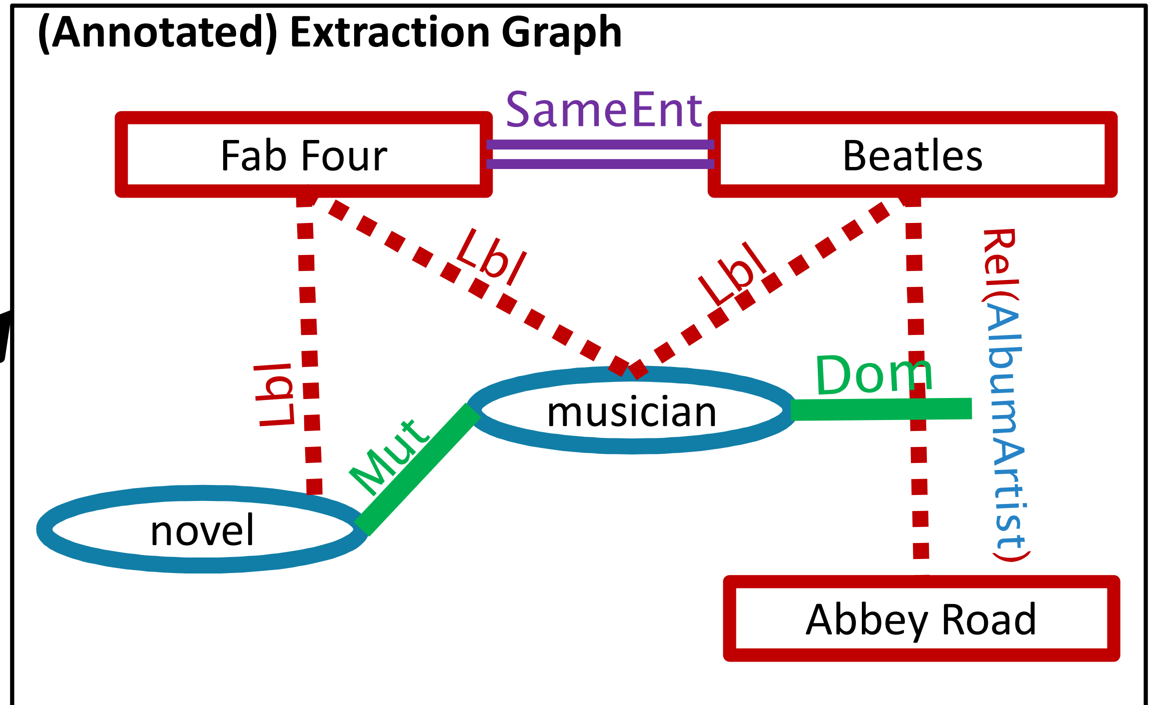
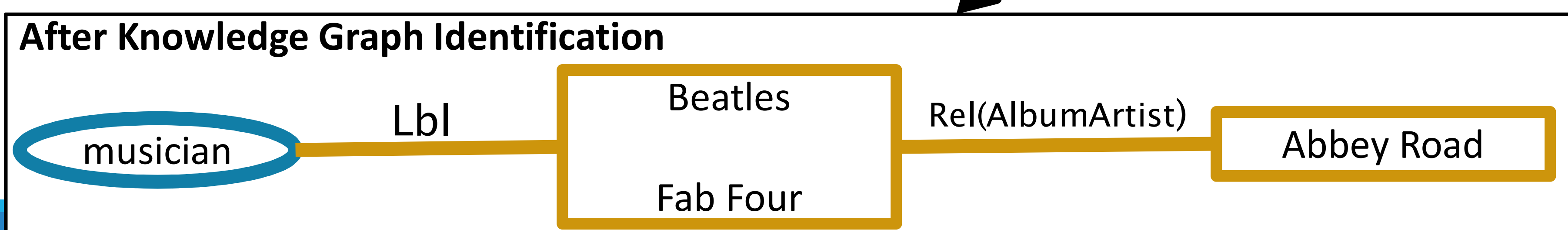
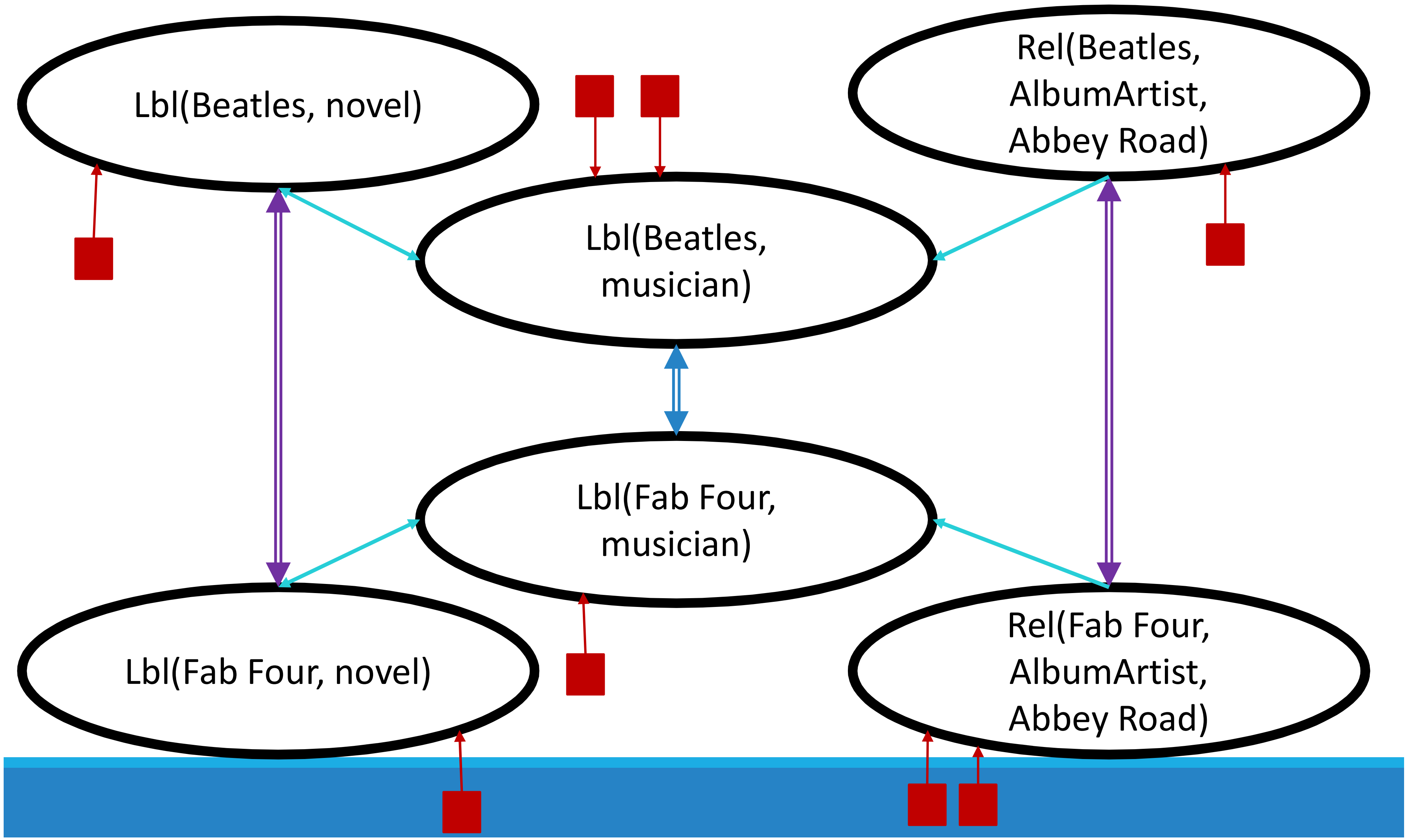




PUJARA+ISWC13; PUJARA+AIMAG15

Probabilistic graphical model for KG



Defining graphical models

- Many options for defining a graphical model
- We focus on two approaches, MLNs and PSL, that use **rules**
- **MLNs** treat facts as Boolean, use sampling for satisfaction
- **PSL** infers a “truth value” for each fact via optimization

Rules for KG Model

```
100:    Subsumes(L1,L2)    & Label(E,L1)        ->  Label(E,L2)
100:    Exclusive(L1,L2)   & Label(E,L1)        -> !Label(E,L2)

100:    Inverse(R1,R2)     & Relation(R1,E,O)   ->  Relation(R2,O,E)
100:    Subsumes(R1,R2)    & Relation(R1,E,O)   ->  Relation(R2,E,O)
100:    Exclusive(R1,R2)   & Relation(R1,E,O)   -> !Relation(R2,E,O)

100:    Domain(R,L)        & Relation(R,E,O)    ->  Label(E,L)
100:    Range(R,L)         & Relation(R,E,O)    ->  Label(O,L)

10:     SameEntity(E1,E2)  & Label(E1,L)        ->  Label(E2,L)
10:     SameEntity(E1,E2)  & Relation(R,E1,O)   ->  Relation(R,E2,O)

1:      Label_OBIE(E,L)                         ->  Label(E,L)
1:      Label_OpenIE(E,L)                       ->  Label(E,L)
1:      Relation_Pattern(R,E,O)                 ->  Relation(R,E,O)
1:                                                 !Relation(R,E,O)
1:                                                 !Label(E,L)
```

Rules to Distributions

- Rules are *grounded* by substituting literals into formulas

$$\mathbf{w_r} : \textsc{SameEnt}(\text{Fab Four}, \text{Beatles}) \;\wedge$$
$$\textsc{Lbl}(\text{Beatles}, \text{musician}) \Rightarrow \textsc{Lbl}(\text{Fab Four}, \text{musician})$$

- Each ground rule has a weighted *satisfaction* derived from the formula's truth value

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

- Together, the ground rules provide a joint probability distribution over knowledge graph facts, conditioned on the extractions

Probability Distribution over KGs

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

$$\begin{aligned}
&\textsc{CandLbl}_T(\texttt{FabFour}, \texttt{novel}) && \Rightarrow \textsc{Lbl}(\texttt{FabFour}, \texttt{novel}) \\
&\textsc{Mut}(\texttt{novel}, \texttt{musician}) && \wedge\ \textsc{Lbl}(\texttt{Beatles}, \texttt{novel}) \\
& && \Rightarrow \neg\textsc{Lbl}(\texttt{Beatles}, \texttt{musician}) \\
&\textsc{SameEnt}(\texttt{Beatles}, \texttt{FabFour}) && \wedge\ \textsc{Lbl}(\texttt{Beatles}, \texttt{musician}) \\
& && \Rightarrow \textsc{Lbl}(\texttt{FabFour}, \texttt{musician})
\end{aligned}$$

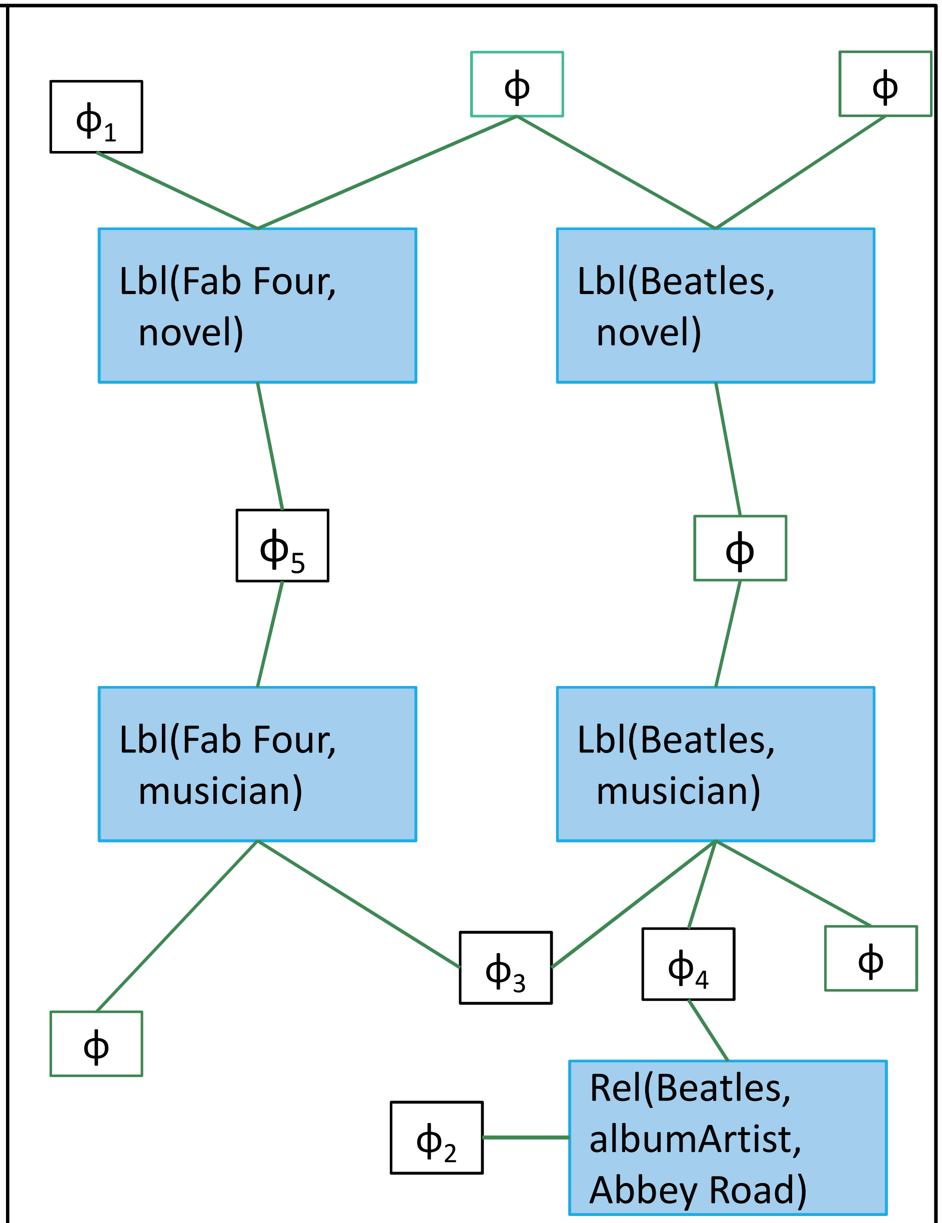
$[\phi_1]\ \textsc{CandLbl}_{\text{struct}}(\texttt{FabFour}, \texttt{novel})$
$\Rightarrow\ \textsc{Lbl}(\texttt{FabFour}, \texttt{novel})$

$[\phi_2]\ \textsc{CandRel}_{\text{pat}}(\texttt{Beatles}, \texttt{AlbumArtist}, \texttt{AbbeyRoad})$
$\Rightarrow\ \textsc{Rel}(\texttt{Beatles}, \texttt{AlbumArtist}, \texttt{AbbeyRoad})$

$[\phi_3]\ \textsc{SameEnt}(\texttt{Beatles}, \texttt{FabFour})$
$\wedge\ \textsc{Lbl}(\texttt{Beatles}, \texttt{musician})$
$\Rightarrow \textsc{Lbl}(\texttt{FabFour}, \texttt{musician})$

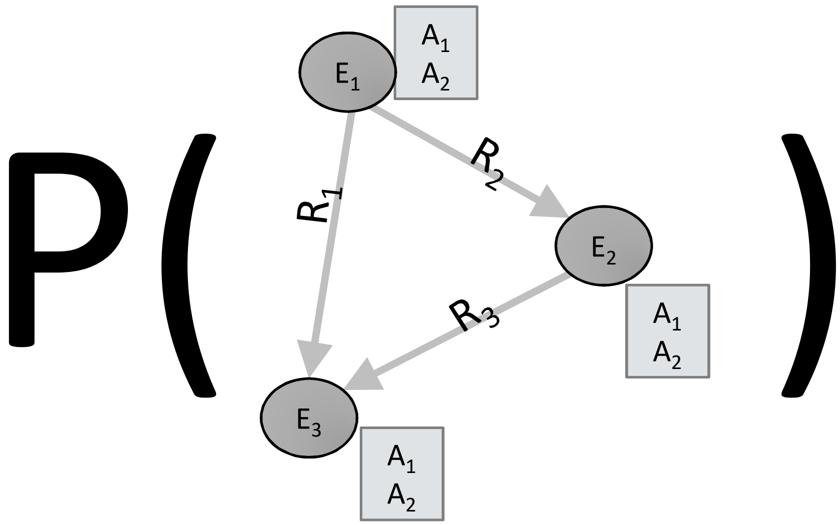
$[\phi_4]\ \textsc{Dom}(\texttt{AlbumArtist}, \texttt{musician})$
$\wedge\ \textsc{Rel}(\texttt{Beatles}, \texttt{AlbumArtist}, \texttt{AbbeyRoad})$
$\Rightarrow \textsc{Lbl}(\texttt{Beatles}, \texttt{musician})$

$[\phi_5]\ \textsc{Mut}(\texttt{musician}, \texttt{novel})$
$\wedge\ \textsc{Lbl}(\texttt{FabFour}, \texttt{musican})$
$\Rightarrow \neg\textsc{Lbl}(\texttt{FabFour}, \texttt{novel})$

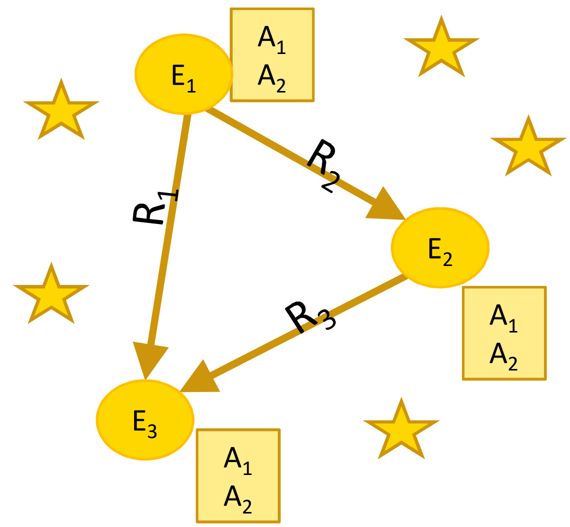


How do we get a knowledge graph?

Have: P(KG) forall KGs



Need: best KG



MAP inference: optimizing over distribution to find the best knowledge graph

Inference and KG optimization

- Finding the best KG satisfying weighed rules: NP Hard

- MLNs [discrete]: Monte Carlo sampling methods
  - Solution quality dependent on burn-in time, iterations, etc.

- PSL [continuous]: optimize convex linear surrogate
  - Fast optimization, ¾-optimal MAX SAT lower bound

Graphical Models Experiments

Data: ~1.5M extractions, ~70K ontological relations, ~500 relation/label types
Task: Collectively construct a KG and evaluate on 25K target facts

Comparisons:

Extract	Average confidences of extractors for each fact in the NELL candidates
Rules	Default, rule-based heuristic strategy used by the NELL project
MLN	Jiang+, ICDM12 – estimates marginal probabilities with MC-SAT
PSL	Pujara+, ISWC13 – convex optimization of continuous truth values with ADMM

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

	AUC	**F1**
Extract	.873	.828
Rules	.765	.673
MLN (Jiang, 12)	.899	.836
PSL (Pujara, 13)	.904	.853

Graphical Models: Pros/Cons

BENEFITS

- Define probability distribution over KGs
- Easily specified via rules
- Fuse knowledge from many different sources

DRAWBACKS

- Requires optimization over all KG facts - overkill
- Dependent on rules from ontology/expert
- Require probabilistic semantics - unavailable

Graph Construction

Probabilistic Models

TOPICS:

OVERVIEW

GRAPHICAL MODELS

RANDOM WALK METHODS

Random Walk Overview

- Given: a query of an **entity** and **relation**
- Starting at the entity, **randomly walk** the KG
- Random walk ends when reaching an appropriate **goal**
- Learned **parameters** bias choices in the random walk
- Output **relative probabilities** of goal states

Random Walk Illustration

Query: R(Lennon, PlaysInstrument, ?)

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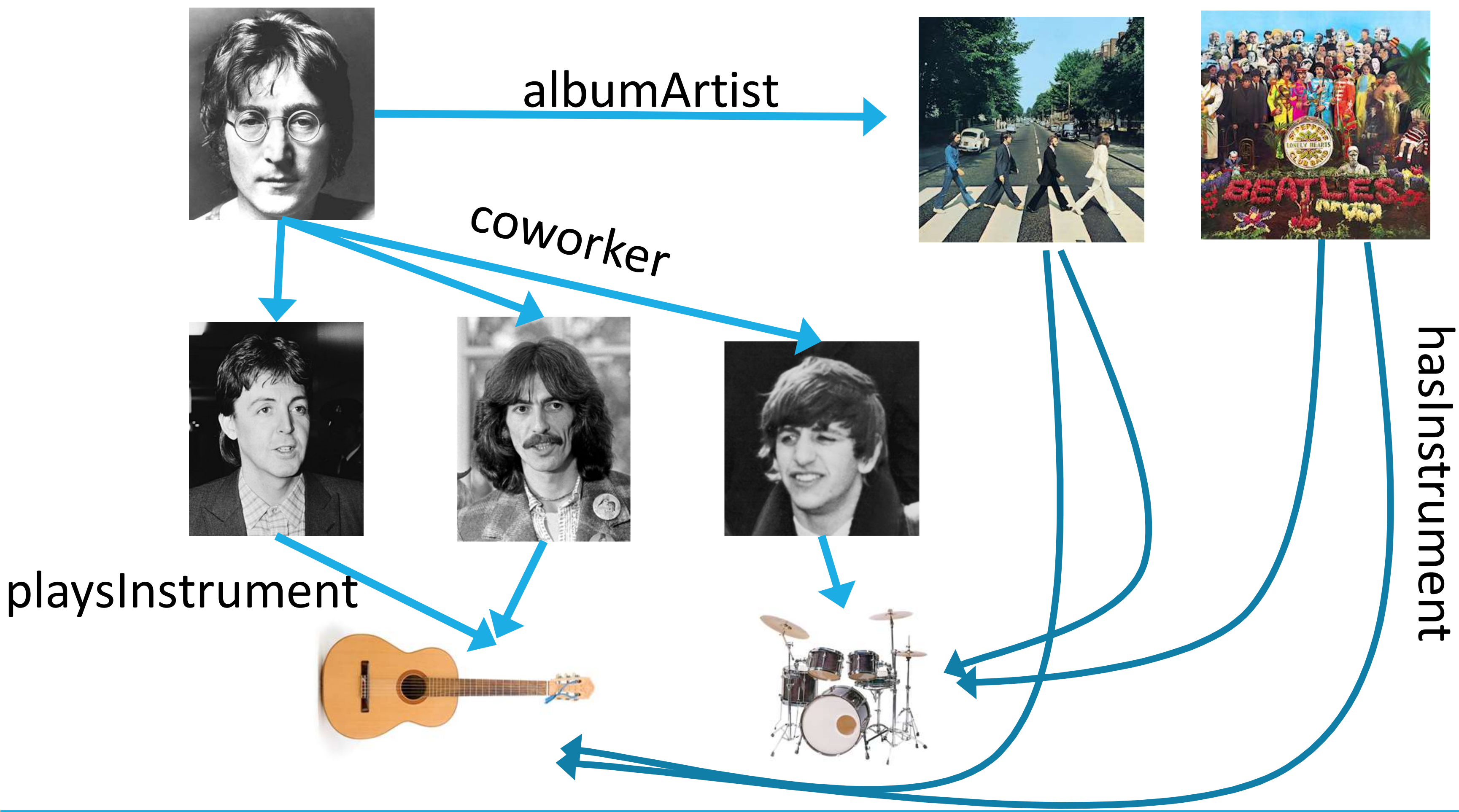

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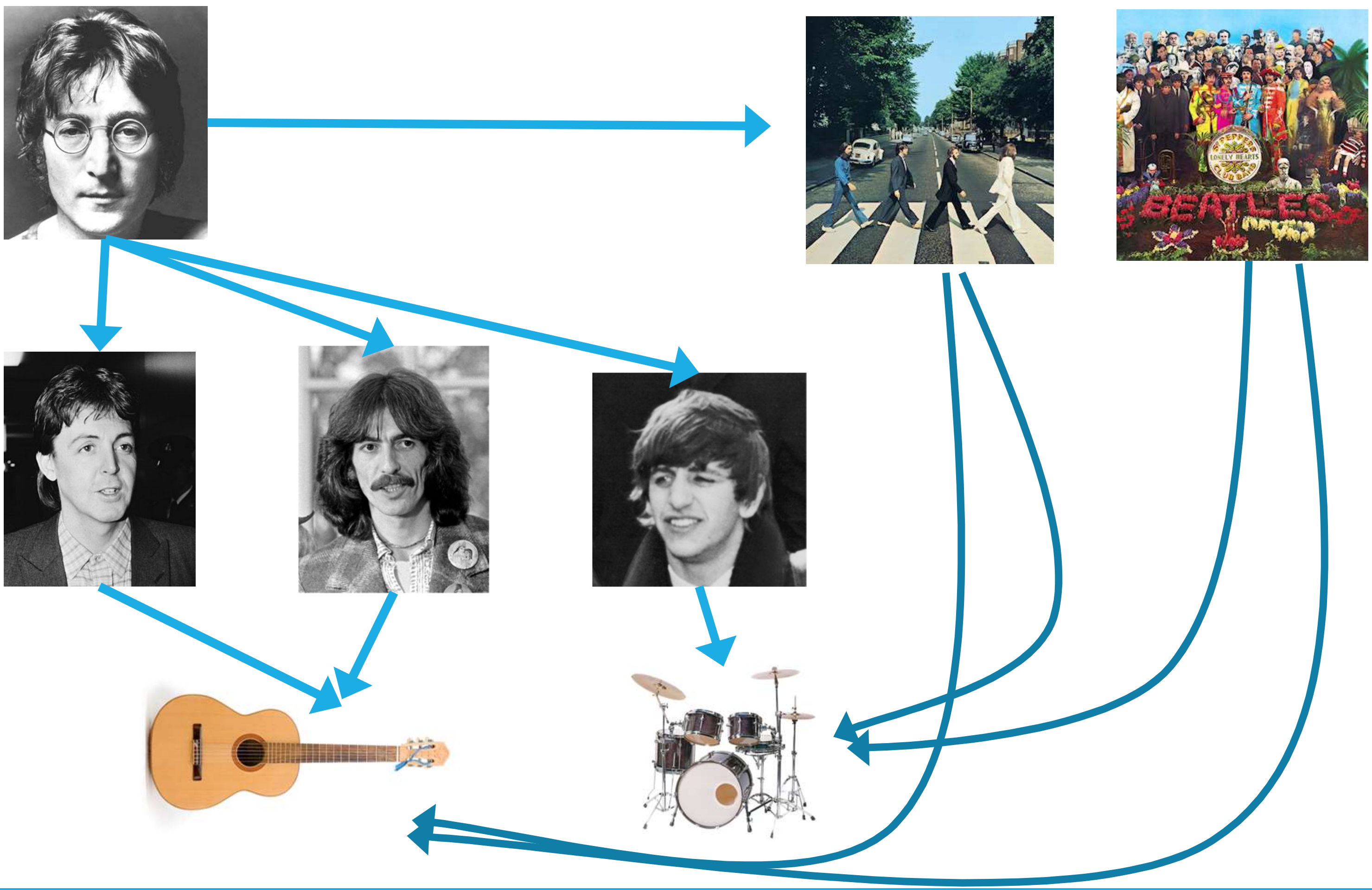

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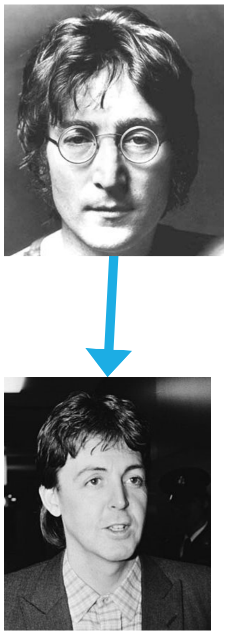

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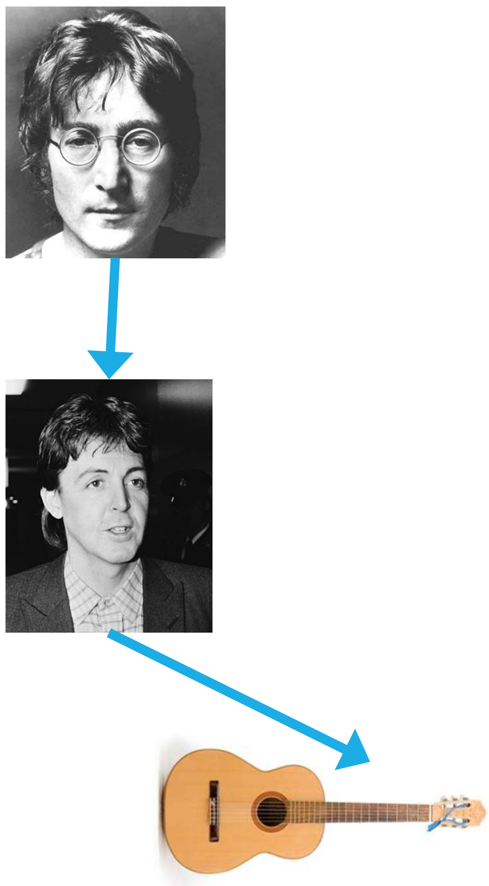

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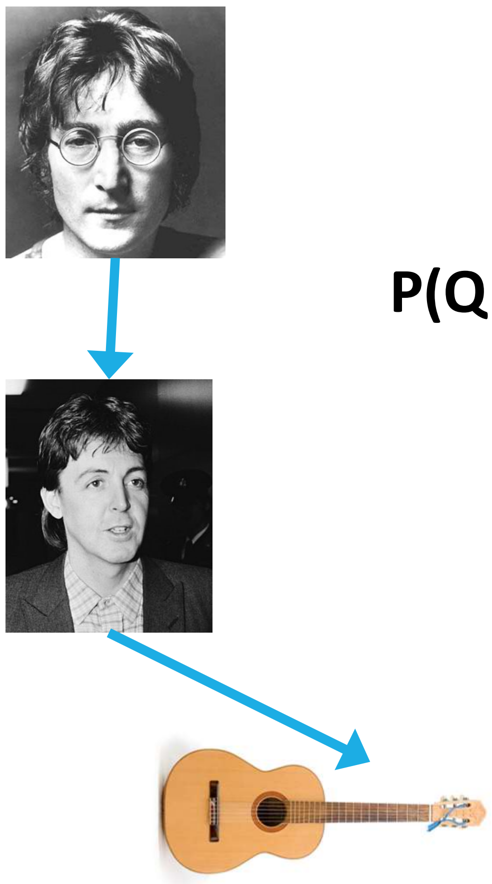

Path

Weight of path

$$P(Q|\pi=\langle coworker,playsInstrument\rangle)\ W_\pi$$

Random Walk Illustration

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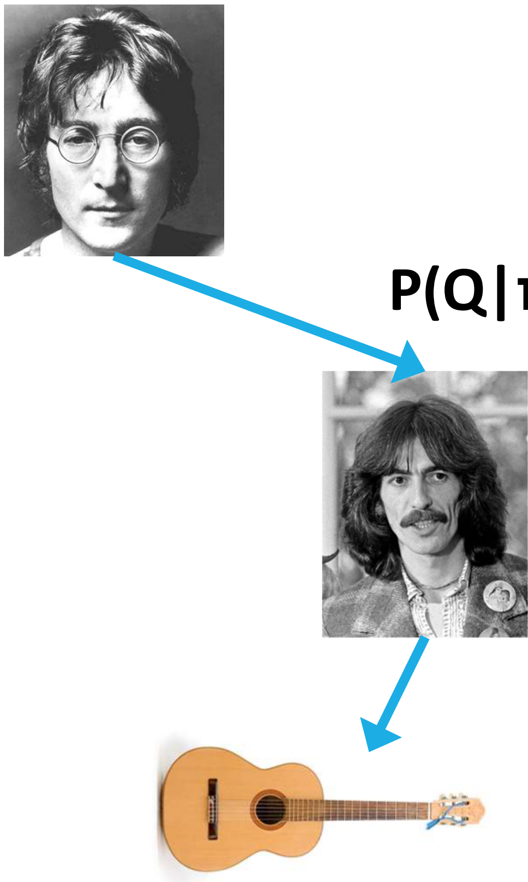

P(Q|π=<coworker,playsInstrument>) W_{π}

Random Walk Illustration

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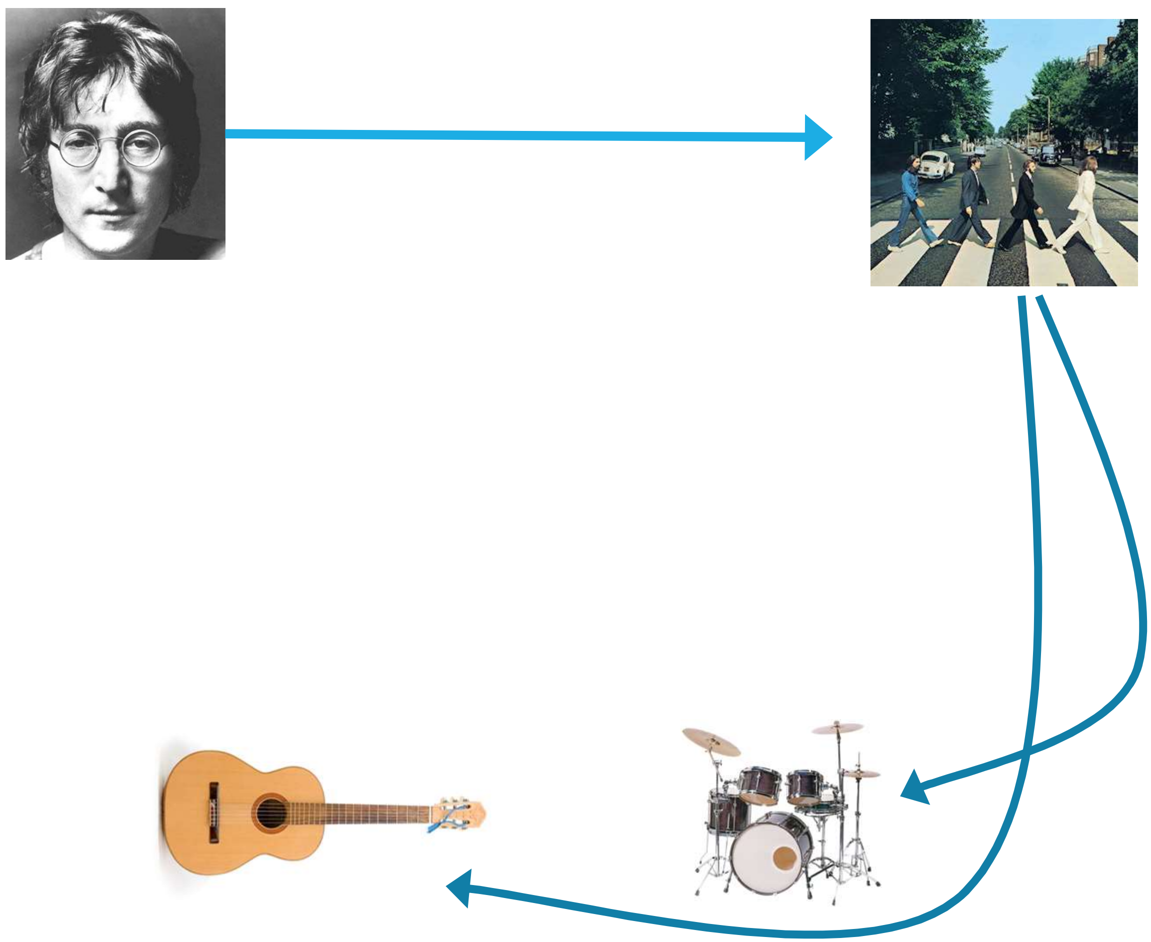

Random Walk Illustration

Query Q: R(Lennon, PlaysInstrument, ?)

$\mathbf{P(Q|\pi=\langle albumArtist,hasInstrument\rangle)\ W_{\pi}}$

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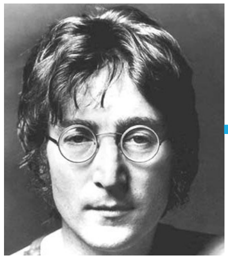

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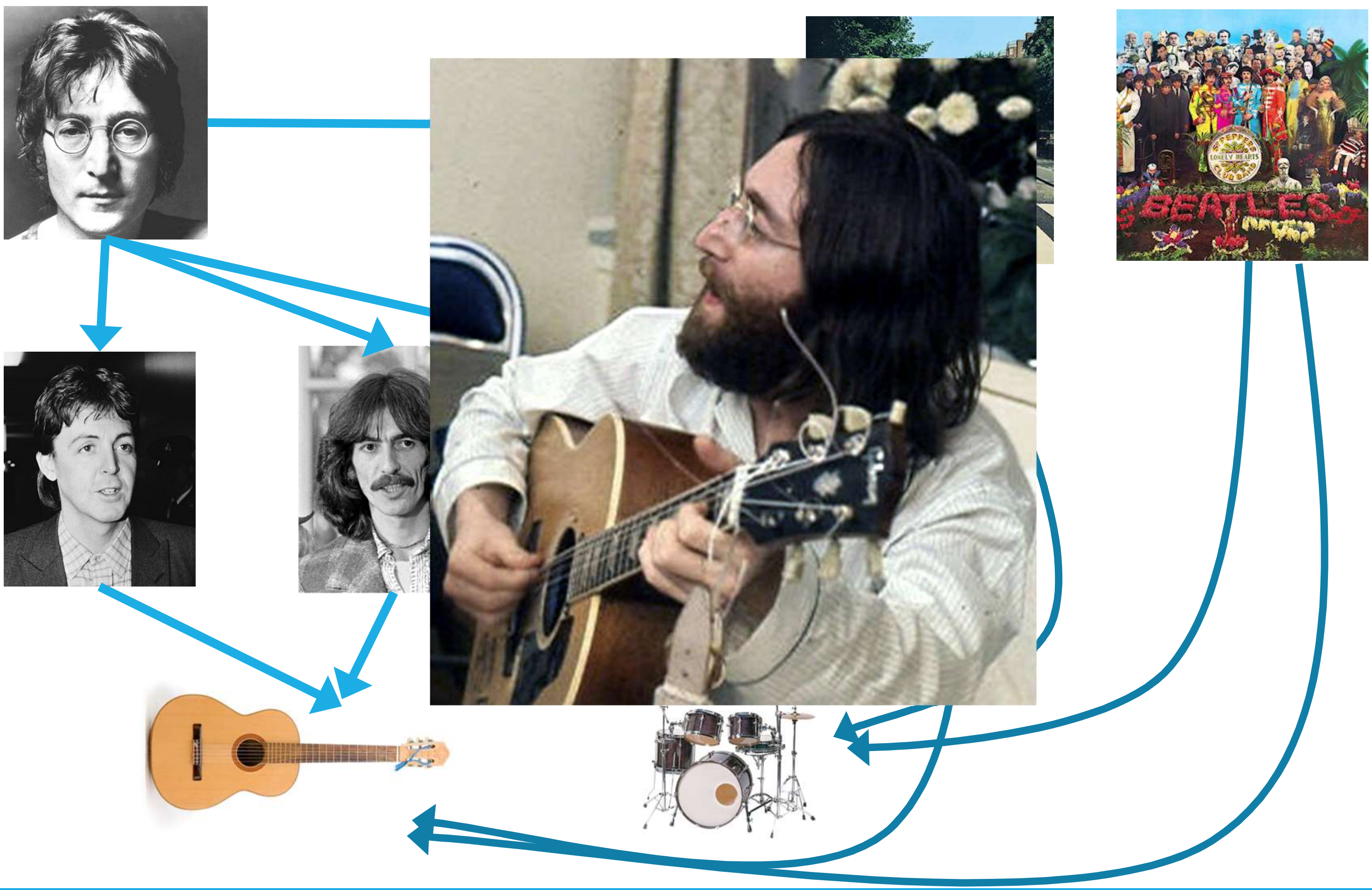

Recent Random Walk Methods

PRA: Path Ranking Algorithm

- Performs random walk of **imperfect knowledge graph**
- Estimates **transition probabilities** using KG
- For each relation, learns **parameters for paths** through the KG

ProPPR: Programming with Personalized PageRank

- Constructs **proof graph**
  - Nodes are partially-ground clauses with one or more facts
  - Edges are proof-transformations
- **Parameters** are learned for each **ground entity** and **rule**

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PRA in a nutshell

$$\mathrm{score}(q.s \rightarrow e; q) = \sum_{\pi_i \in \Pi_b} P(q.s \rightarrow e; \pi_i) W_{\pi_i}$$

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Filter paths based on HITS and accuracy

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Filter paths based on HITS and accuracy

Estimate probabilities efficiently with dynamic programming

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Filter paths based on HITS and accuracy

Estimate probabilities efficiently with dynamic programming

Path weights are learned with logistic regression

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ProPPR: ProbLog + Personalized PageRank

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ProPPR-ized PRA example

Query Q: R(Lennon, PlaysInstrument, ?)

R(,Coworker,X)
R(X,PlaysInstrument,Y)

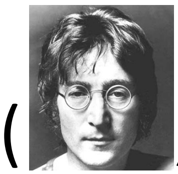
R(,AlbumArtist,J)
R(J,HasInstrument,K)

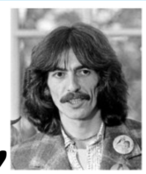
Unbound variables in proof tree!

ProPPR-ized PRA example

Query Q: R(Lennon, PlaysInstrument, ?)

R(,Coworker,X)
R(X,PlaysInstrument,Y)

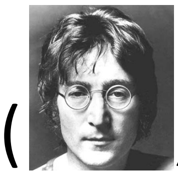
R(,AlbumArtist,J)
R(J,HasInstrument,K)

R(,Coworker,)
R(,PlaysInstrument,Y)

ProPPR-ized PRA example

Query Q: R(Lennon, PlaysInstrument, ?)

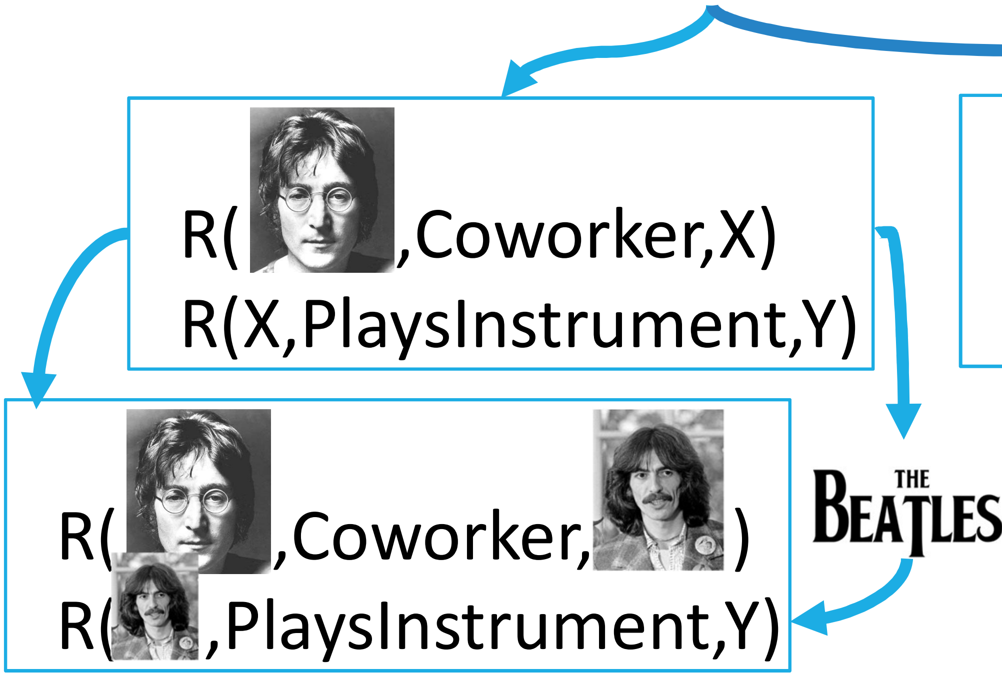
R( ,Coworker,X)
R(X,PlaysInstrument,Y)

R( ,AlbumArtist,J)
R(J,HasInstrument,K)

R( ,Coworker, )
R( ,PlaysInstrument,Y)

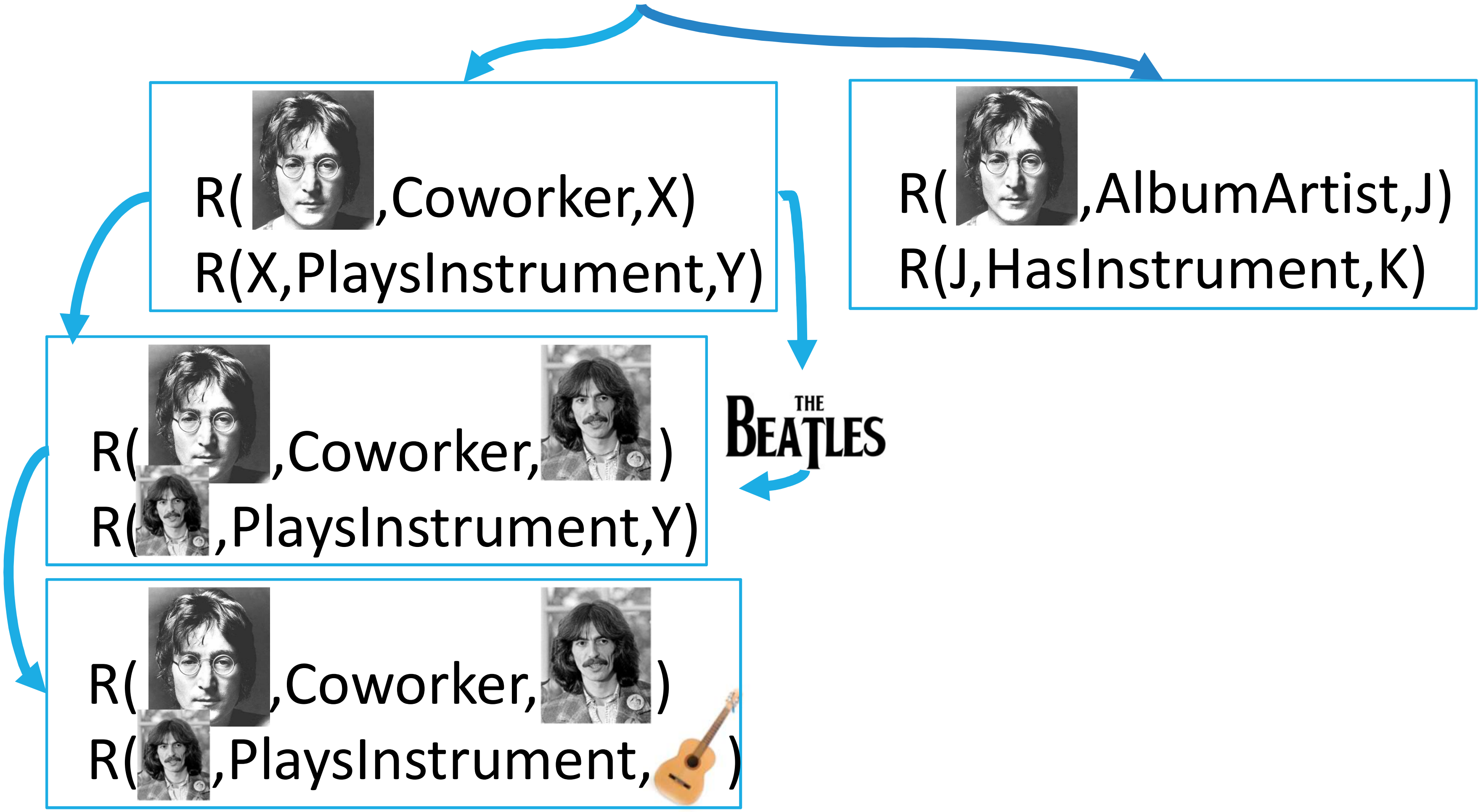
ProPPR-ized PRA example

Query Q: R(Lennon, PlaysInstrument, ?)



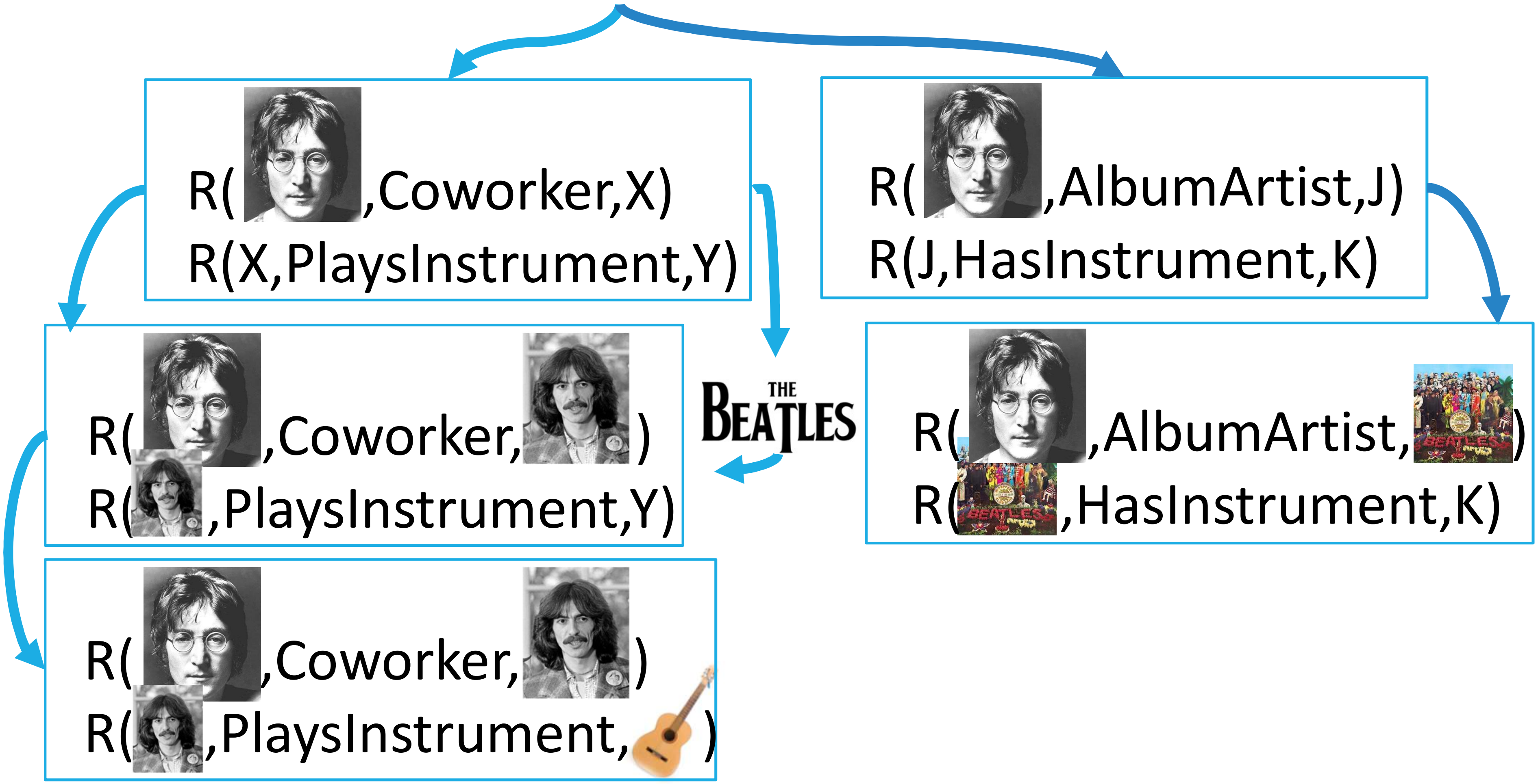
ProPPR-ized PRA example

Query Q: R(Lennon, PlaysInstrument, ?)



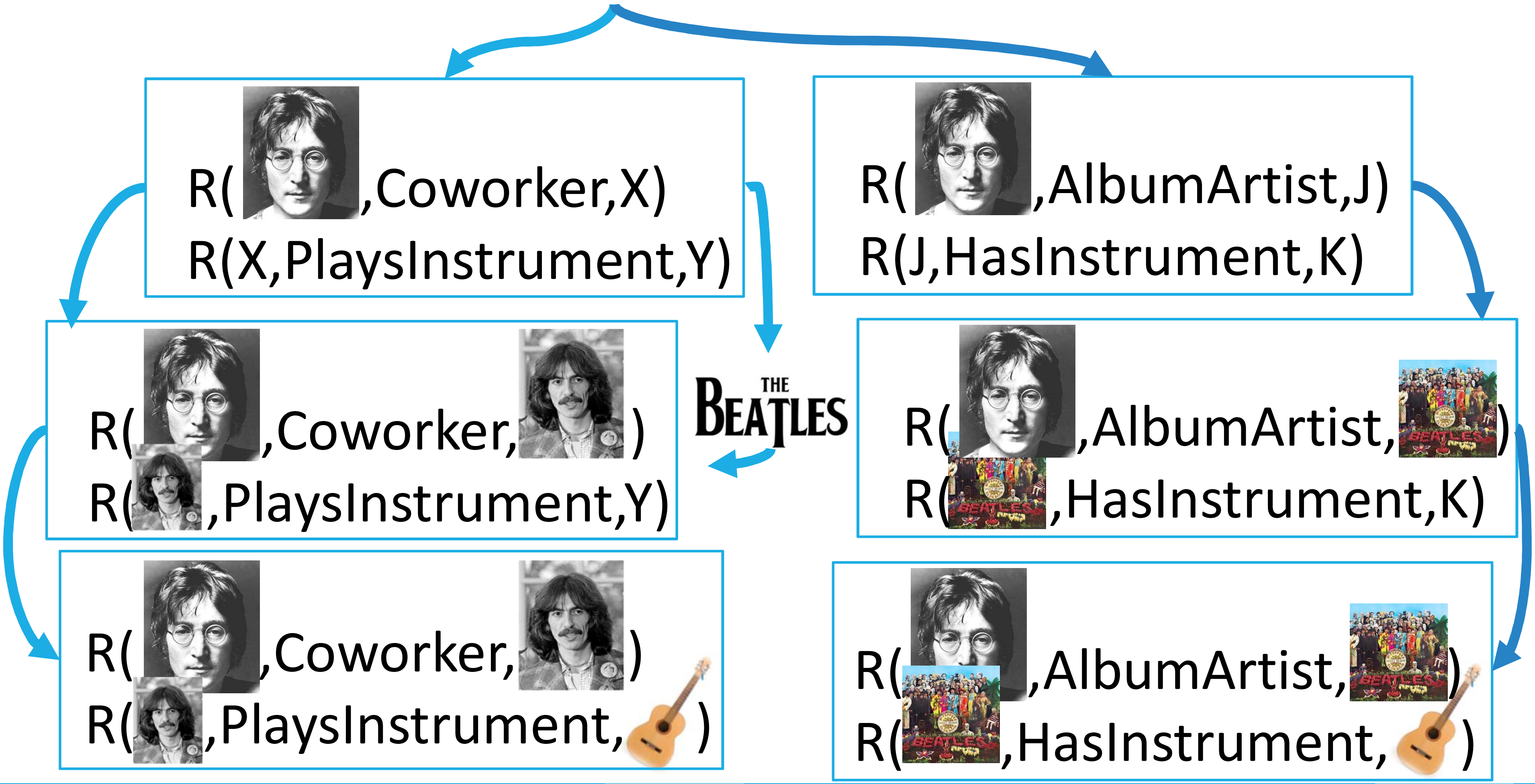
ProPPR-ized PRA example

Query Q: R(Lennon, PlaysInstrument, ?)



ProPPR-ized PRA example

Query Q: R(Lennon, PlaysInstrument, ?)



ProPPR-ized PRA example

Query Q: R(Lennon, PlaysInstrument, ?)

R(,Cowor
R(X,PlaysInstru

lbumArtist,J)
nstrument,K)

R(,Coworker,
R(,PlaysInstrume

,AlbumArtist,)
HasInstrument,K)

R(,Coworker,)
R(,PlaysInstrument,)

R(,AlbumArtist,)
R(,HasInstrument,)

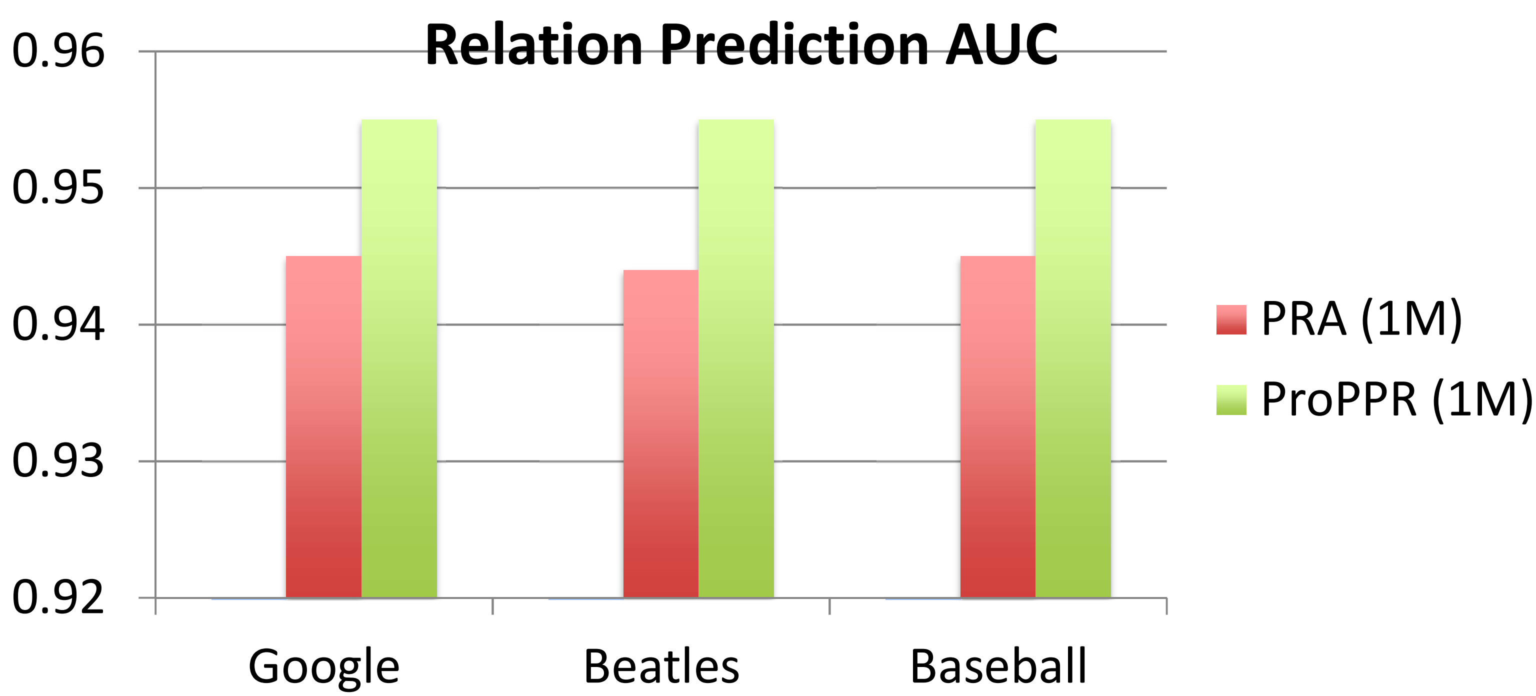
ProPPR in a nutshell

$$\min_{\mathbf{w}} -\left(\sum_{k\in+} \log \mathbf{p}_{\nu_0}[u_+^k] + \sum_{k\in-} \log(1-\mathbf{p}_{\nu_0}[u_-^k]\right) + \mu||\mathbf{w}||_2^2$$

- Input: queries, positive answers, negative answers
- Goal: $\mathbf{p}_{\nu_0}[u_+^k] \geq \mathbf{p}_{\nu_0}[u_-^k]$ (page rank from RW)
- Learn: random walk weights
- Train via stochastic gradient descent

Results from PRA and ProPPR

- Task:
  - 1M extractions for 3 domains;
  - ~100s of training queries
  - ~1000s of test queries
  - AUC of extractions alone is 0.7



Random Walks: Pros/Cons

BENEFITS

- KG query estimation independent of KG size
- Model training produces interpretable, logical rules
- Robust to noisy extractions through probabilistic form

DRAWBACKS

- Full KG completion task inefficient
- Training data difficult to obtain at scale
- Input must follow probabilistic semantics

Two classes of Probabilistic Models

GRAPHICAL MODELS

- Possible facts in KG are variables
- Logical rules relate facts
- Probability $\propto$ satisfied rules
- Universally-quantified

RANDOM WALK METHODS

- Possible facts posed as queries
- Random walks of the KG constitute "proofs"
- Probability $\propto$ path lengths/transitions
- Locally grounded