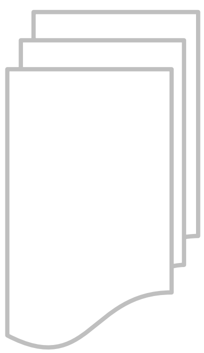
Knowledge Graph Construction from Text

AAAI 2017

Jay Pujara, Sameer Singh, Bhavana Dalvi

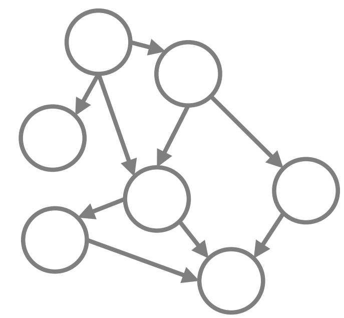
Tutorial Overview

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 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:

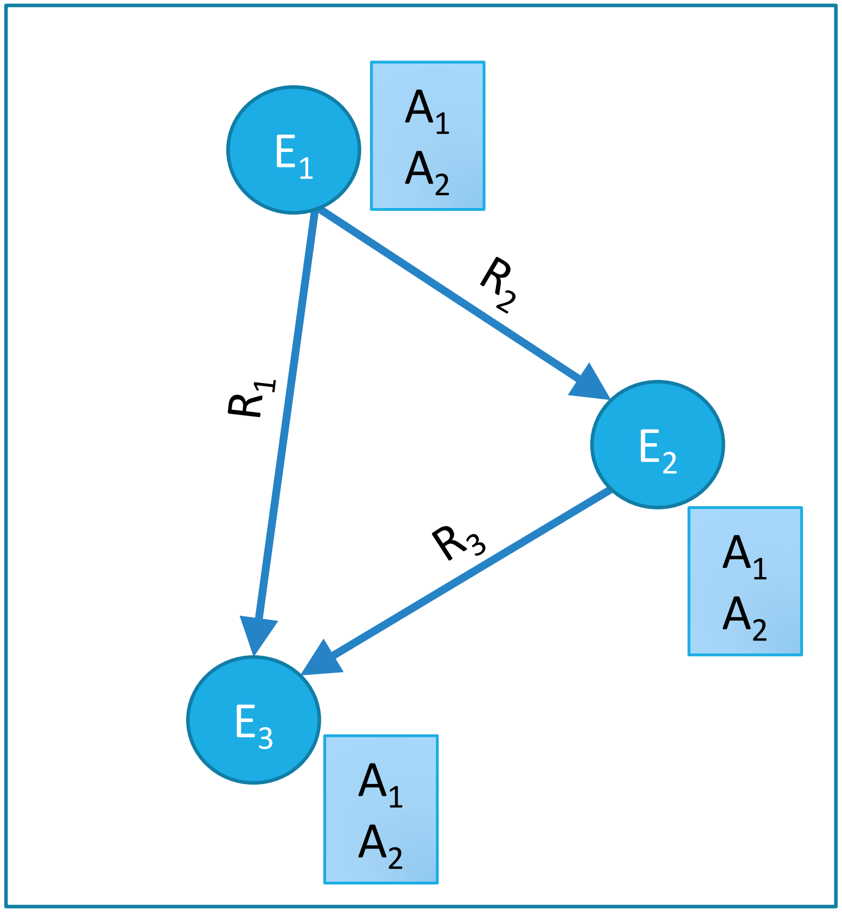
PROBLEM SETTING

PROBABILISTIC MODELS

EMBEDDING TECHNIQUES

Reminder: Basic problems

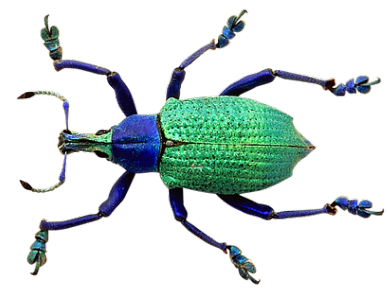
- **Who** are the entities (nodes) in the graph?
- **What** are their attributes and types (labels)?
- **How** are they related (edges)?



Graph Construction Issues

Extracted knowledge is:

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

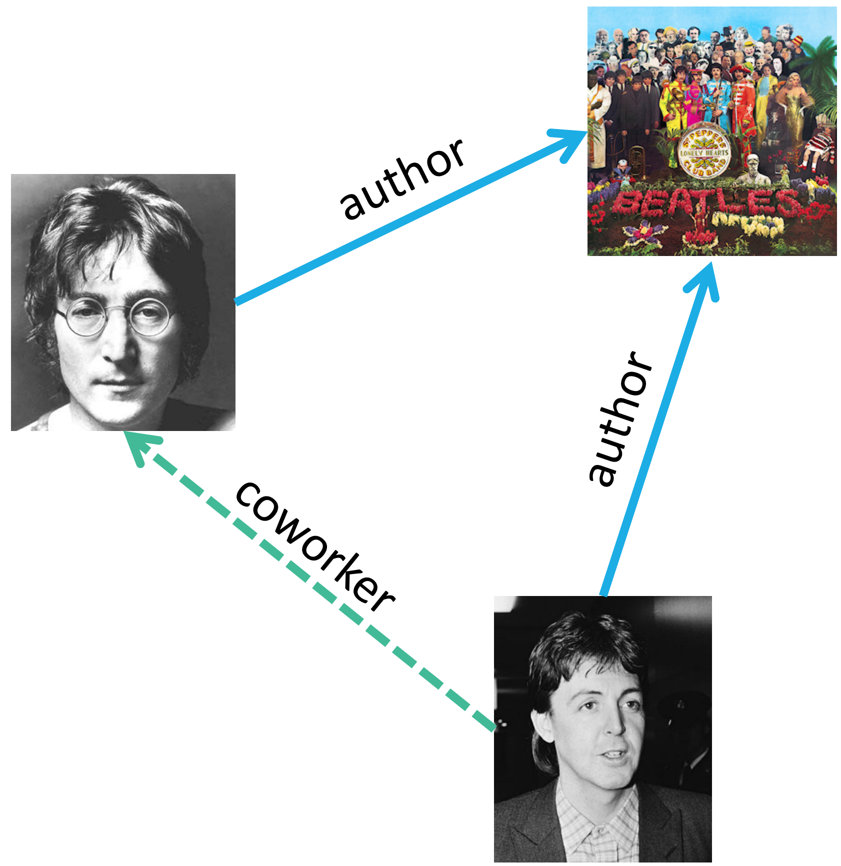


Graph Construction Issues

Extracted knowledge is:

- ambiguous

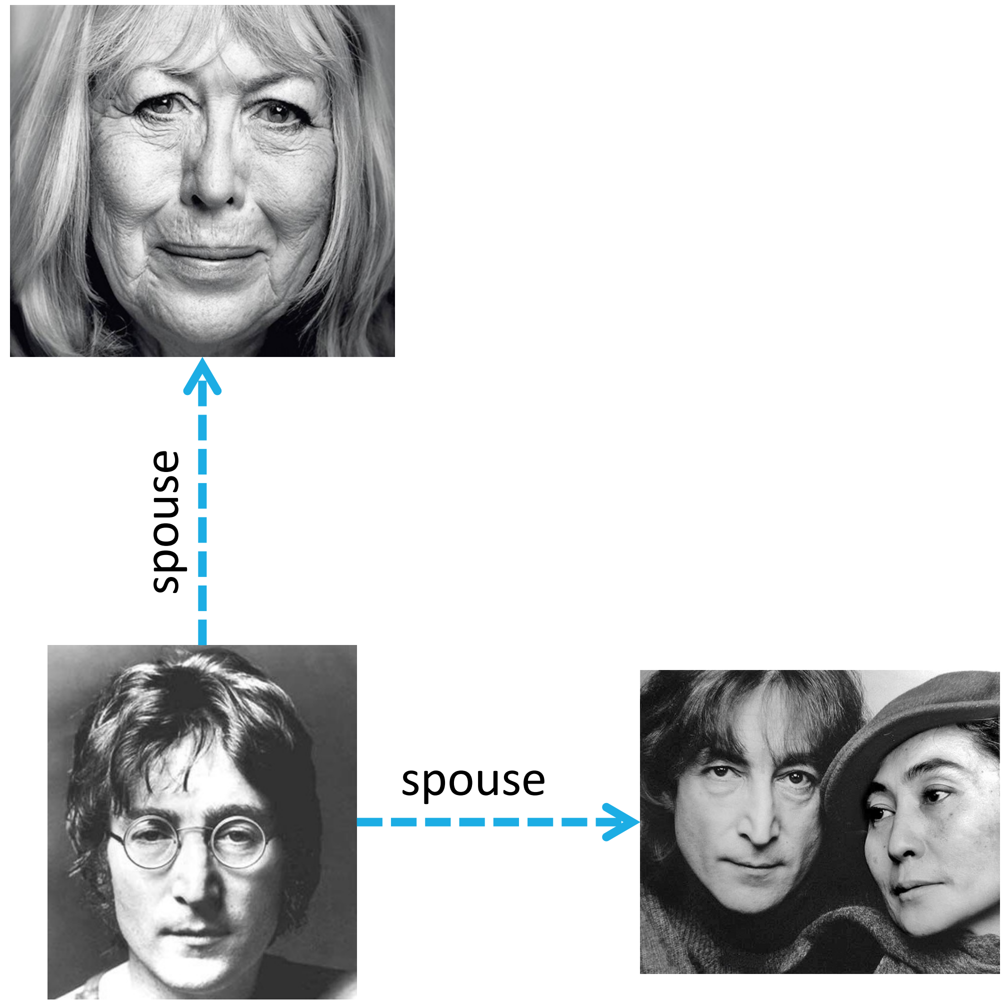
- incomplete
  - Ex: missing relationships
  - Ex: missing labels
  - Ex: missing entities



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

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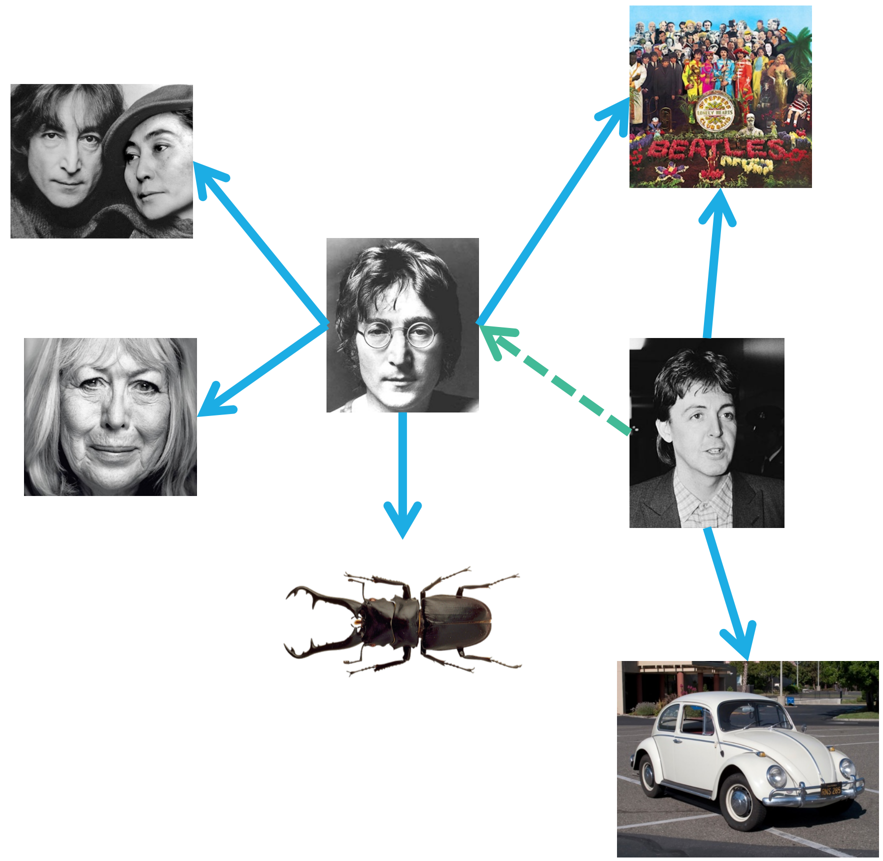
- ambiguous
- incomplete
- inconsistent



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

<u>PROBABILISTIC MODELS</u>

EMBEDDING TECHNIQUES

Graph Construction
Probabilistic Models

TOPICS:

OVERVIEW

GRAPHICAL MODELS

RANDOM WALK METHODS

Graph Construction
Probabilistic Models

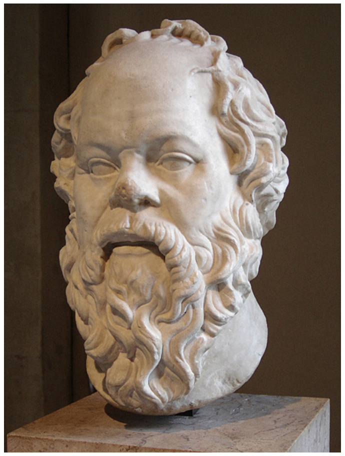
TOPICS:

Overview

Graphical models

Random Walk Methods

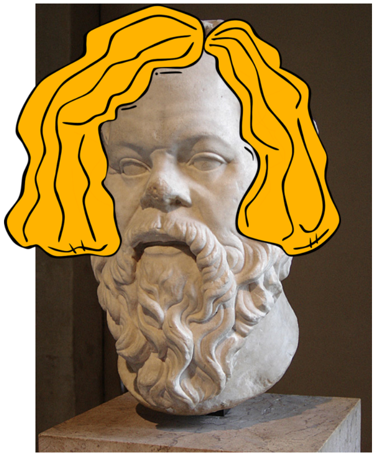
Beyond Pure Reasoning



- 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

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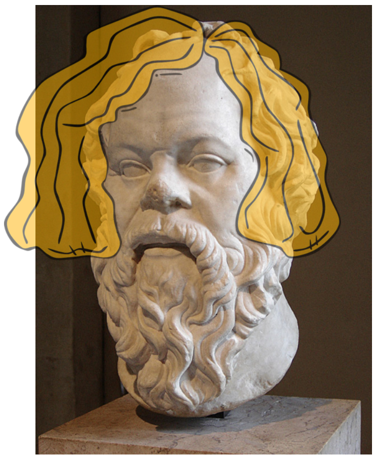
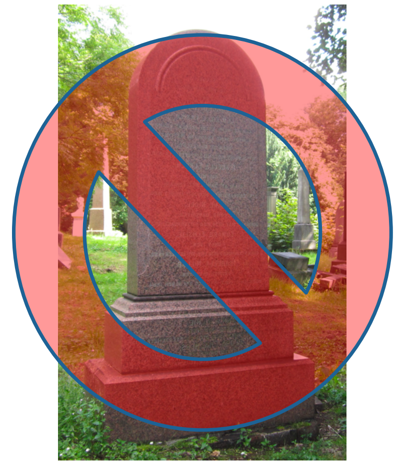




- Classical AI approach to knowledge: reasoning

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

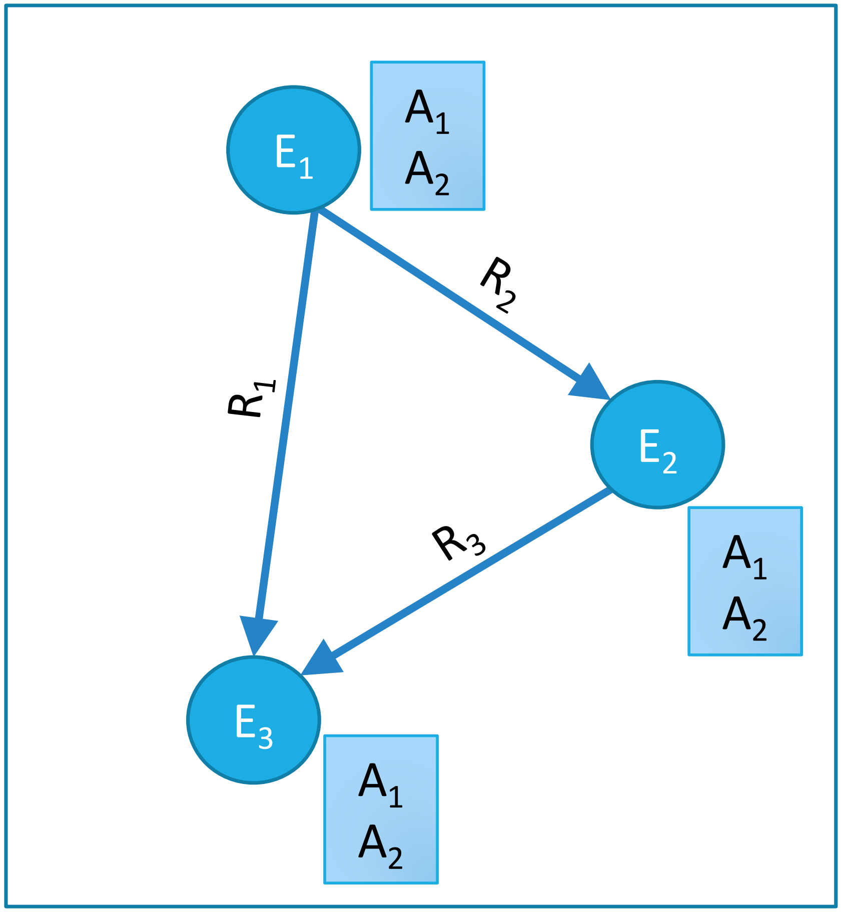
Graphical Models: Overview

- 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

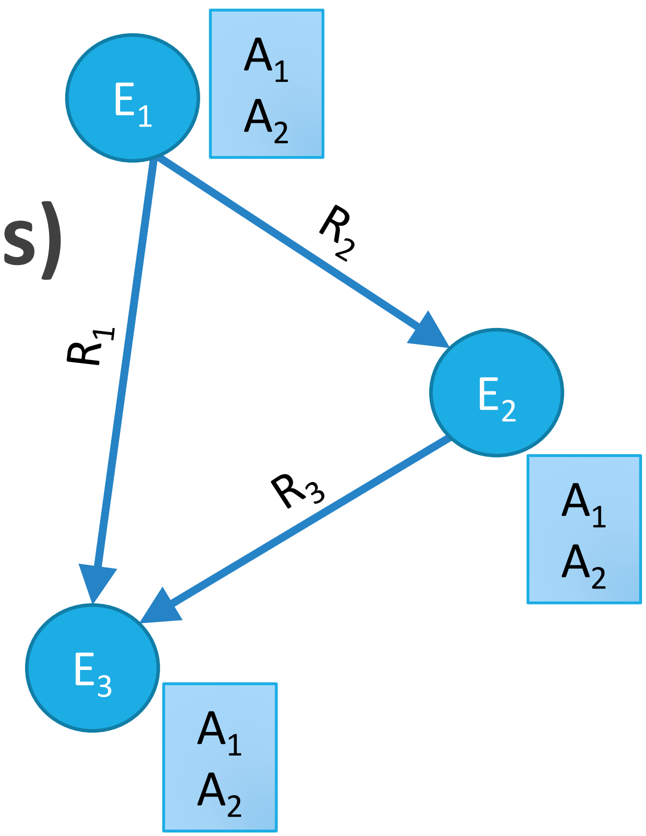
Define a graphical model to perform all three of these tasks simultaneously!

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



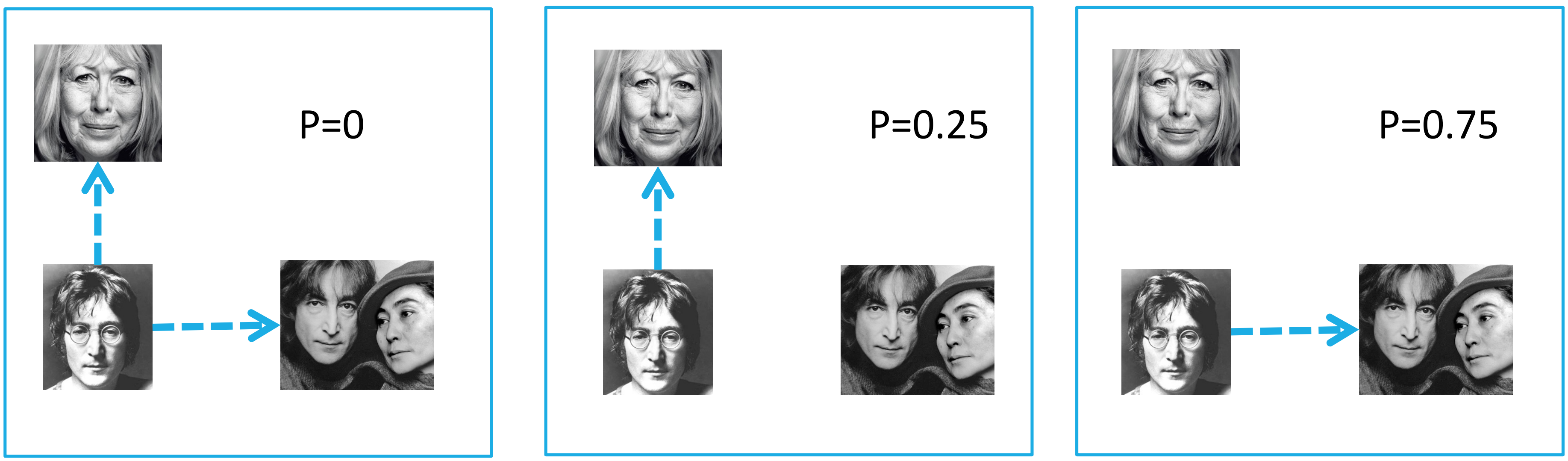
Knowledge Graph Identification

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**

What determines probability?

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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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- **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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  - 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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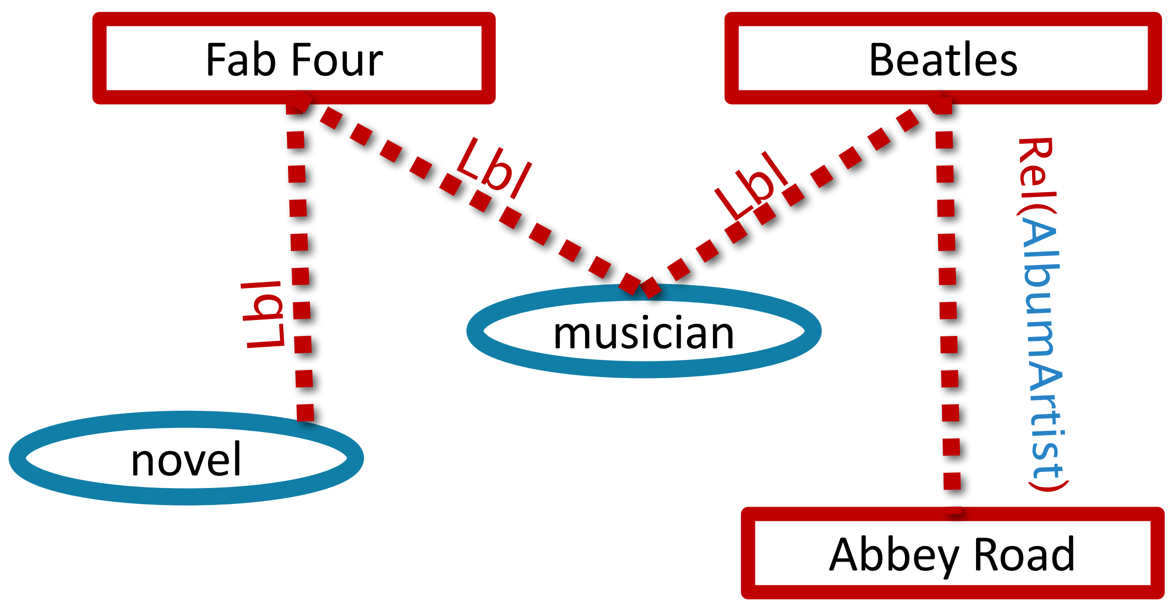
(Annotated) Extraction Graph



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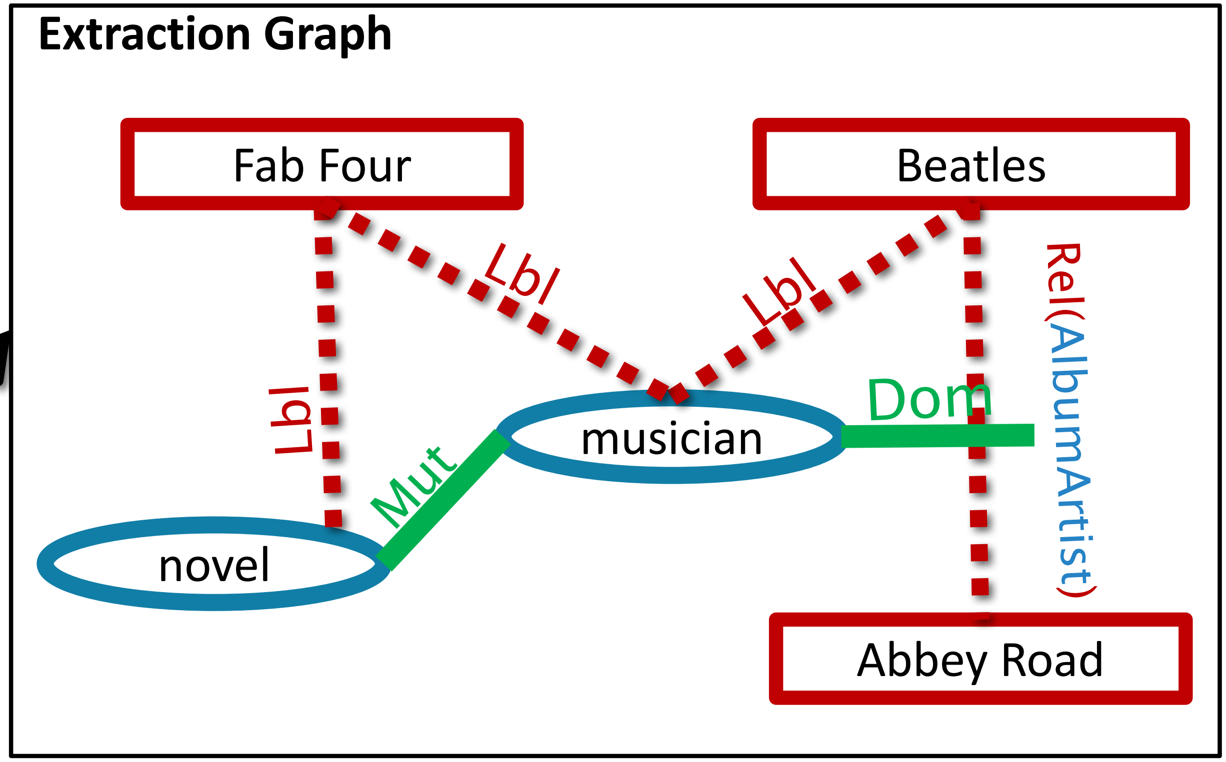
Ontology:
Dom(albumArtist, musician)
Mut(novel, musician)



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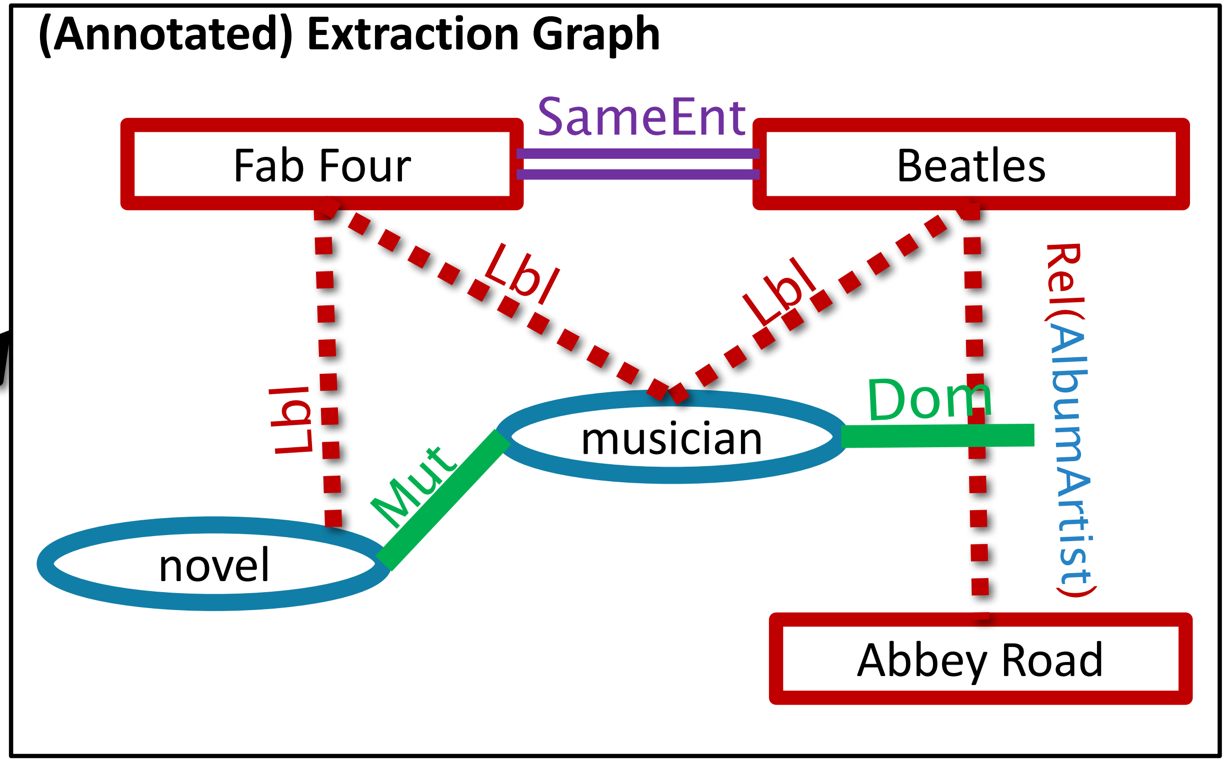
Entity Resolution:
SameEnt(Fab Four, Beatles)



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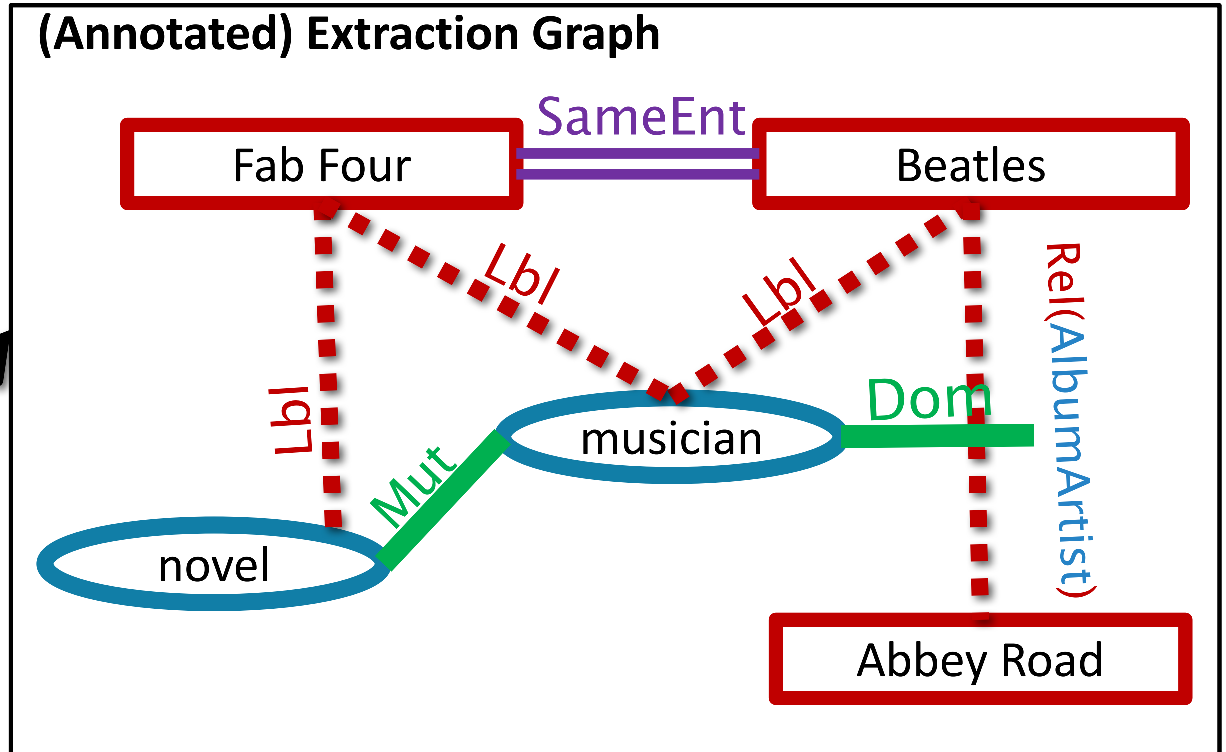
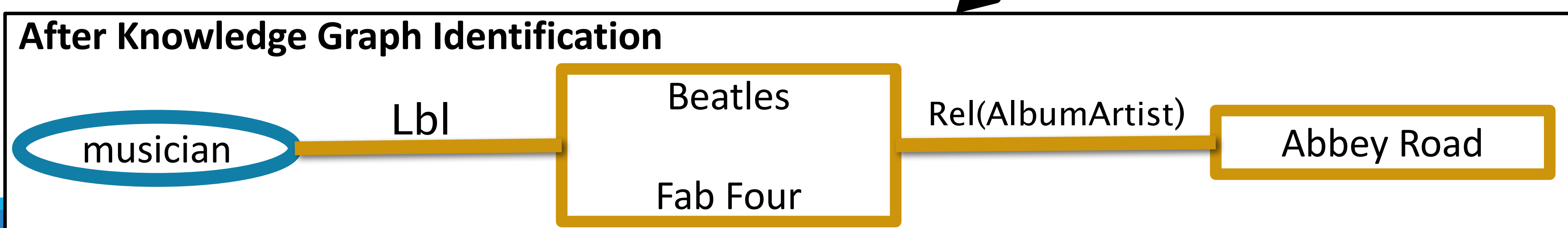
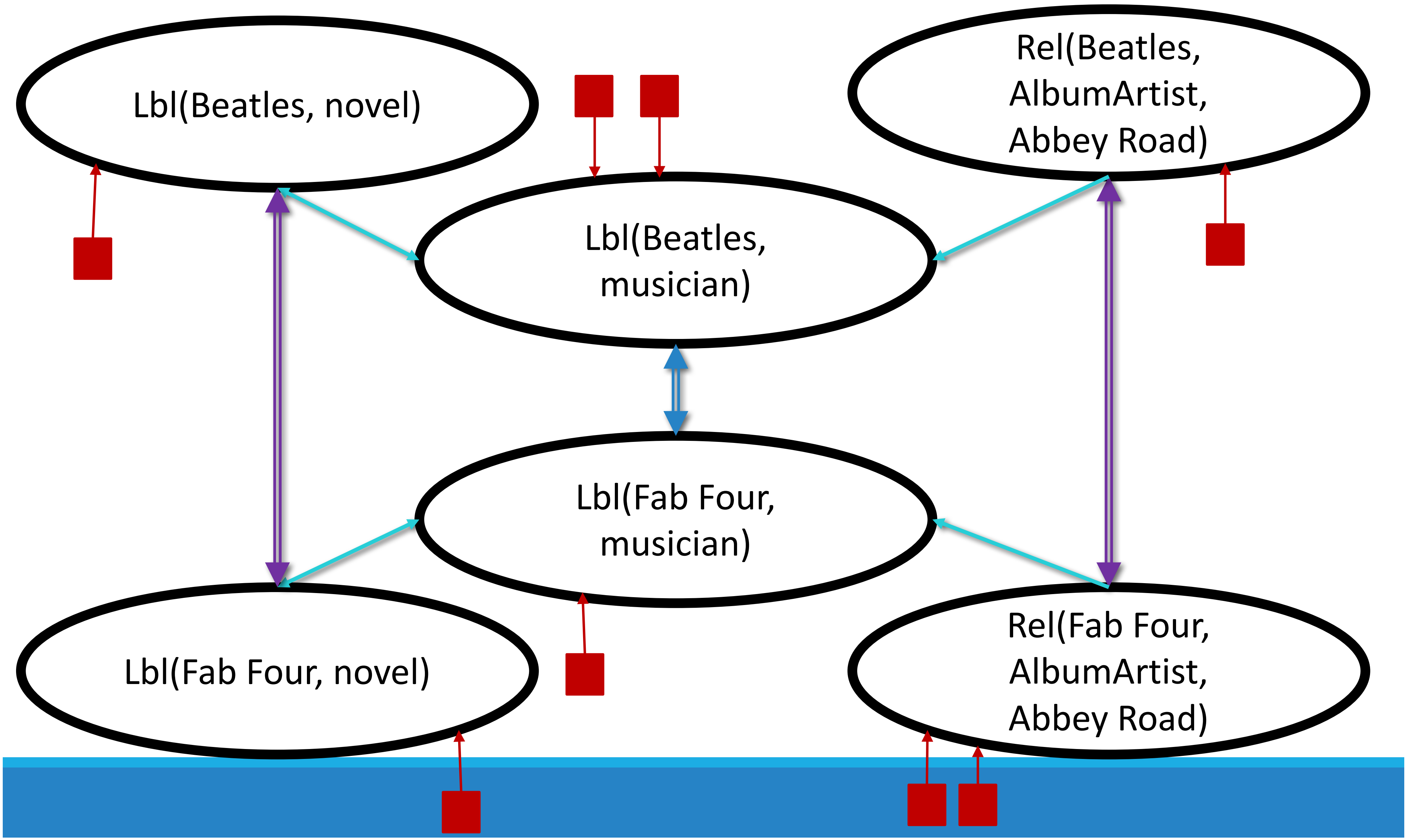




Probabilistic graphical model for KG



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_NYT(E,L)                        ->  Label(E,L)
1:      Label_YouTube(E,L)                    ->  Label(E,L)
1:      Relation_LATimes(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

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

$$\textsc{CandLbl}_T(\texttt{FabFour}, \texttt{novel}) \Rightarrow \textsc{Lbl}(\texttt{FabFour}, \texttt{novel})$$

$$\textsc{Mut}(\texttt{novel}, \texttt{musician}) \wedge \textsc{Lbl}(\texttt{Beatles}, \texttt{novel}) \Rightarrow \neg\textsc{Lbl}(\texttt{Beatles}, \texttt{musician})$$

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

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

$\Rightarrow \textsc{Lbl}(\texttt{FabFour}, \texttt{novel})$

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

$\Rightarrow \textsc{Rel}(\texttt{Beatles}, \texttt{AlbumArtist}, \texttt{AbbeyRoad})$

$[\phi_3]$ $\textsc{SameEnt}(\texttt{Beatles}, \texttt{FabFour})$

$\wedge\ \textsc{Lbl}(\texttt{Beatles}, \texttt{musician})$

$\Rightarrow \textsc{Lbl}(\texttt{FabFour}, \texttt{musician})$

$[\phi_4]$ $\textsc{Dom}(\texttt{AlbumArtist}, \texttt{musician})$

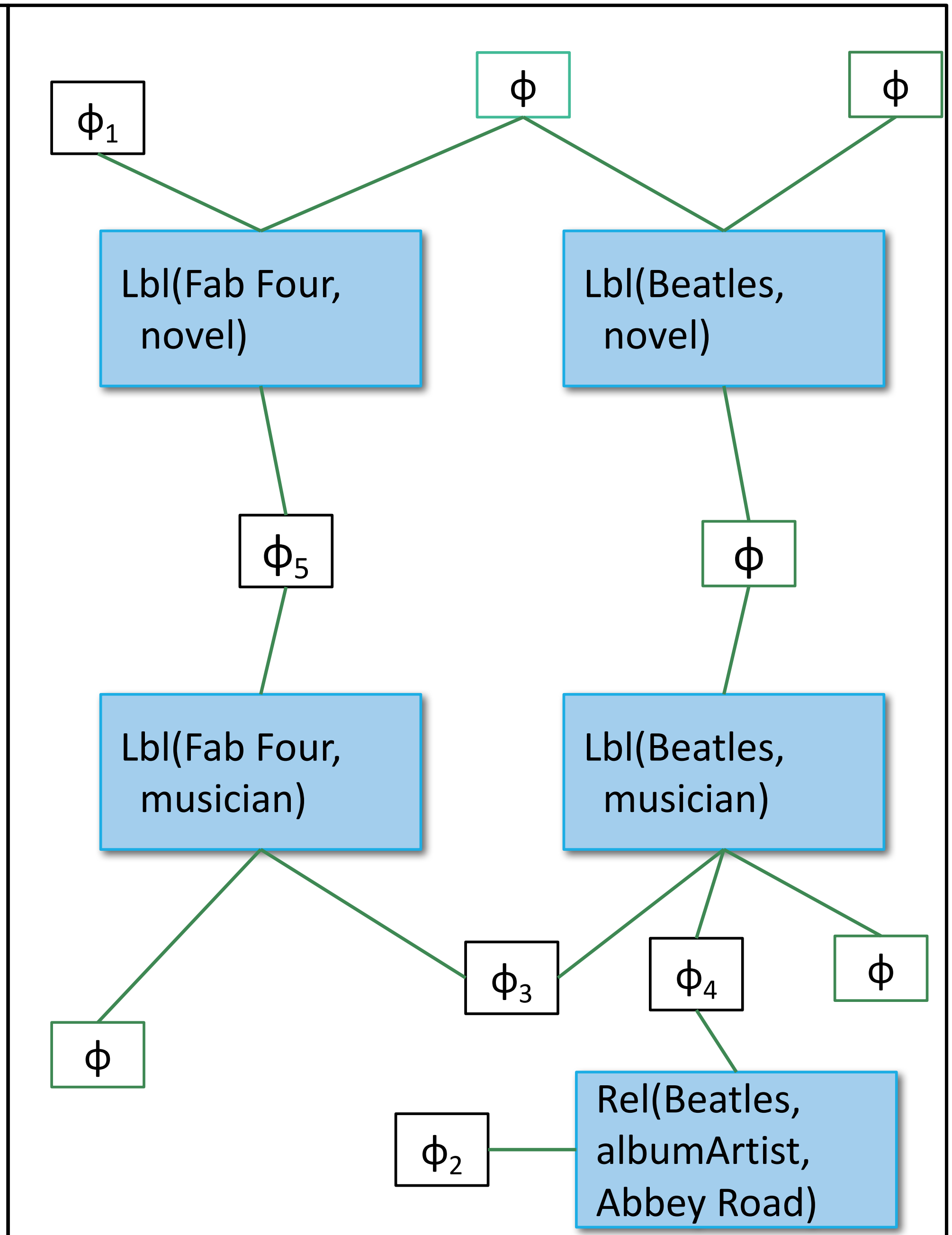
$\wedge\ \textsc{Rel}(\texttt{Beatles}, \texttt{AlbumArtist}, \texttt{AbbeyRoad})$

$\Rightarrow \textsc{Lbl}(\texttt{Beatles}, \texttt{musician})$

$[\phi_5]$ $\textsc{Mut}(\texttt{musician}, \texttt{novel})$

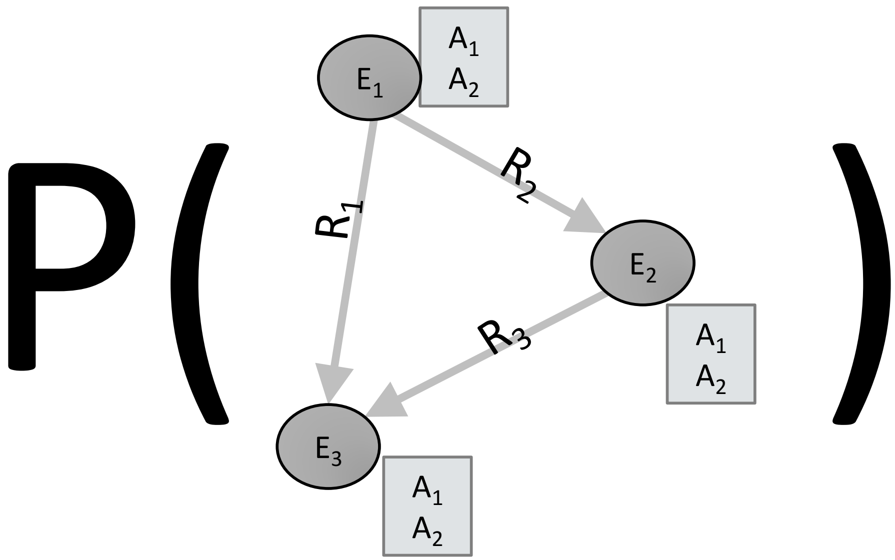
$\wedge\ \textsc{Lbl}(\texttt{FabFour}, \texttt{musican})$

$\Rightarrow \neg\textsc{Lbl}(\texttt{FabFour}, \texttt{novel})$

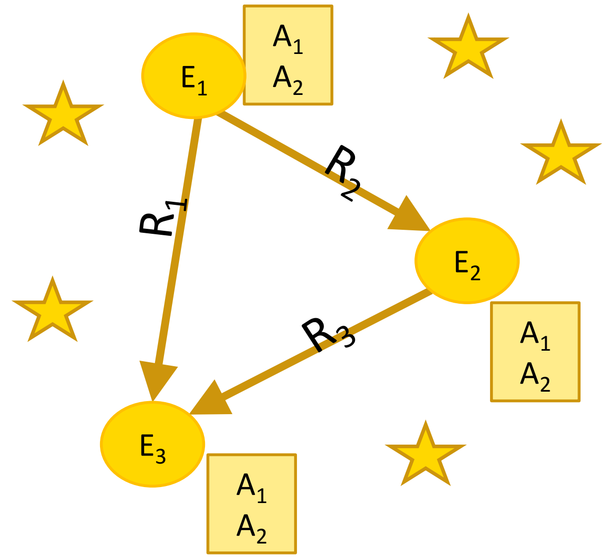


How do we get a knowledge graph?

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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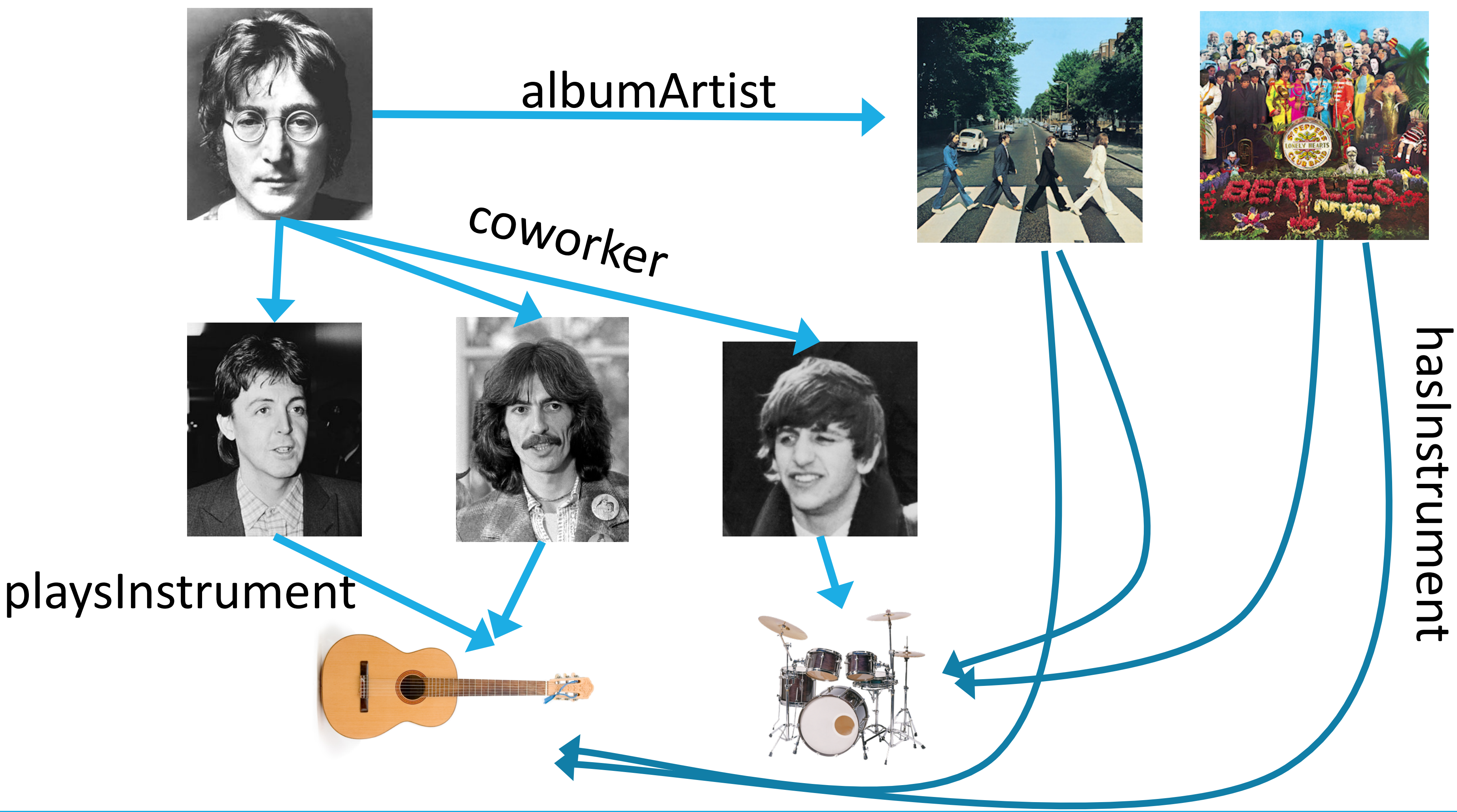

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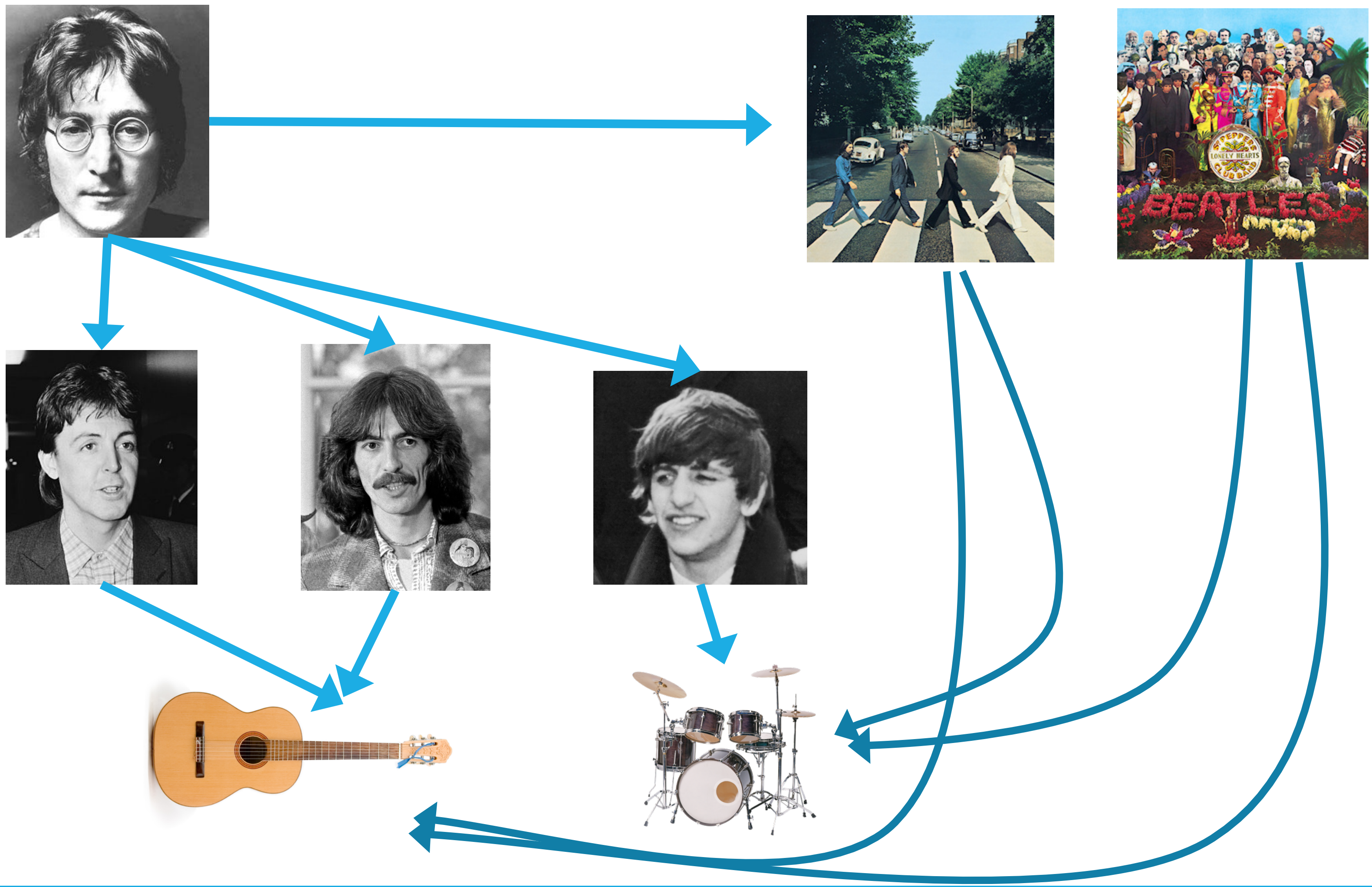

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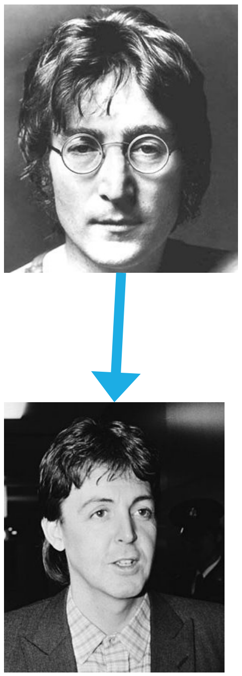

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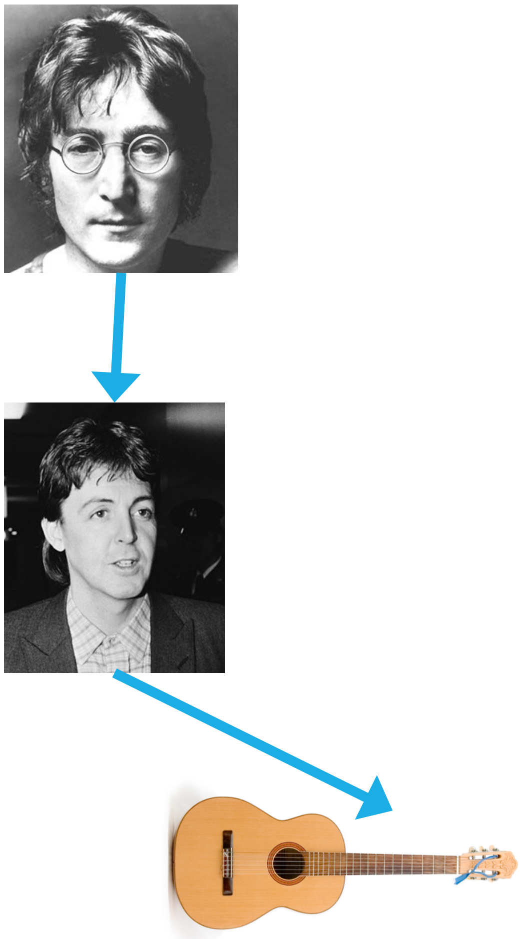

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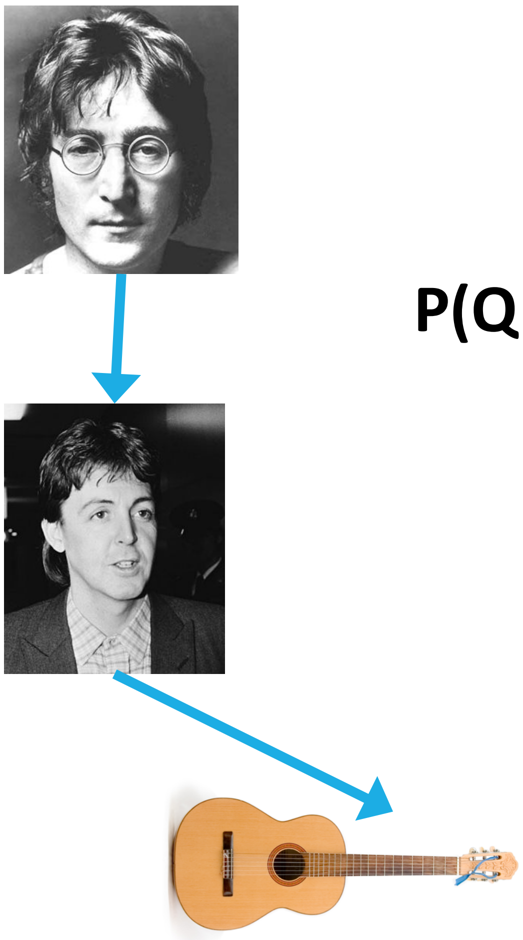


Path

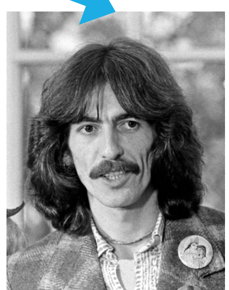
Weight of path

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

Random Walk Illustration

Query Q: R(Lennon, PlaysInstrument, ?)

P(Q|π=<coworker,playsInstrument>) W_π



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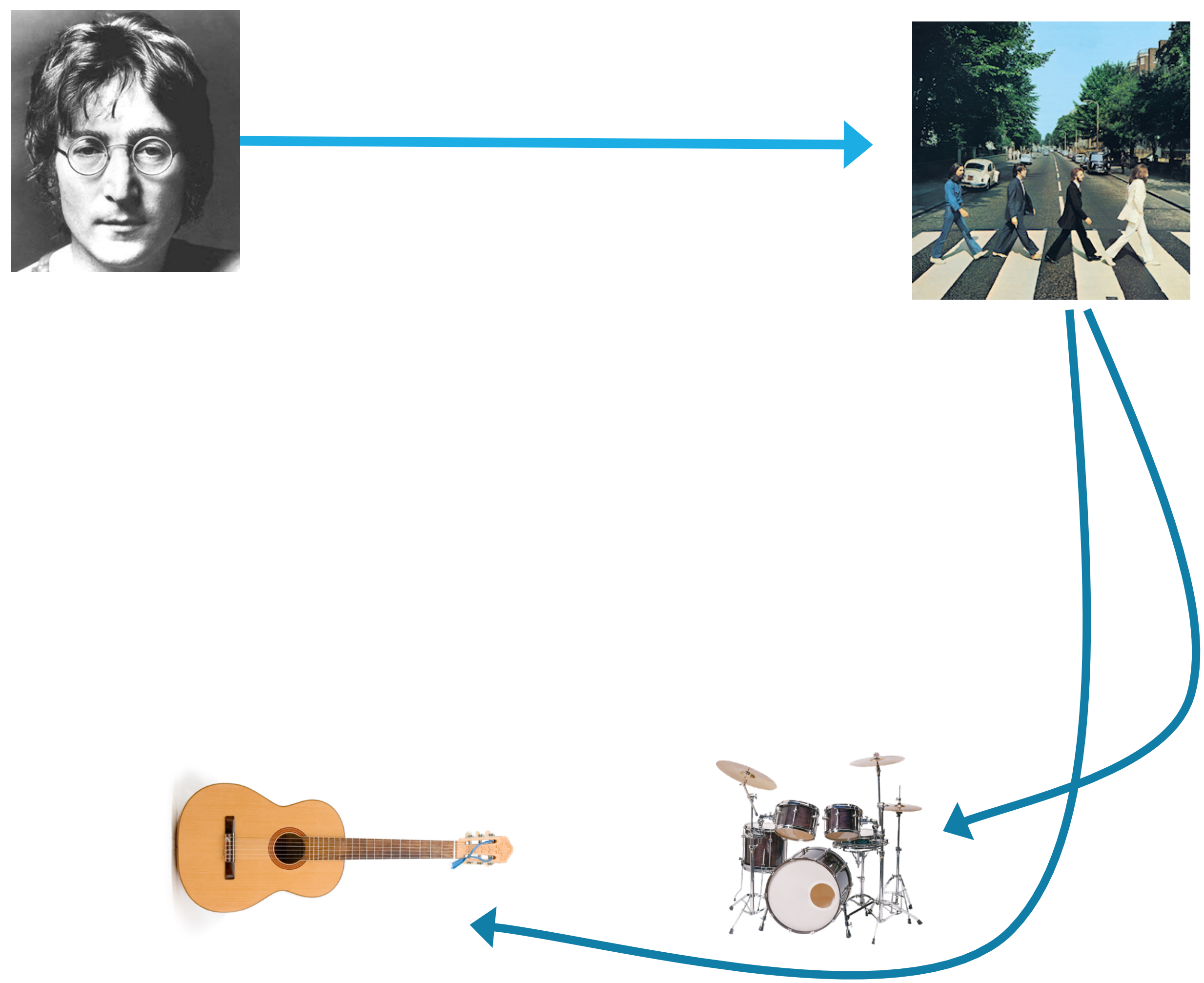

Random Walk Illustration

Query Q: R(Lennon, PlaysInstrument, ?)

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

Random Walk Illustration

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

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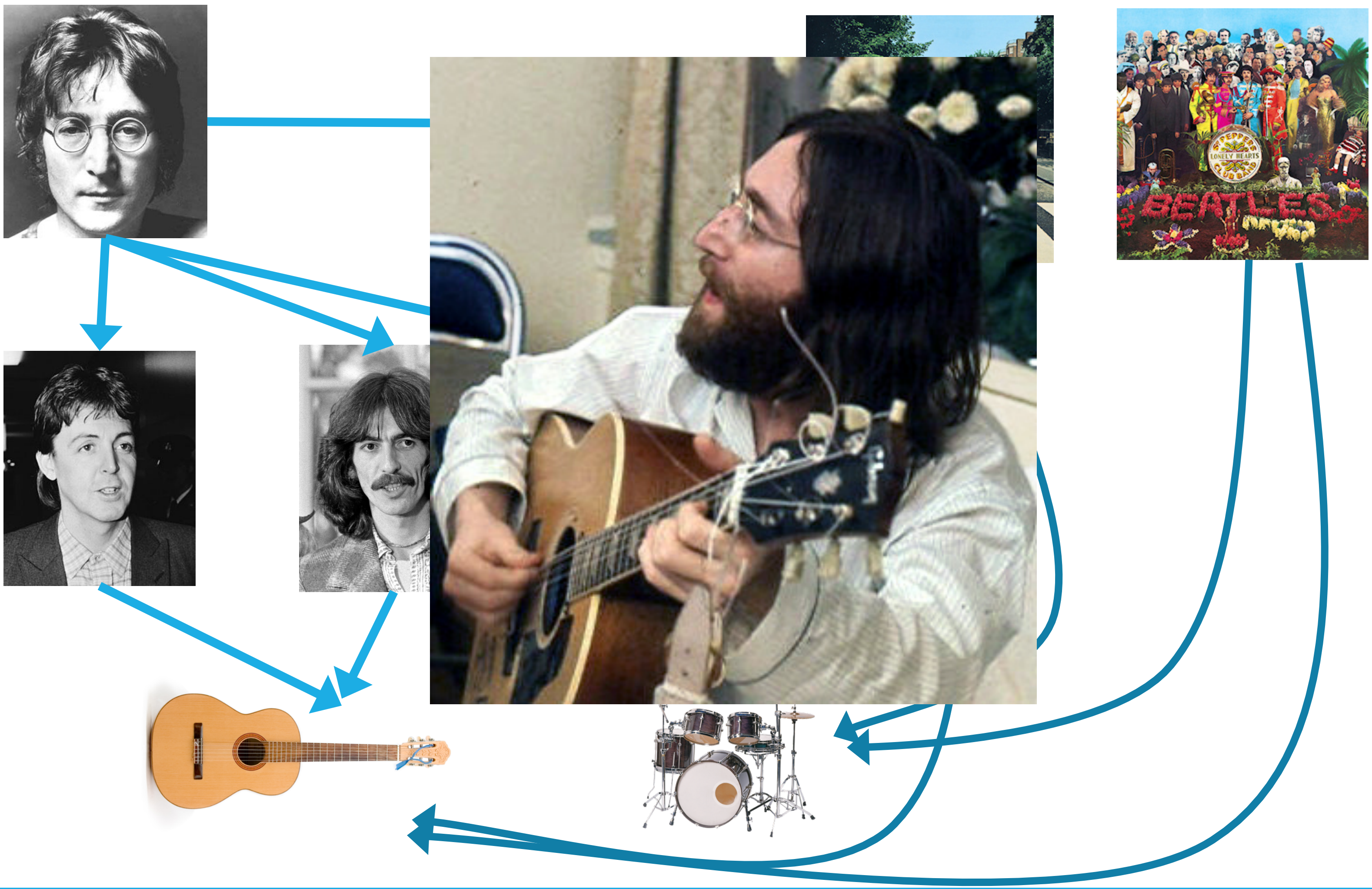

Recent Random Walk Methods

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

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

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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)

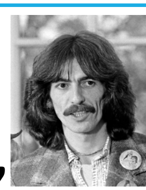
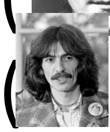
Unbound variables in proof tree!

ProPPR-ized PRA example

Query Q: R(Lennon, PlaysInstrument, ?)

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

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

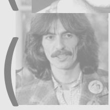
R(,Coworker,)
R(,PlaysInstrument,Y)

ProPPR-ized PRA example

Query Q: R(Lennon, PlaysInstrument, ?)

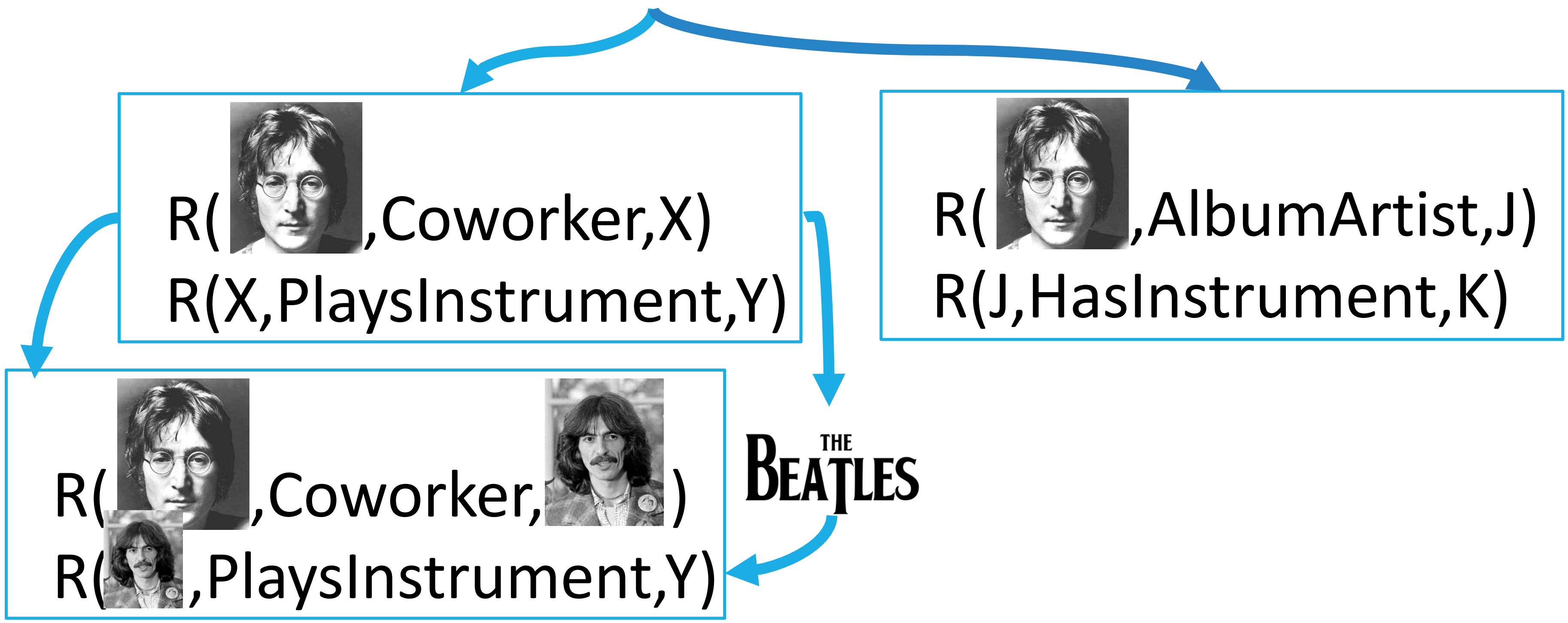
R(,Coworker,X)
R(X,PlaysInstrument,Y)

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

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

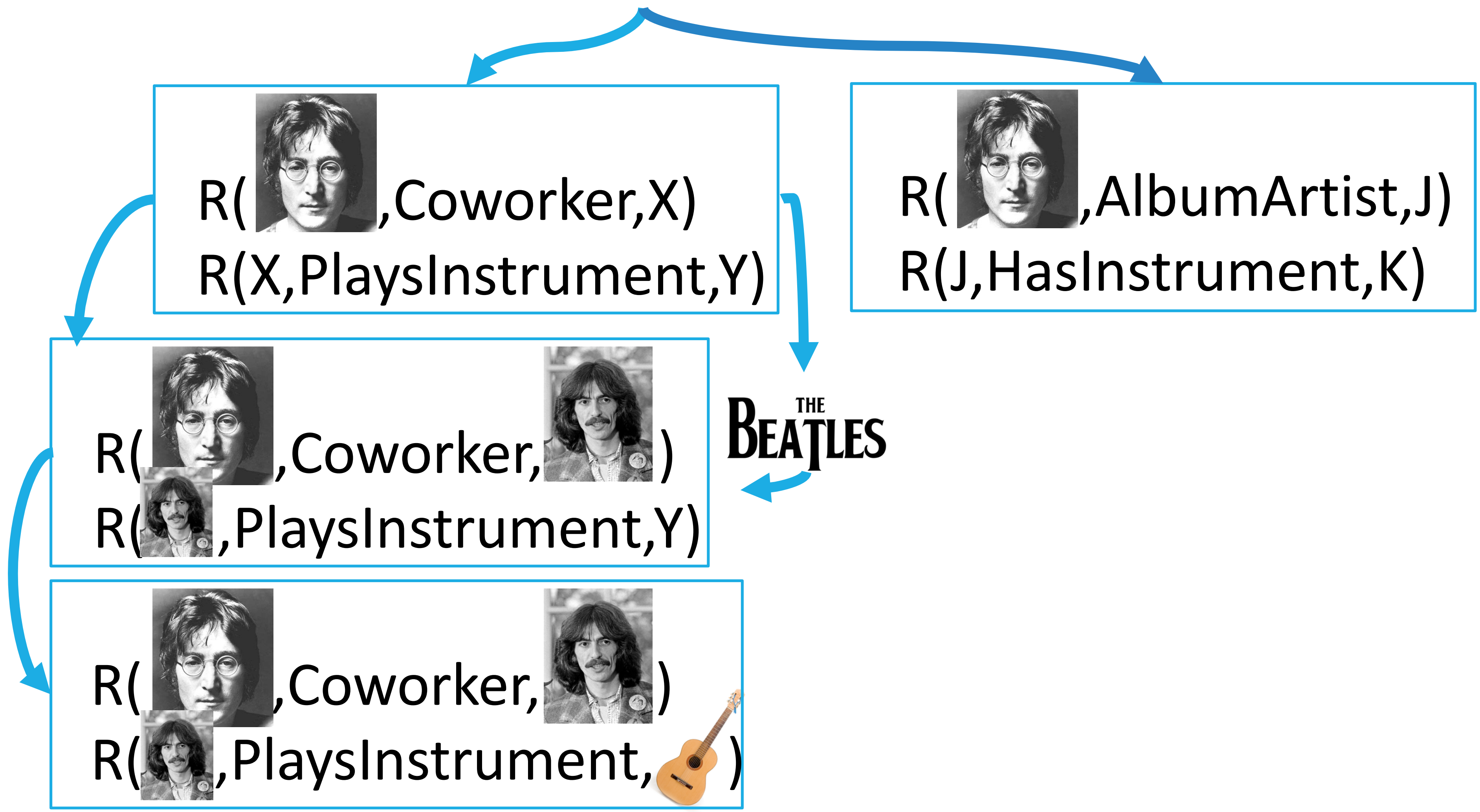
ProPPR-ized PRA example

Query Q: R(Lennon, PlaysInstrument, ?)



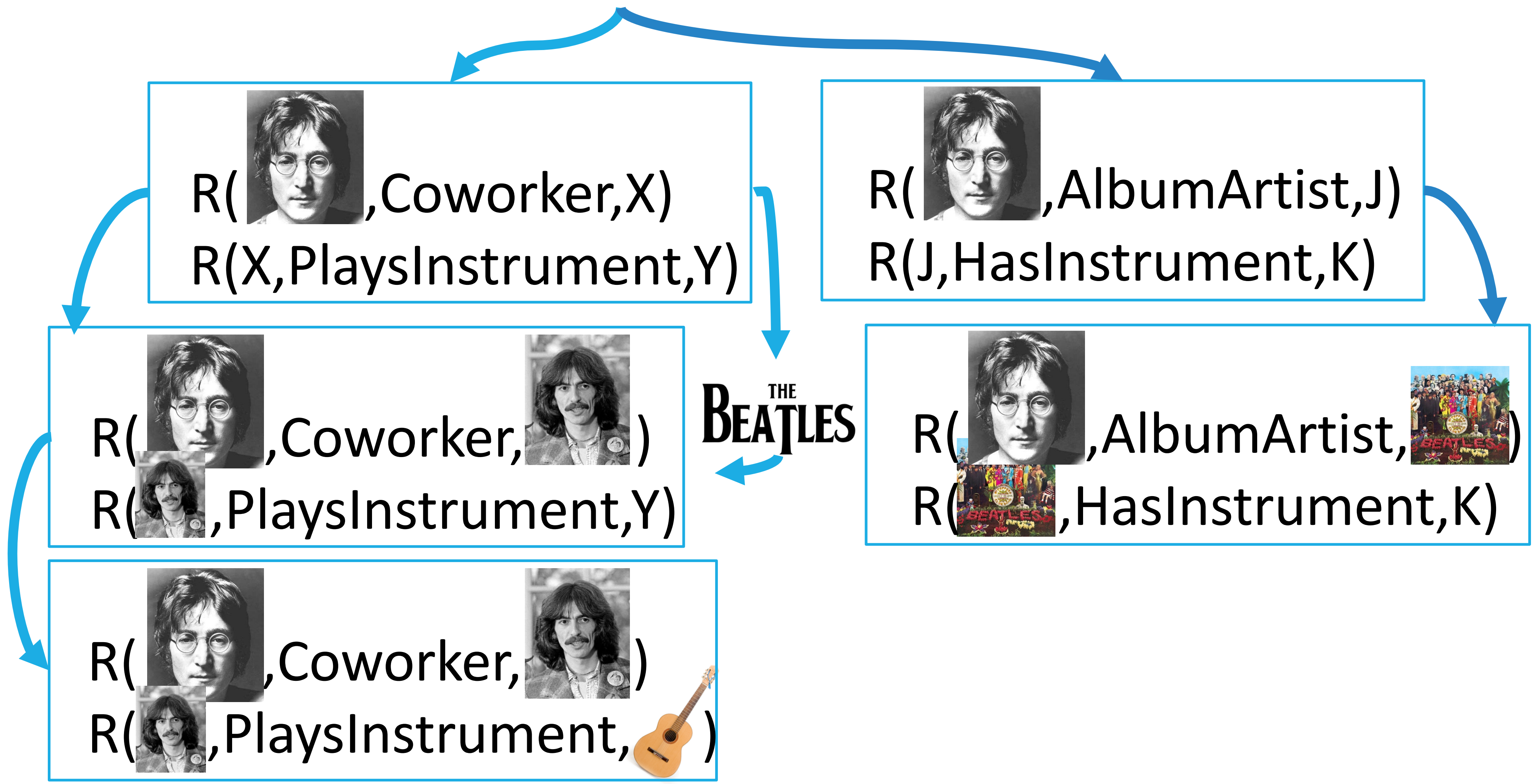
ProPPR-ized PRA example

Query Q: R(Lennon, PlaysInstrument, ?)



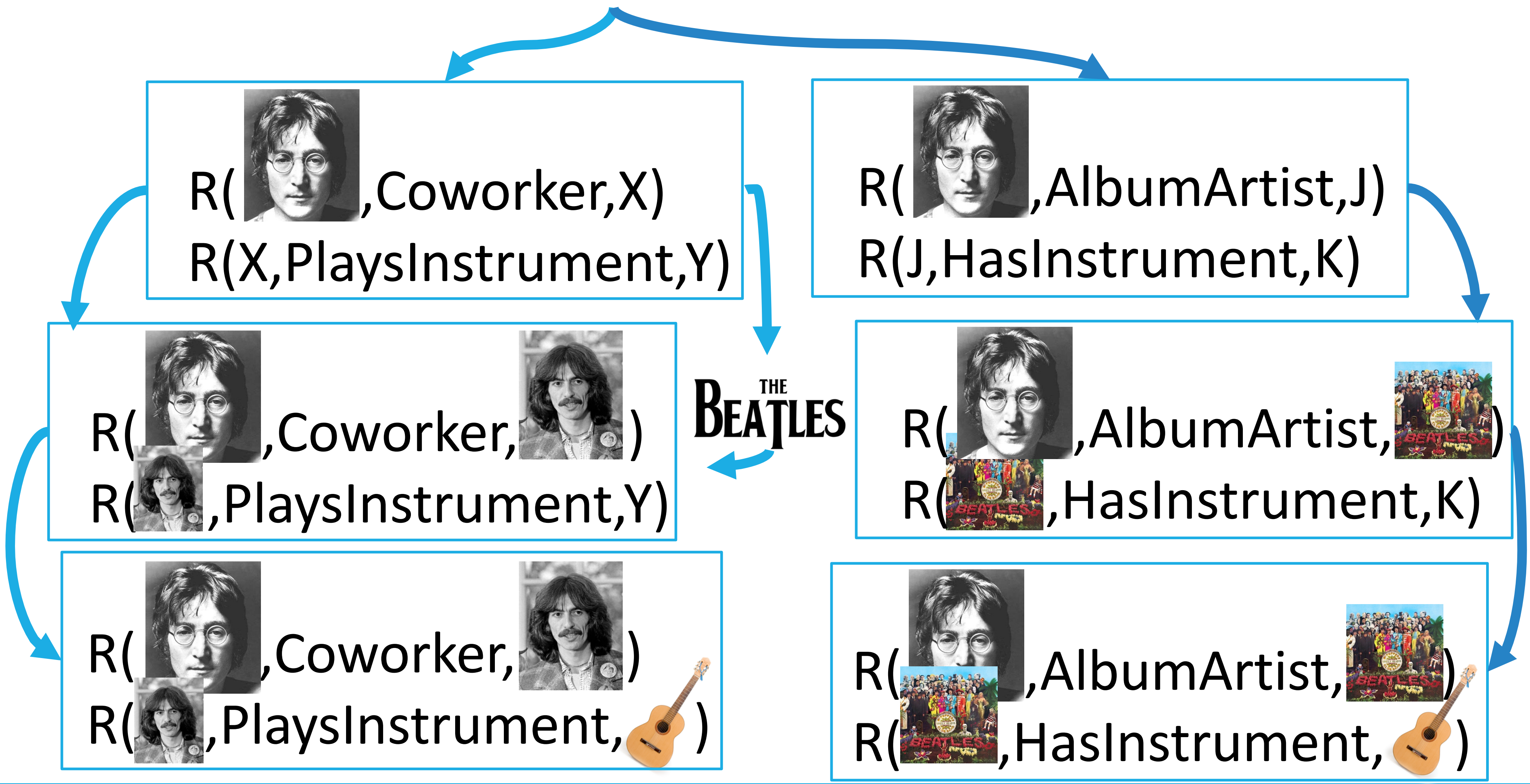
ProPPR-ized PRA example

Query Q: R(Lennon, PlaysInstrument, ?)



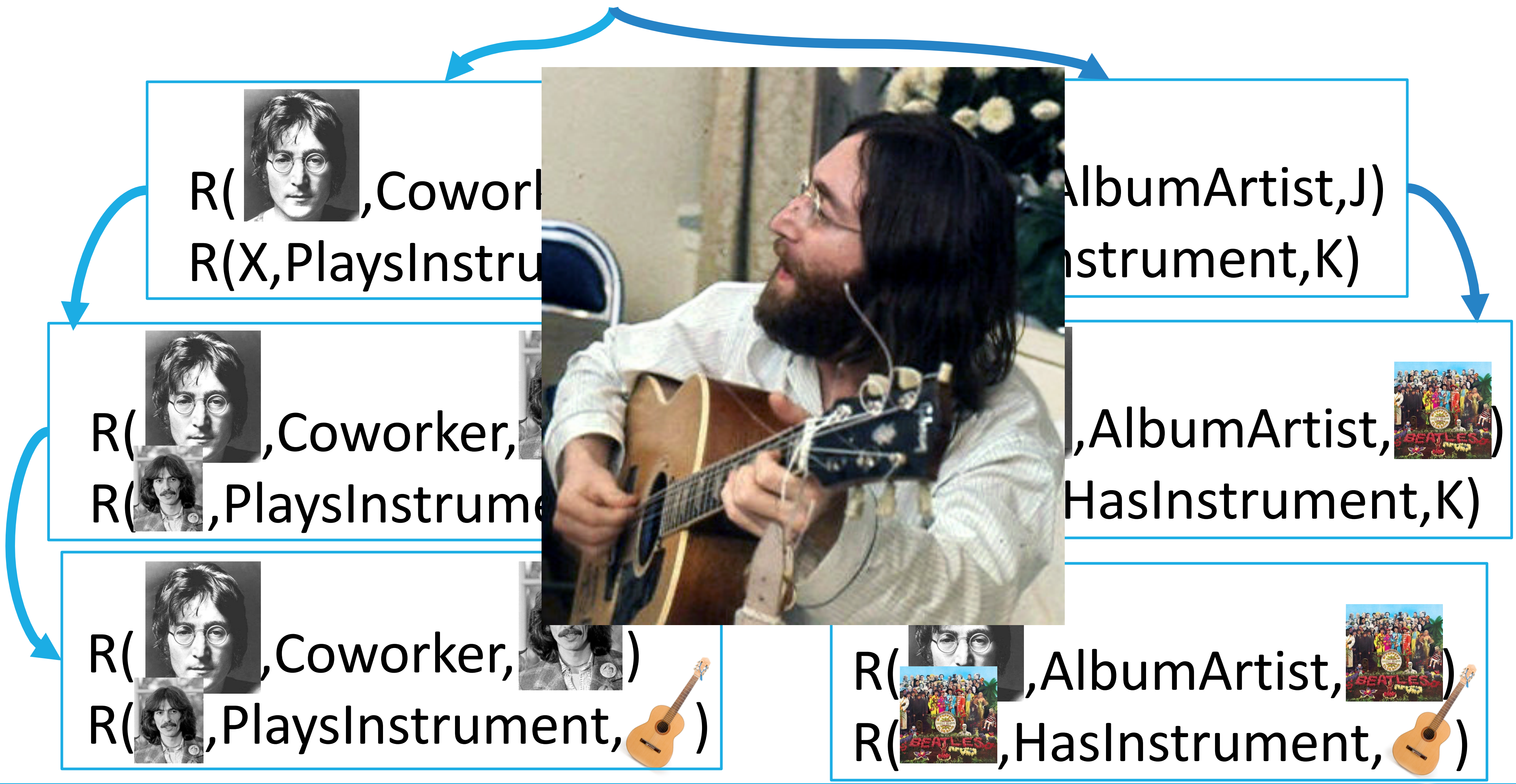
ProPPR-ized PRA example

Query Q: R(Lennon, PlaysInstrument, ?)



ProPPR-ized PRA example

Query Q: R(Lennon, PlaysInstrument, ?)



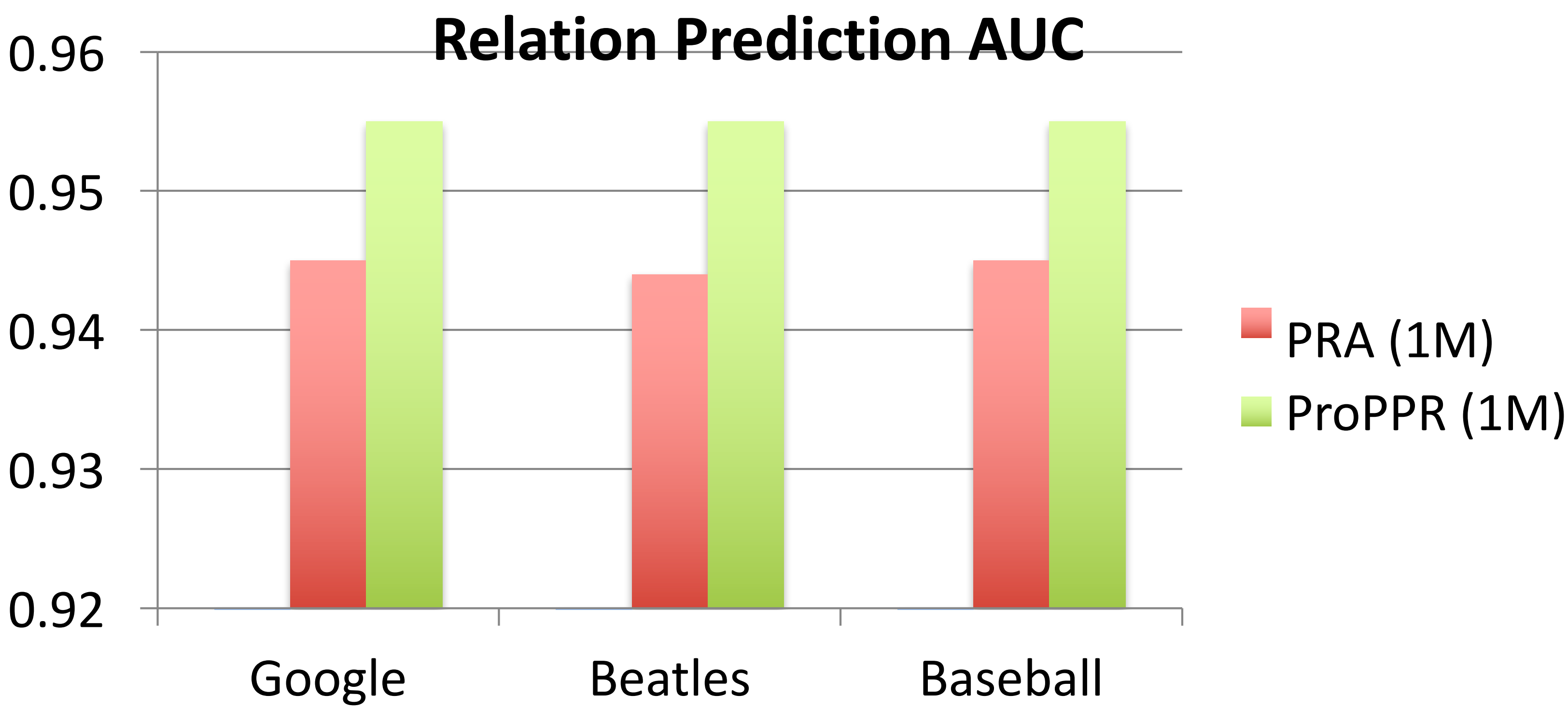
ProPPR in a nutshell

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

- 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