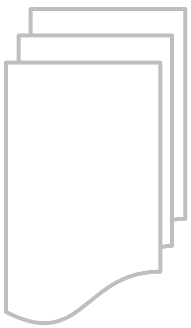
Knowledge Graph Construction from Text

AAAI 2017

Jay Pujara, Sameer Singh, Bhavana Dalvi

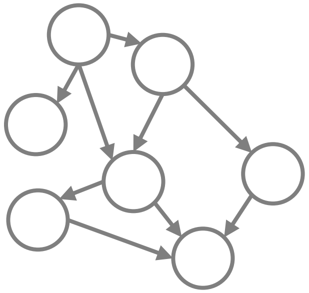
Tutorial Overview

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:

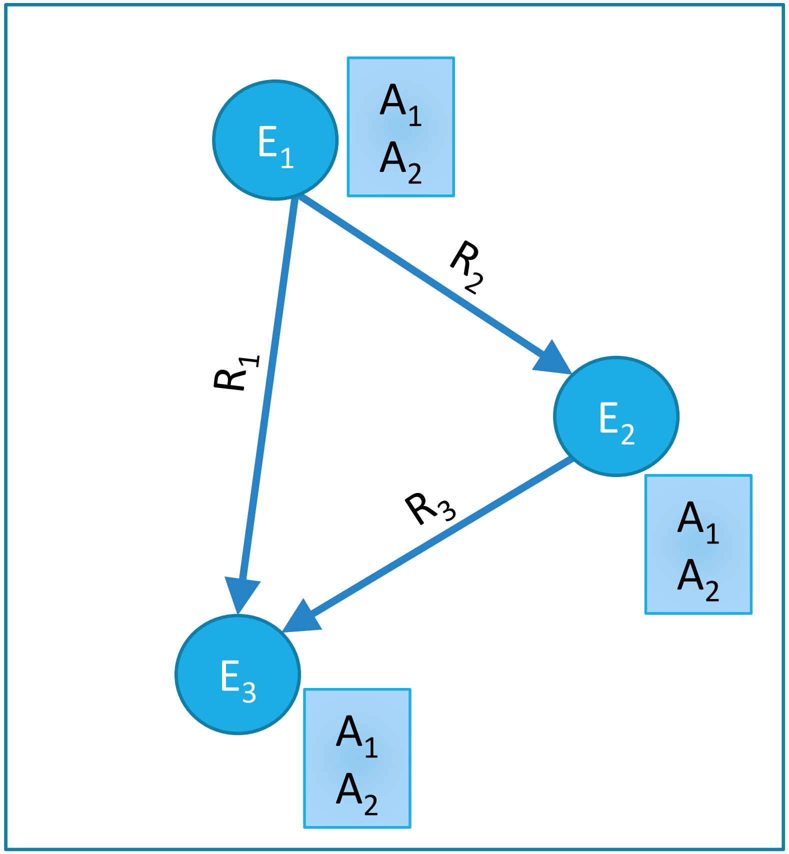
Problem Setting

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:

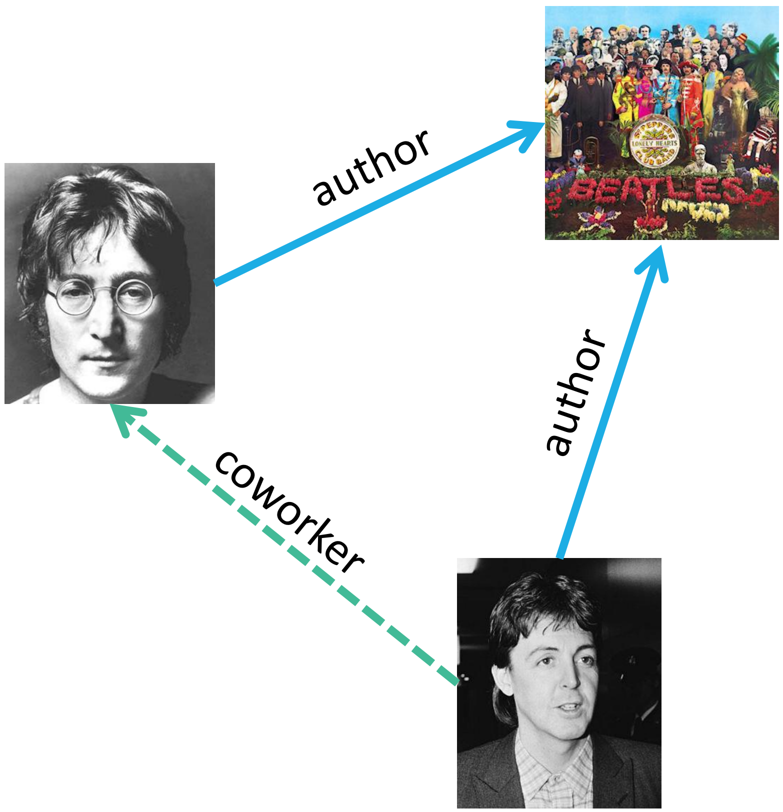
- ambiguous:
  - Ex: Beetles, beetles, Beatles
  - Ex: citizenOf, livedIn, bornIn

Graph Construction Issues

Extracted knowledge is:

- ambiguous

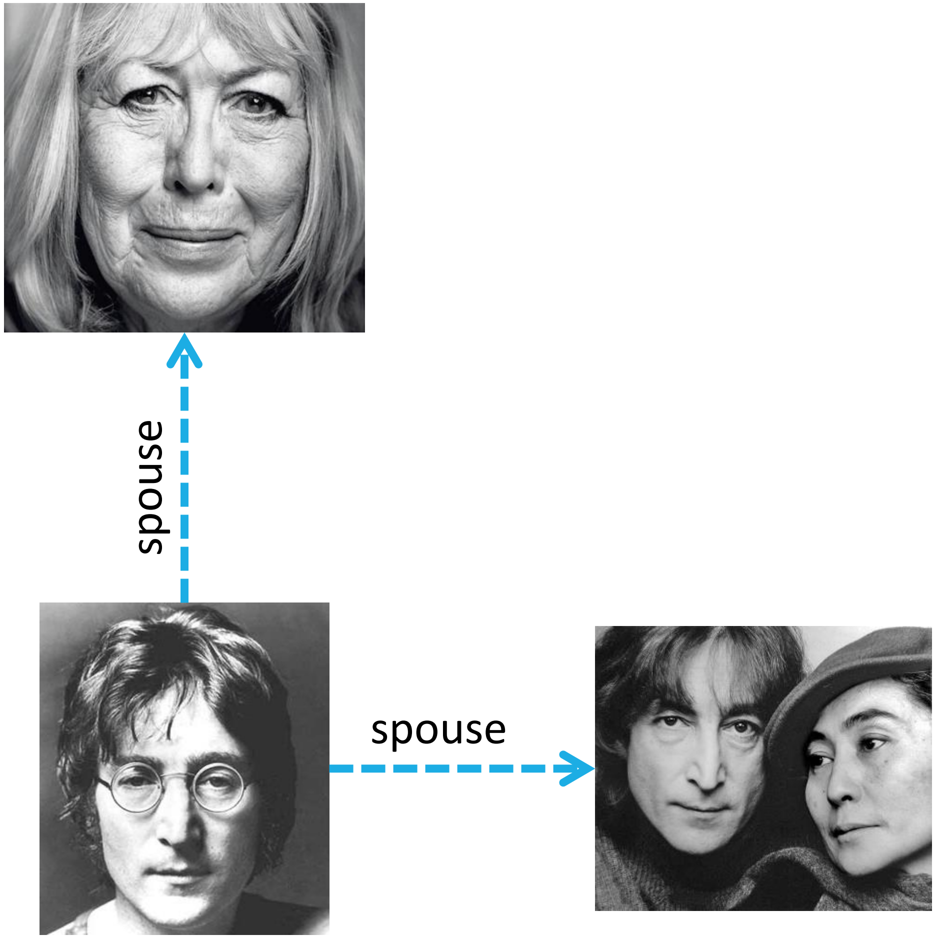
- incomplete
  - Ex: missing relationships
  - Ex: missing labels
  - Ex: missing entities



Graph Construction Issues

Extracted knowledge is:

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



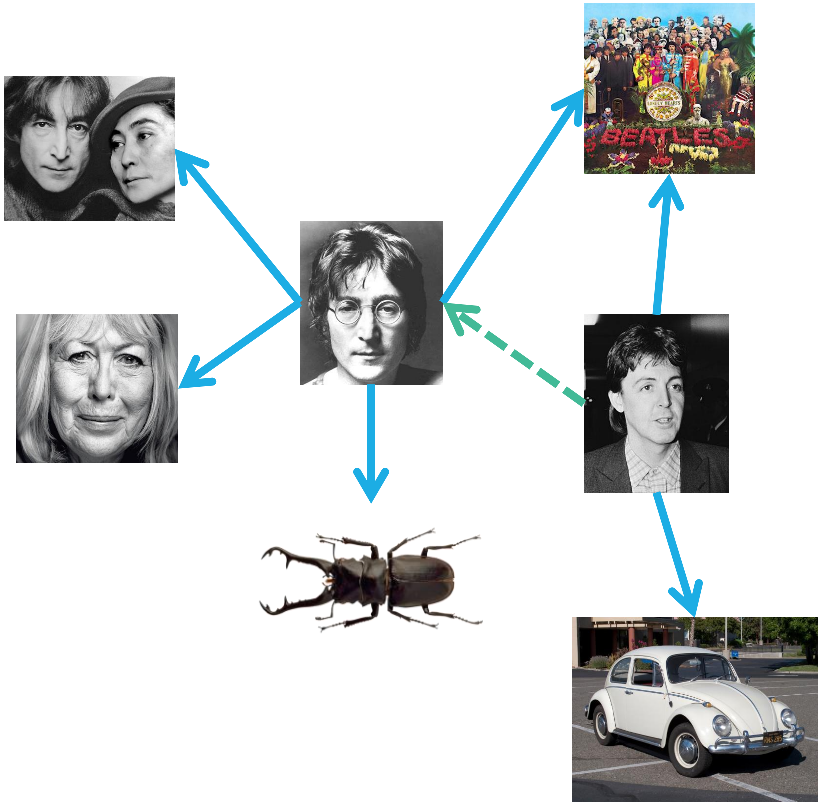
Graph Construction Issues

Extracted knowledge is:

- ambiguous

- incomplete

- inconsistent



Graph Construction approach

- Graph construction **cleans** and **completes** extractions

- 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

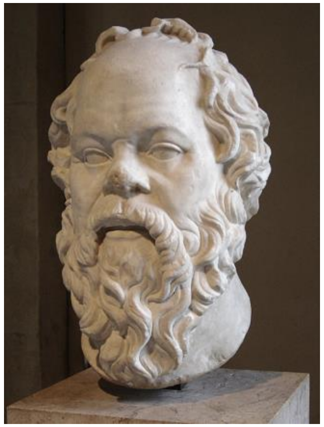
TOPICS:

Overview

Graphical models

Random Walk Methods

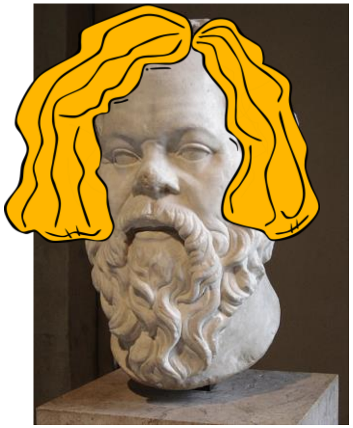
Beyond Pure Reasoning



- Classical AI approach to knowledge: reasoning

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

Beyond Pure Reasoning



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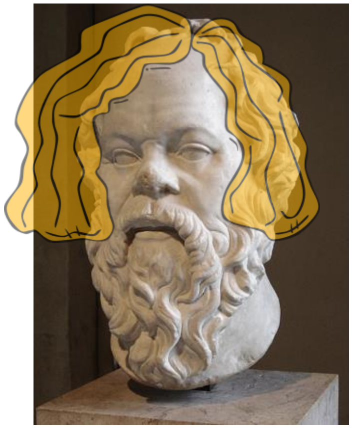
- Reasoning difficult when extracted knowledge has errors

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

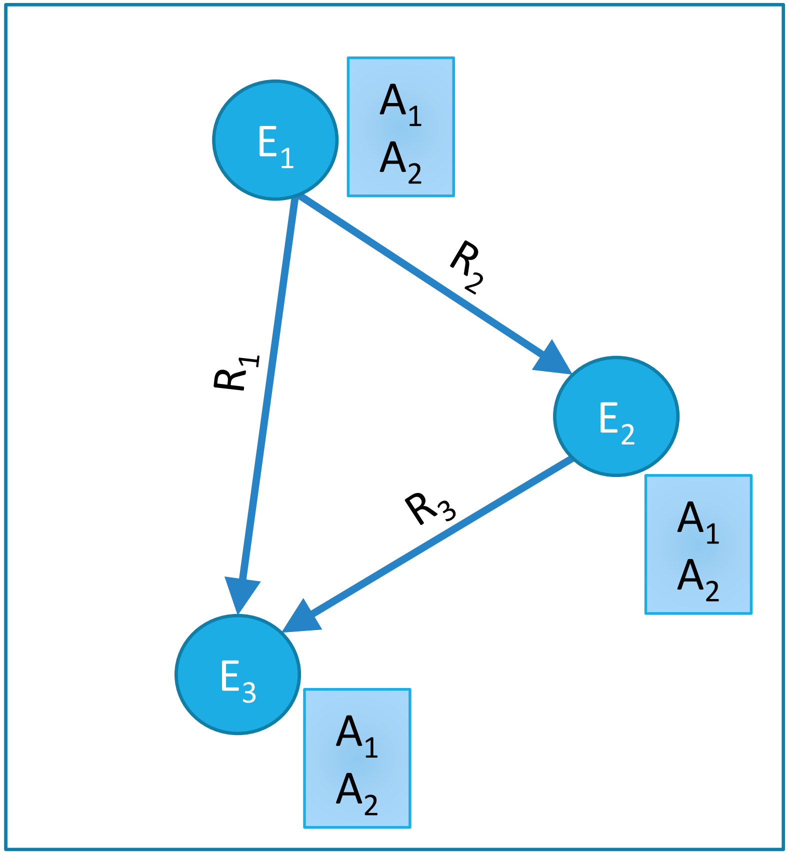
Graphical Models: Overview

- 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

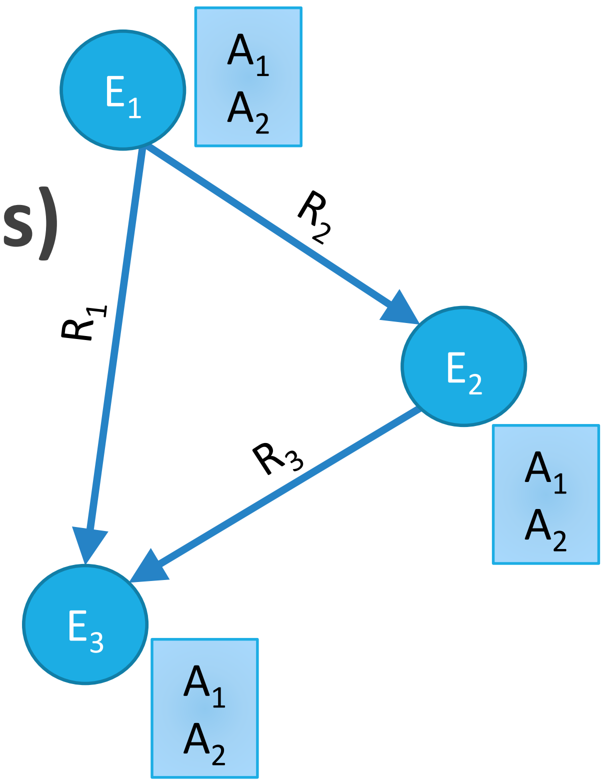
Define a graphical model to perform all three of these tasks simultaneously!

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



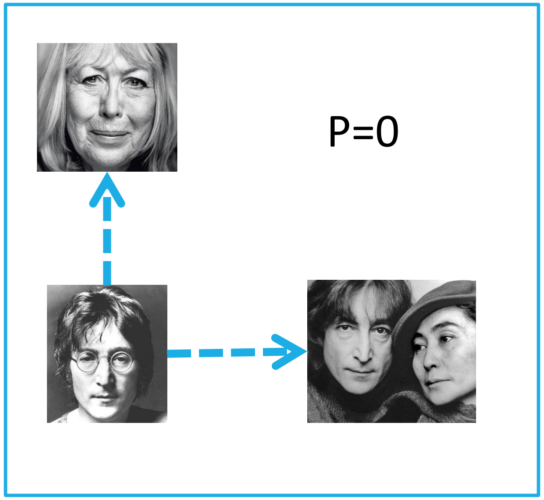
Knowledge Graph Identification

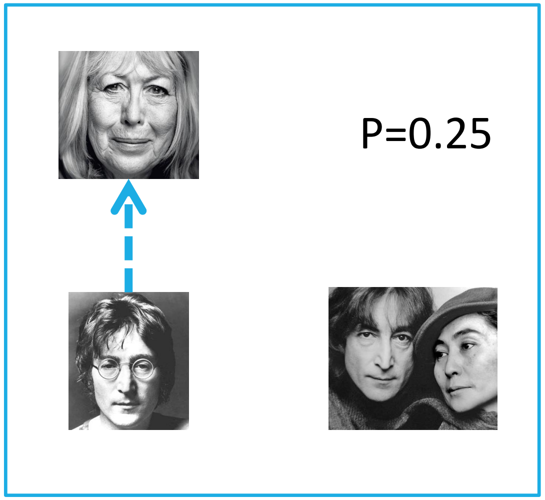
P(Who, What, How | Extractions)

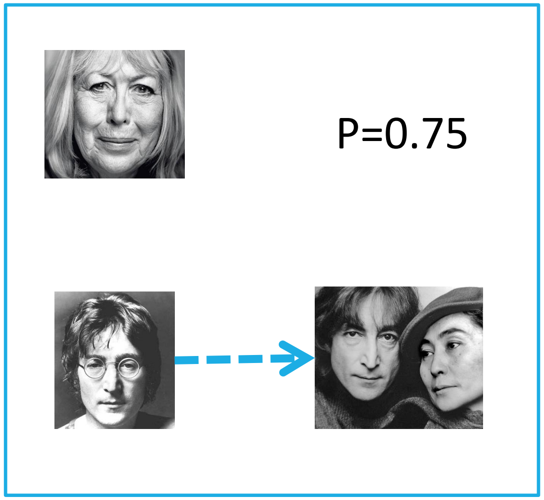


Probabilistic Models

- Use dependencies between facts in KG
- Probability defined *jointly* over facts







What determines probability?

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

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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**

What determines probability?

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

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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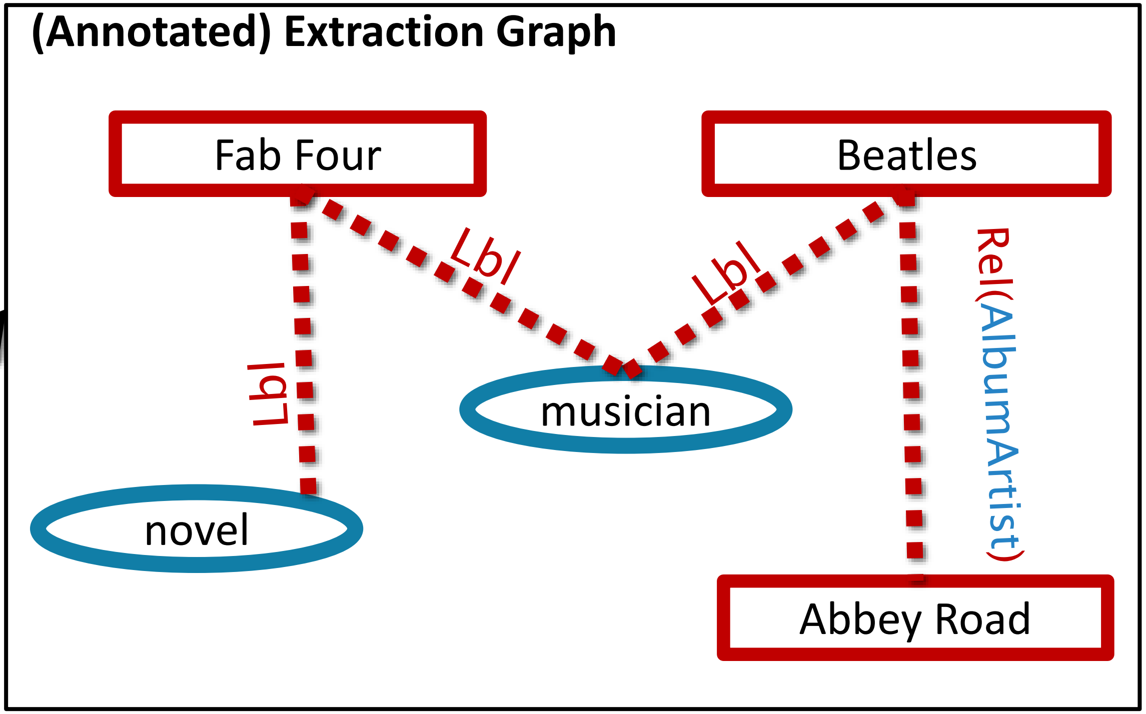

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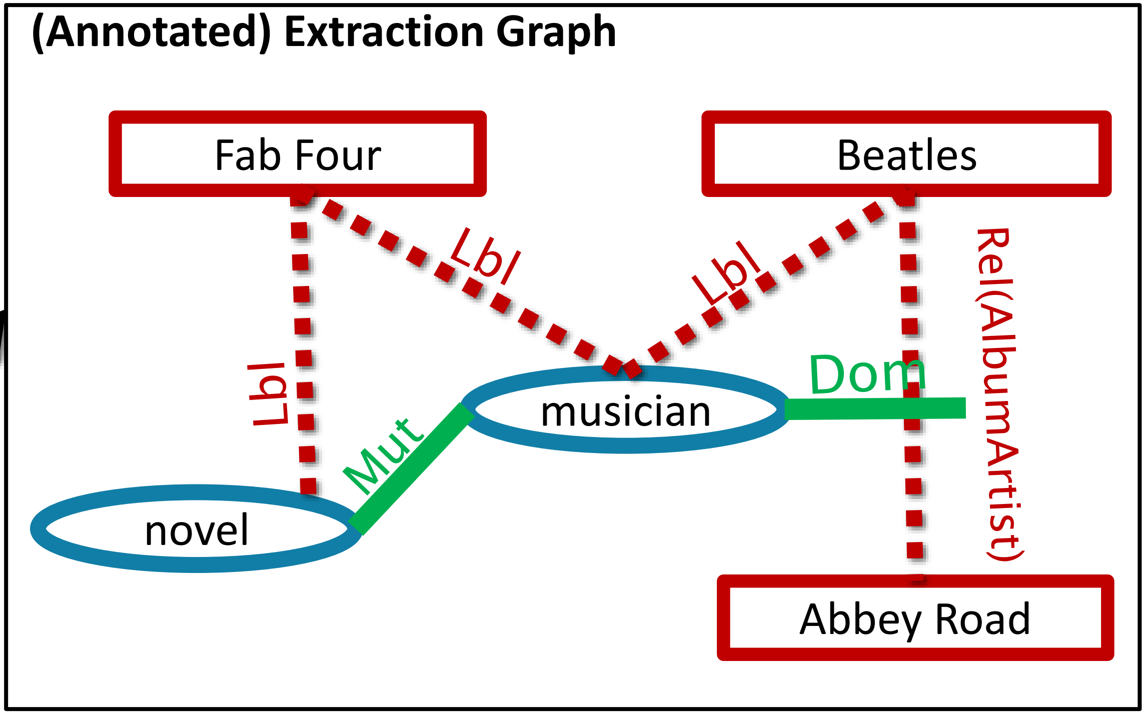
Ontology:

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



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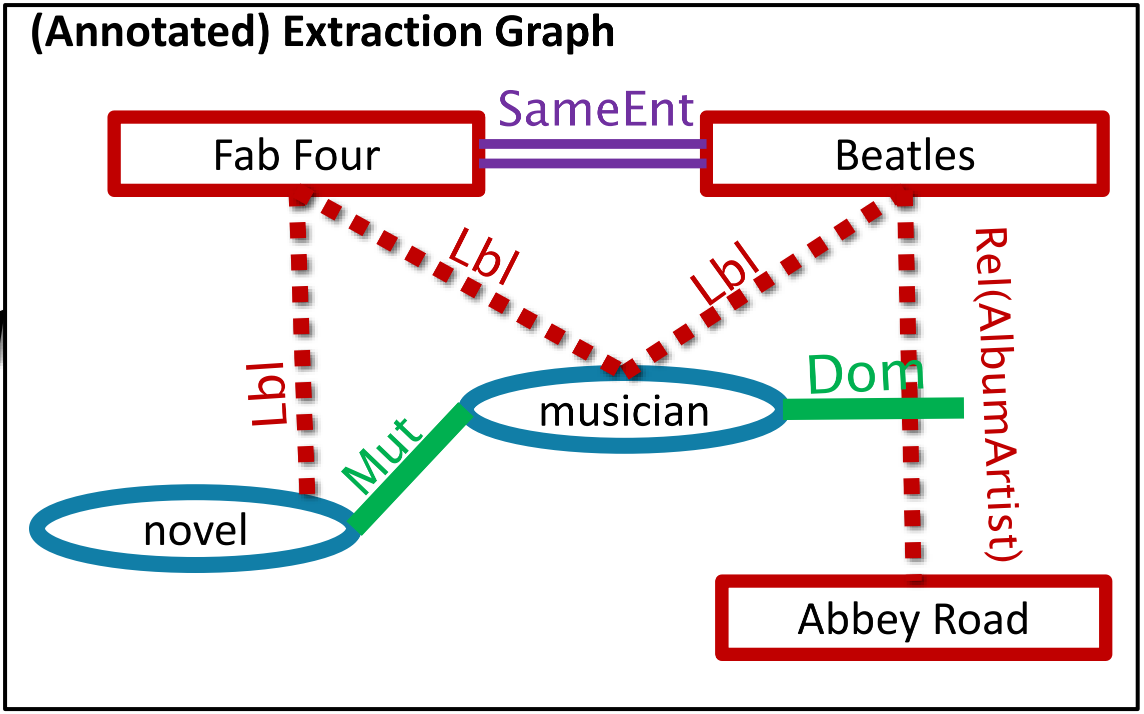
Entity Resolution:
SameEnt(Fab Four, Beatles)



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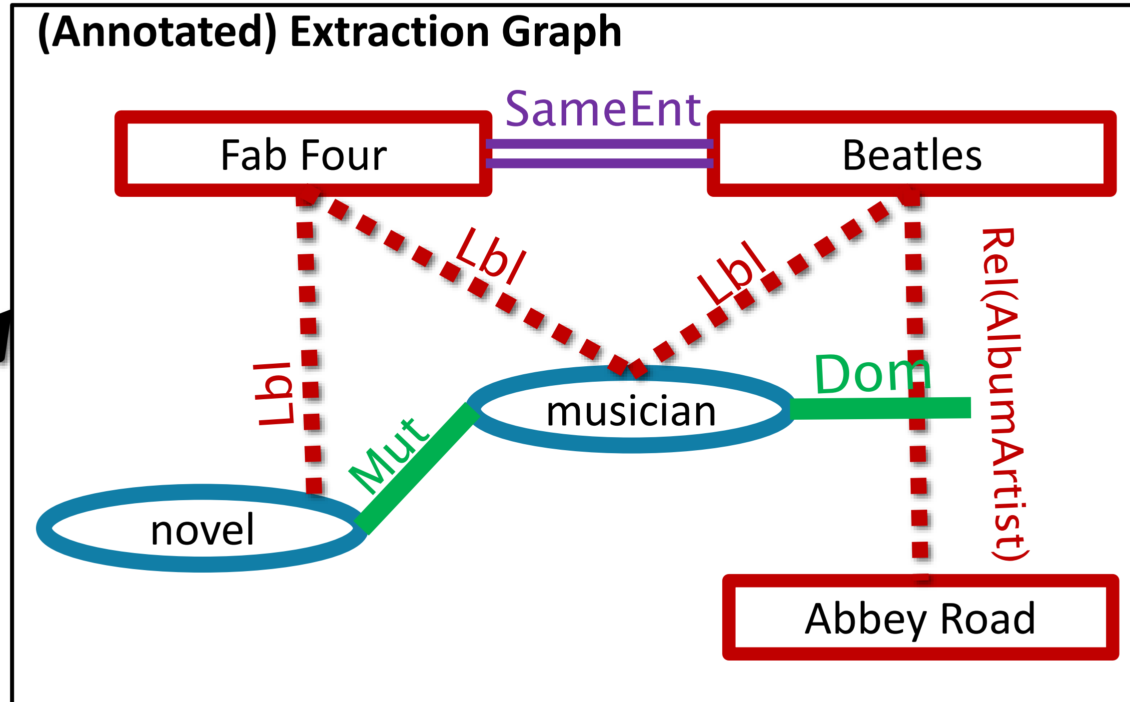
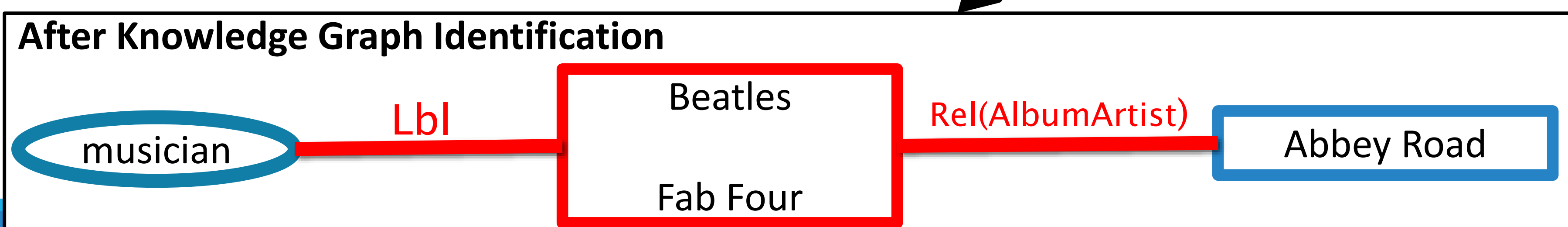
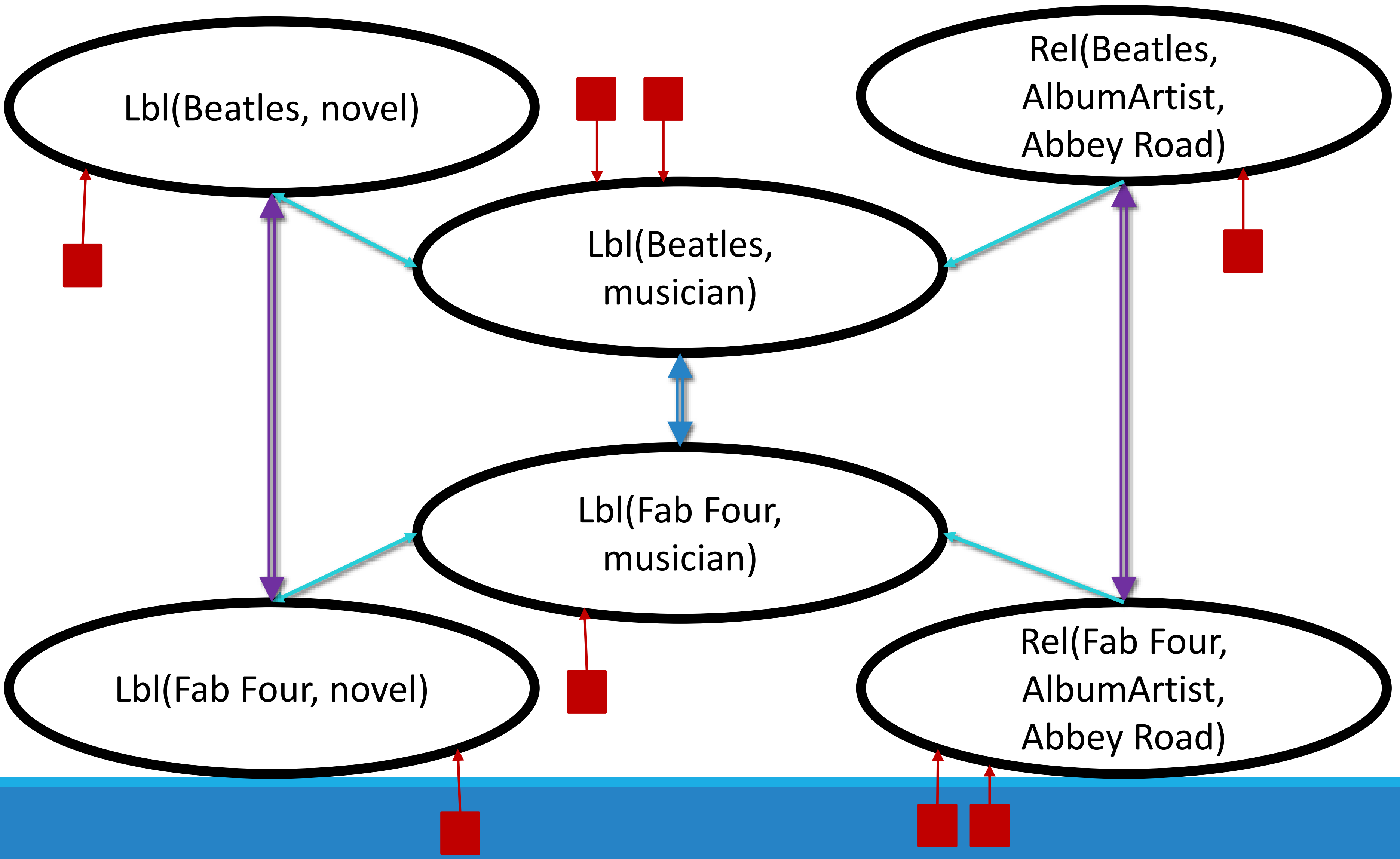




Probabilistic graphical model for KG



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: Uncertain Extractions

Weight for signal T (relations)

Predicate representing uncertain relation extraction using signal T

Relation in Knowledge Graph

$$\mathbf{w_{CR-T}} : \ \textsc{CandRel}_T(E_1, E_2, R) \quad \Rightarrow \quad \textsc{Rel}(E_1, E_2, R)$$

$$\mathbf{w_{CL-T}} : \ \textsc{CandLbl}_T(E, L) \quad \Rightarrow \quad \textsc{Lbl}(E, L)$$

Weight for signal T (labels)

Predicate representing uncertain label extraction using signal T

Label in Knowledge Graph

Rules: Entity Resolution

$$\mathbf{w_{EL}} : \textsc{SameEnt}(E_1, E_2) \wedge \textsc{Lbl}(E_1, L) \Rightarrow \textsc{Lbl}(E_2, L)$$
$$\mathbf{w_{ER}} : \textsc{SameEnt}(E_1, E_2) \wedge \textsc{Rel}(E_1, E, R) \Rightarrow \textsc{Rel}(E_2, E, R)$$
$$\mathbf{w_{ER}} : \textsc{SameEnt}(E_1, E_2) \wedge \textsc{Rel}(E, E_1, R) \Rightarrow \textsc{Rel}(E, E_2, R)$$

SameEnt 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

Rules: Ontology

Inverse:

$$\mathbf{w_O} : \textsc{Inv}(R,S) \wedge \textsc{Rel}(E_1,E_2,R) \Rightarrow \textsc{Rel}(E_2,E_1,S)$$

Selectional Preference:

$$\mathbf{w_O} : \textsc{Dom}(R,L) \wedge \textsc{Rel}(E_1,E_2,R) \Rightarrow \textsc{Lbl}(E_1,L)$$
$$\mathbf{w_O} : \textsc{Rng}(R,L) \wedge \textsc{Rel}(E_1,E_2,R) \Rightarrow \textsc{Lbl}(E_2,L)$$

Subsumption:

$$\mathbf{w_O} : \textsc{Sub}(L,P) \wedge \textsc{Lbl}(E,L) \Rightarrow \textsc{Lbl}(E,P)$$
$$\mathbf{w_O} : \textsc{RSub}(R,S) \wedge \textsc{Rel}(E_1,E_2,R) \Rightarrow \textsc{Rel}(E_1,E_2,S)$$

Mutual Exclusion:

$$\mathbf{w_O} : \textsc{Mut}(L_1,L_2) \wedge \textsc{Lbl}(E,L_1) \Rightarrow \neg\textsc{Lbl}(E,L_2)$$
$$\mathbf{w_O} : \textsc{RMut}(R,S) \wedge \textsc{Rel}(E_1,E_2,R) \Rightarrow \neg\textsc{Rel}(E_1,E_2,S)$$

(JIANG ET AL., ICDM 2012;
PUJARA ET AL., ISWC13)

Rules to Distributions

- Rules are *grounded* by substituting literals into formulas

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

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

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

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

(PUJARA ET AL., ISWC13)

Probability Distribution over KGs

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

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

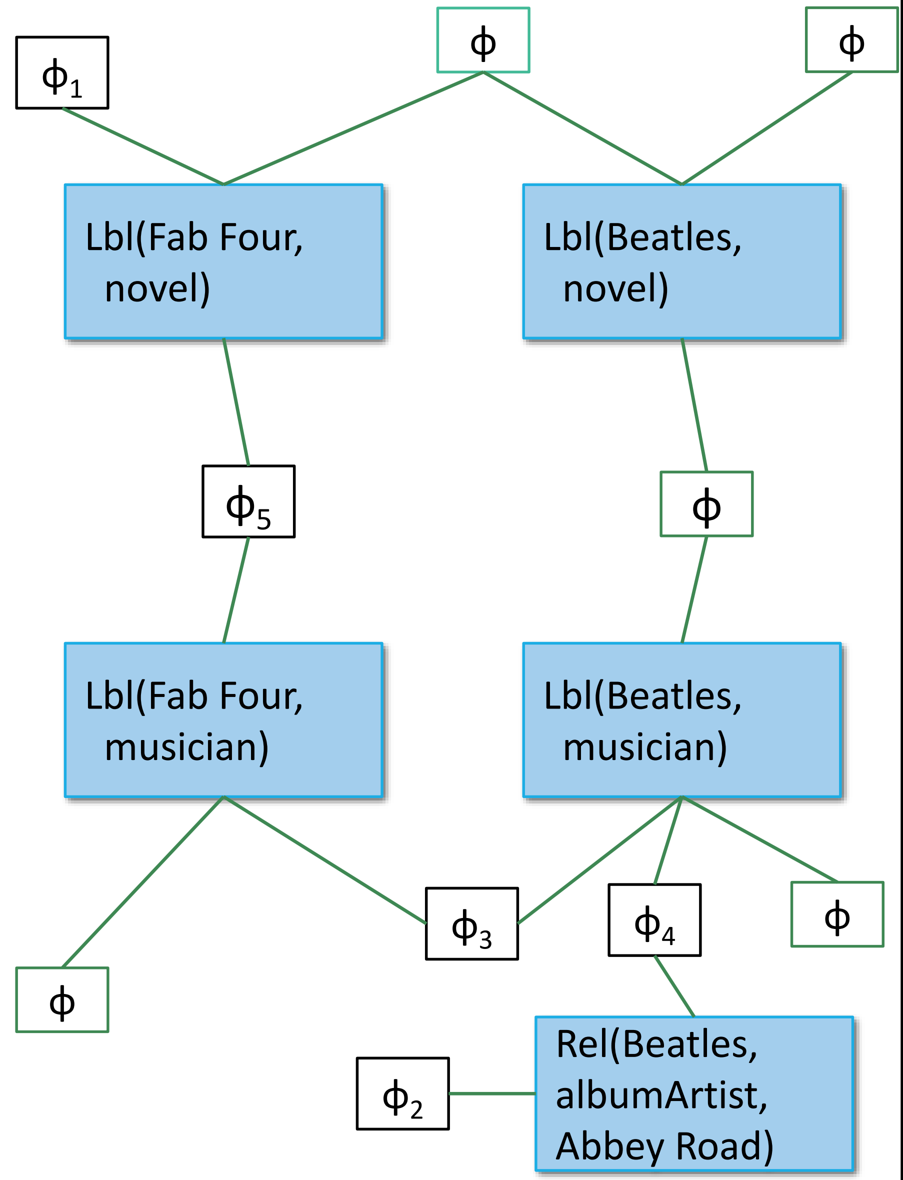
$[\phi_1]$ $\textsc{CandLbl}_{\text{struct}}(\texttt{FabFour}, \texttt{novel})$
$\Rightarrow \ \textsc{Lbl}(\texttt{FabFour}, \texttt{novel})$

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

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

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

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



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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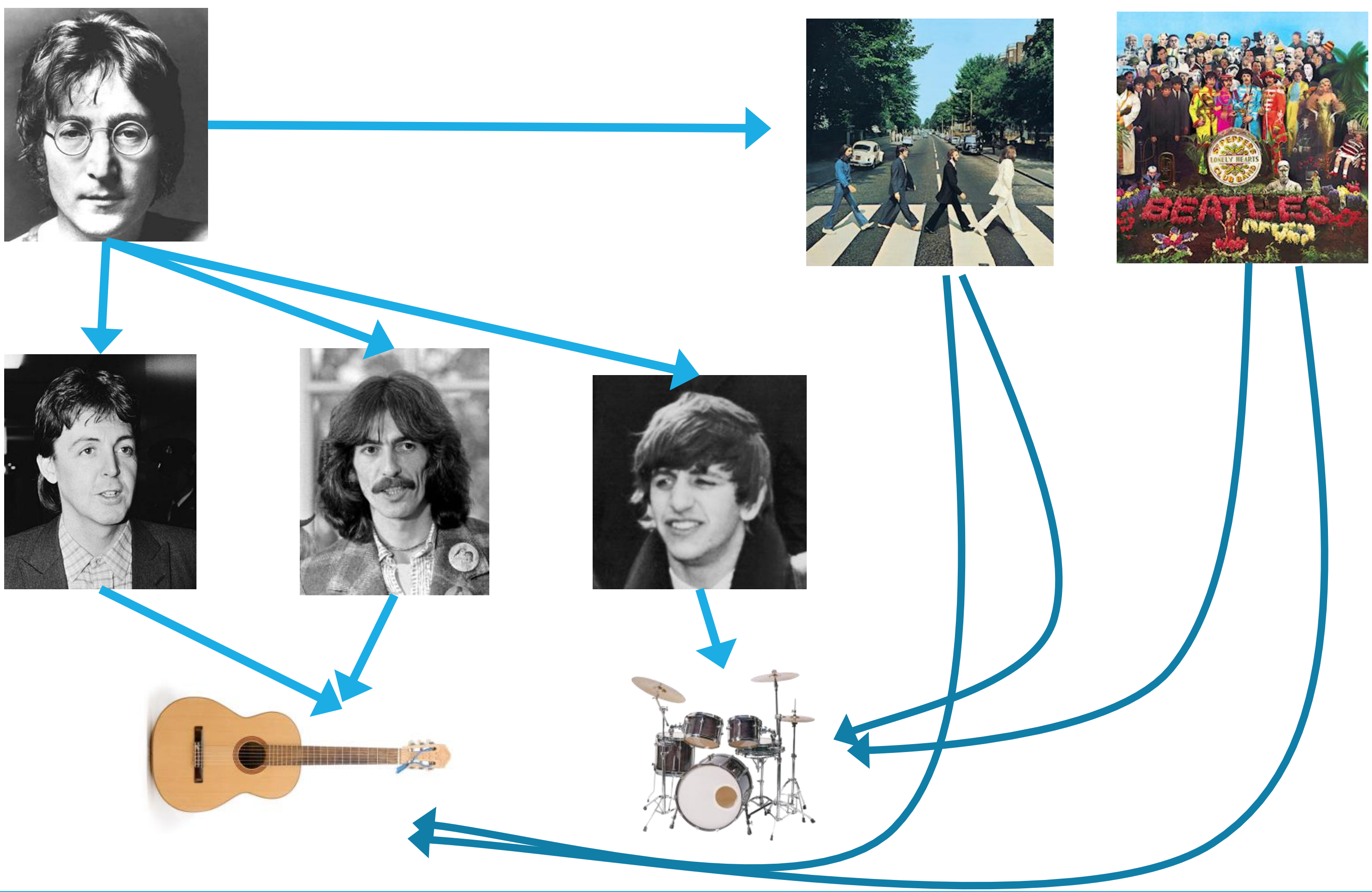

Random Walk Illustration

Query Q: R(Lennon, PlaysInstrument, ?)

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

Random Walk Illustration

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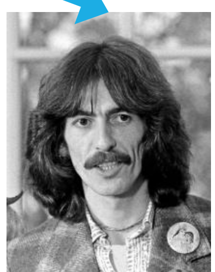

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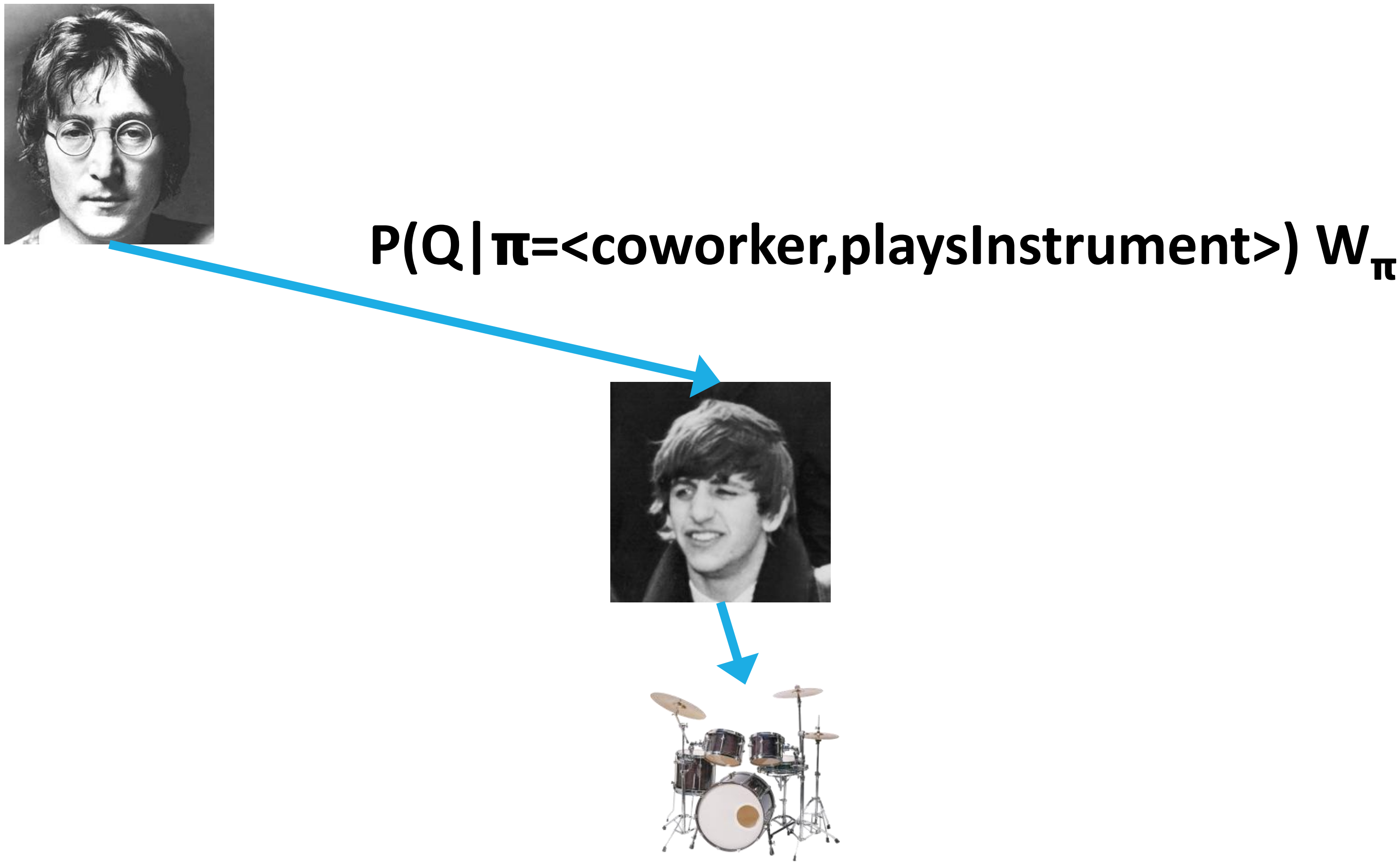

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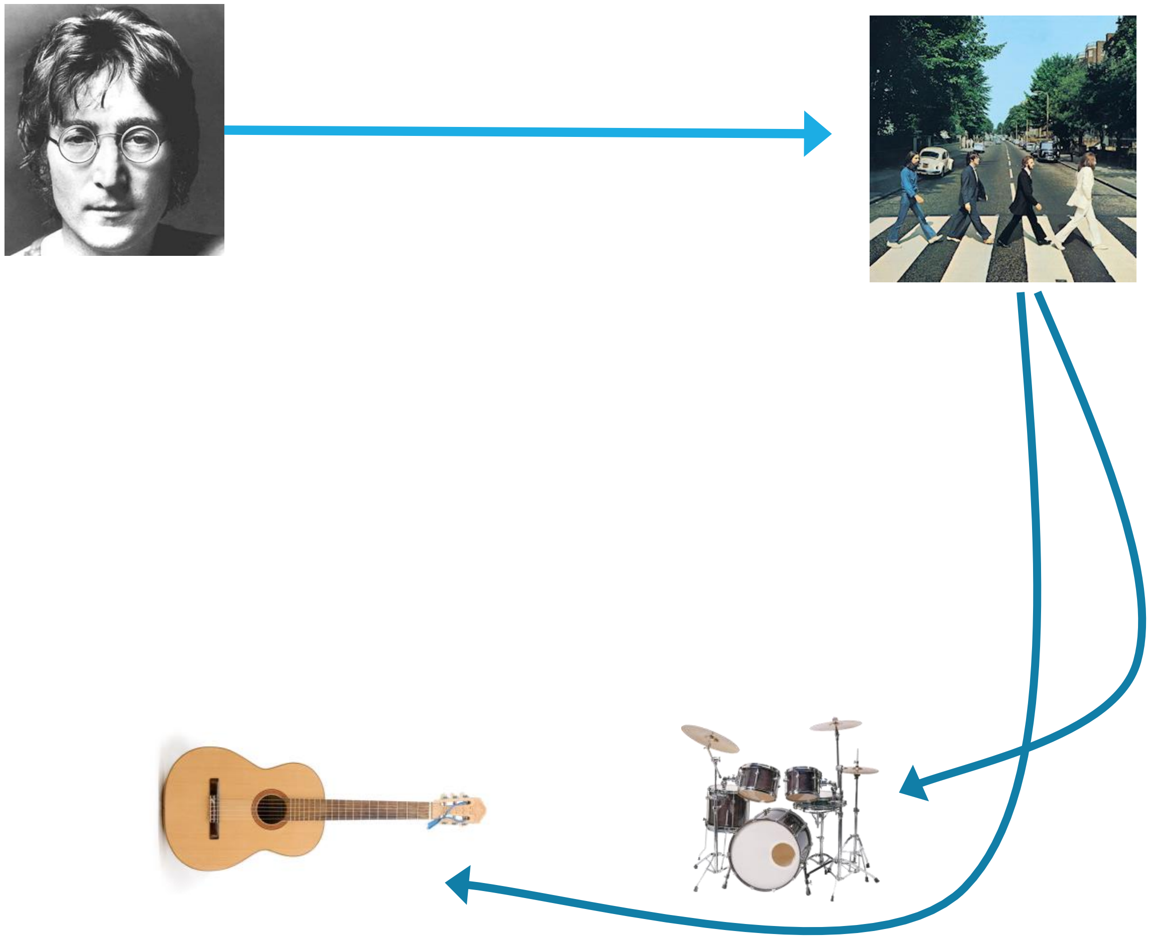

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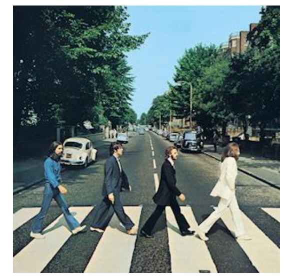

$P(Q|\pi=<\text{albumArtist},\text{hasInstrument}>)\ W_{\pi}$

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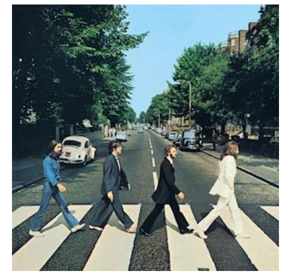

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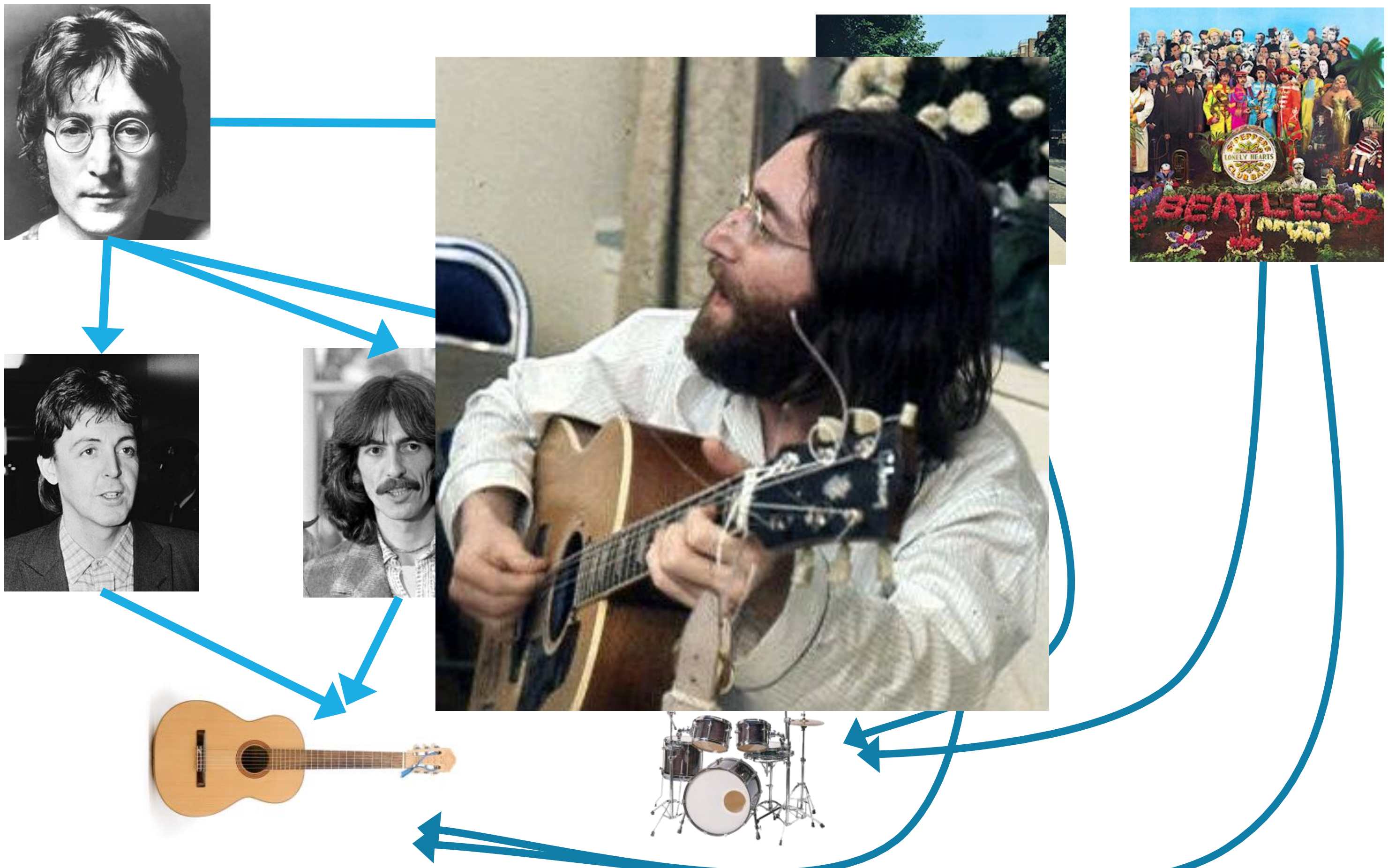


Recent Random Walk Methods

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: ProbLog + 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**

PRA in a nutshell

Path Ranking Algorithm (PRA)

(Lao & Cohen, MLJ 2010)

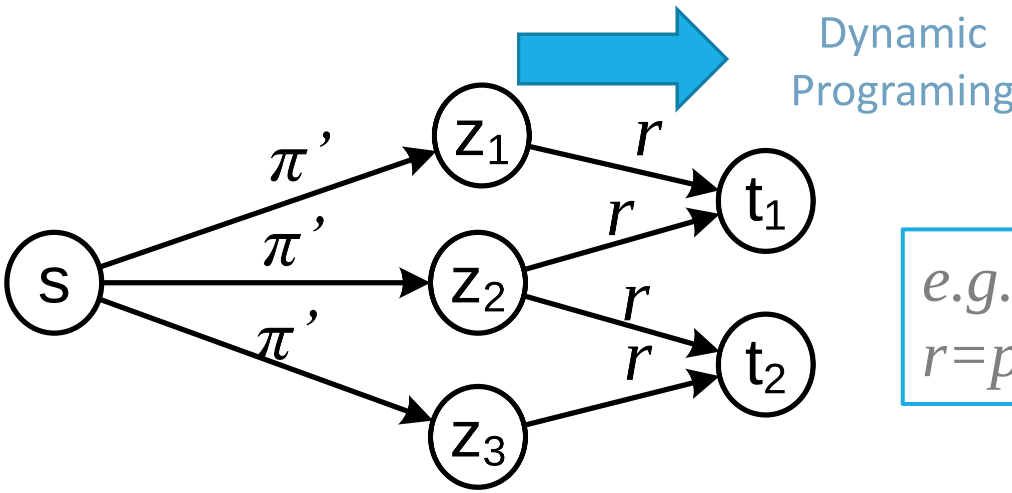
$$score(s,t) = \sum_{\pi \in \boxed{B}} \boxed{P(s \to t; \pi)} \boxed{\theta_\pi}$$

a weight

e.g. π=<coworker,playsInstrument>

Random Walk Calculation

$$score(s,t) = \sum_{\pi \in B} \boxed{P(s \to t; \pi)} \theta_\pi$$



e.g. π'=<coworker>
r=playsInstrument

$$P(s \to t; \pi) = \sum_z P(s \to z; \pi') P(z \to t; r)$$

Pruning paths using labeled data

$$score(s,t) = \sum_{\pi \in \boxed{B}} P(s \rightarrow t; \pi)\theta_\pi$$

given training query set $\{(s_i, G_i)\}$

$$hits(f) = \sum_i I\left[\sum_{j \in G_i} f(s_i, t_j)\right] \geq h$$

$$accuracy(f) = \frac{1}{N}\sum_i \left[\frac{\sum_{j \in G_i} f(s_i, t_j)}{\sum_j f(s_i, t_j)}\right] \geq a$$

I(): the indicator function

N: total number of queries

Estimating θ via Logistic Regression

$$score(s,t) = \sum_{\pi \in B} P(s \to t; \pi)\boxed{\theta_\pi}$$

for a relation *r*

generate positive and negative node pairs $\{(s_i, t_i)\}$

for each (s_i, t_i) generate (x_i, y_i)

x_i is a vector of RW features of different paths π

y_i is a binary label $r(s_i, t_i)$

estimate θ by L1/L2 regularized (elastic-net) logistic regression

ProPPR: ProbLog + PageRank

ProPPR-ized PRA example

Query Q: R(Lennon, PlaysInstrument, ?)

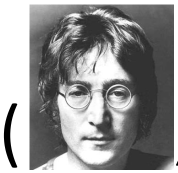
R( ,Coworker,X)
R(X,PlaysInstrument,Y)

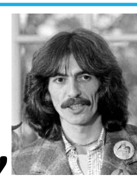
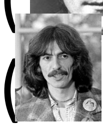
R( ,AlbumArtist,J)
R(J,HasInstrument,K)

ProPPR-ized PRA example

Query Q: R(Lennon, PlaysInstrument, ?)

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

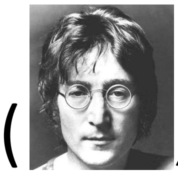
R(,AlbumArtist,J)
R(J,HasInstrument,K)

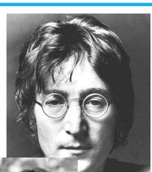
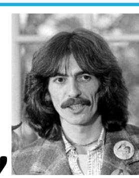
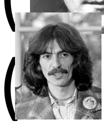
R(,Coworker,)
R(,PlaysInstrument,Y)

ProPPR-ized PRA example

Query Q: R(Lennon, PlaysInstrument, ?)

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

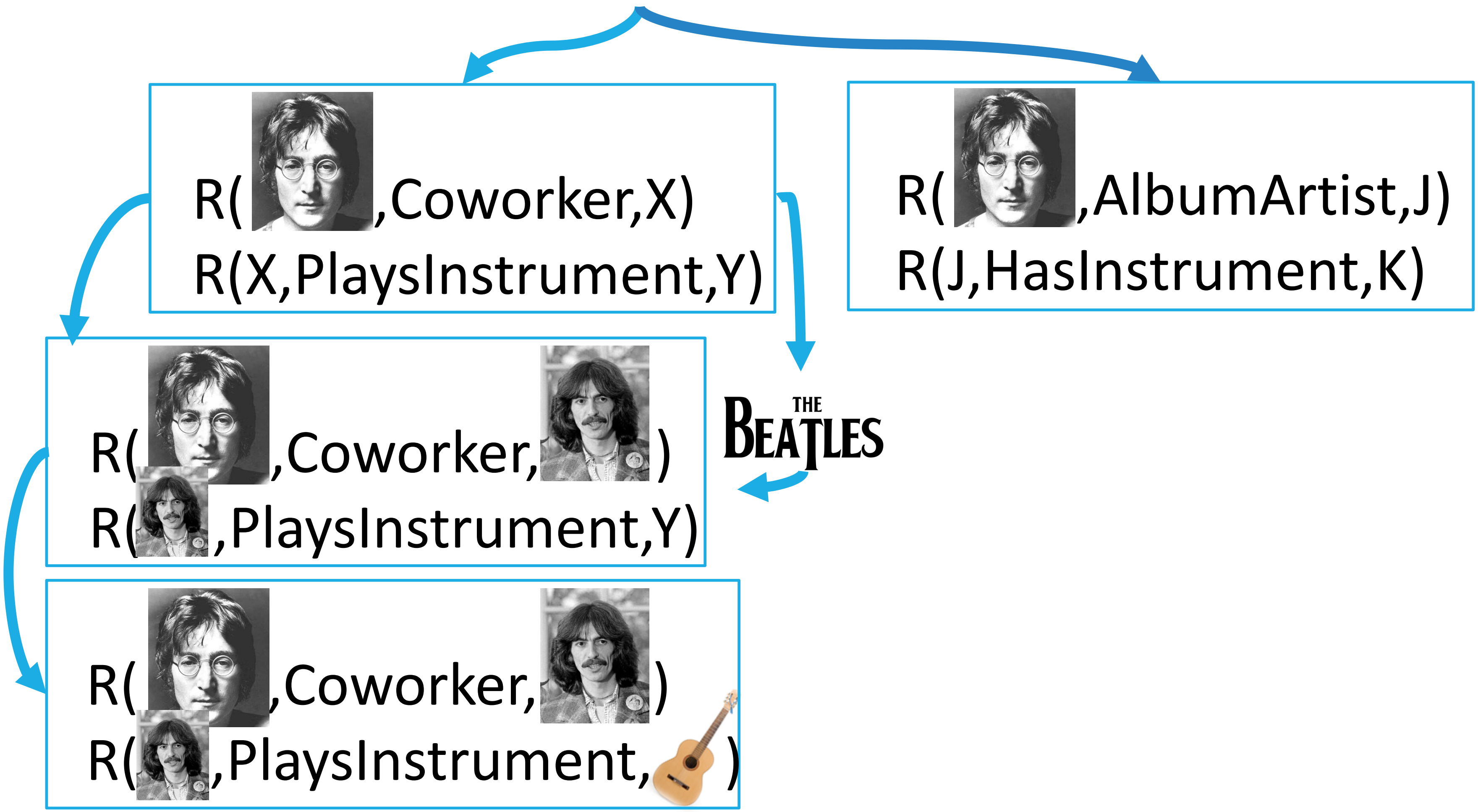
R(,AlbumArtist,J)
R(J,HasInstrument,K)

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

THE BEATLES

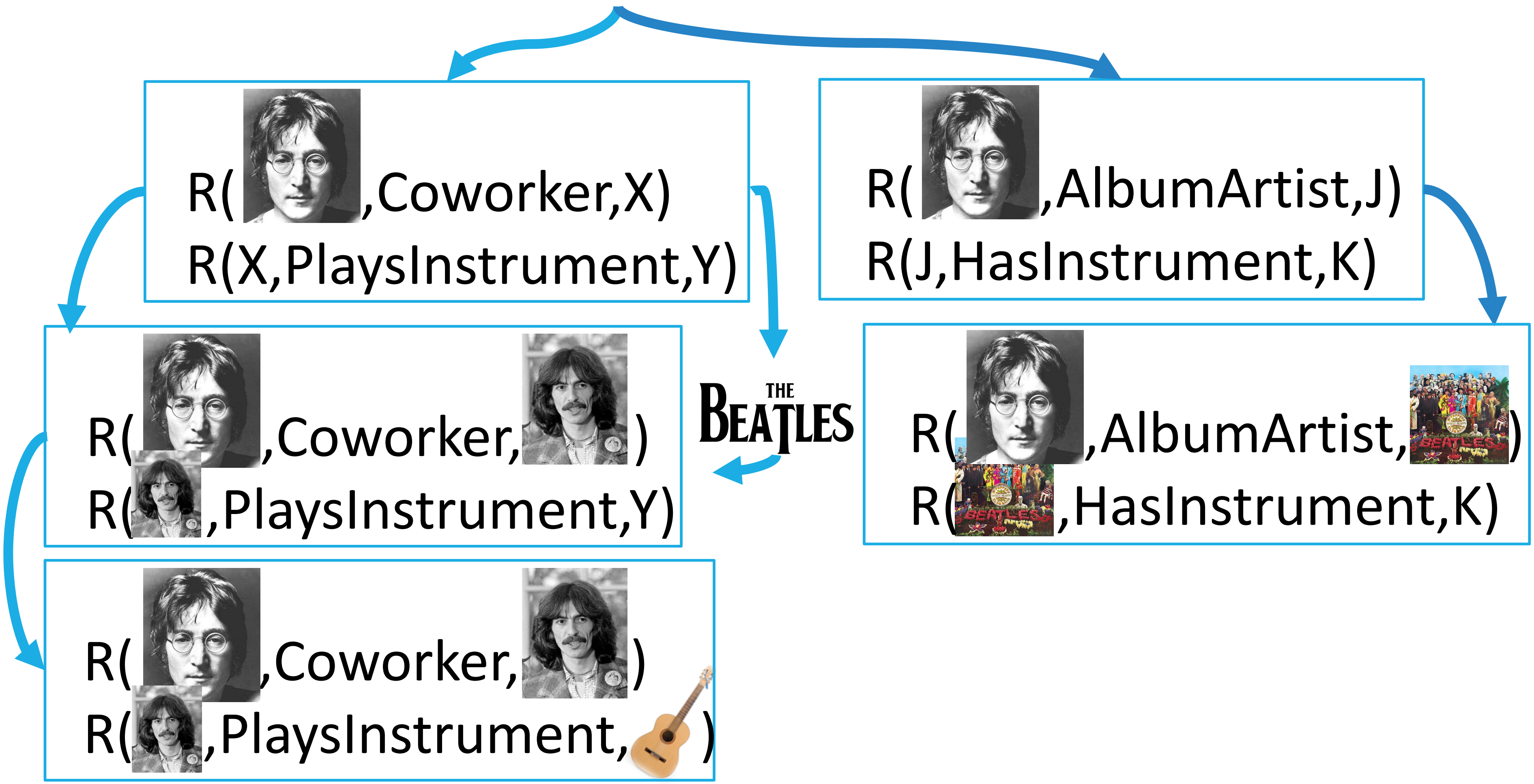
ProPPR-ized PRA example

Query Q: R(Lennon, PlaysInstrument, ?)



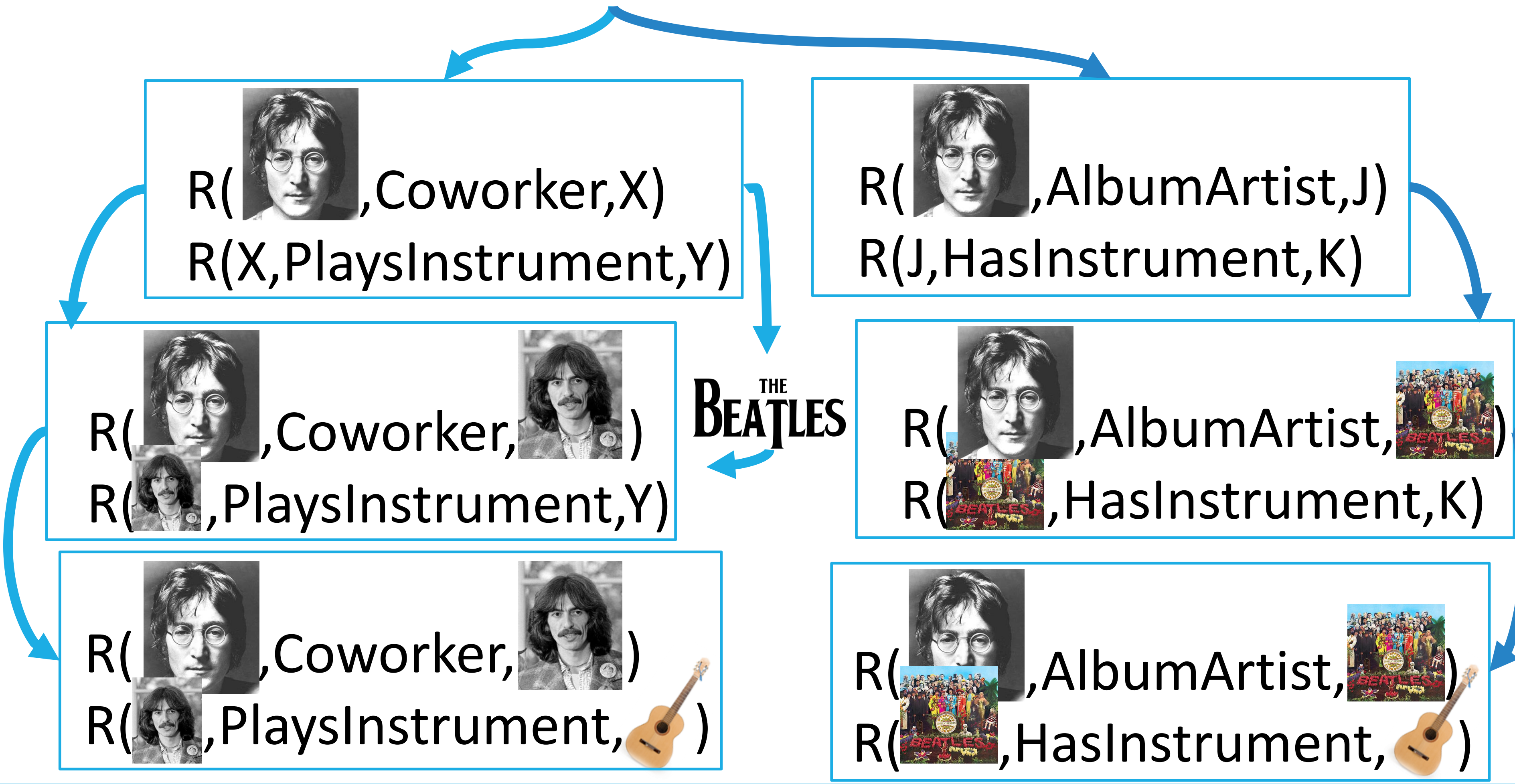
ProPPR-ized PRA example

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,)

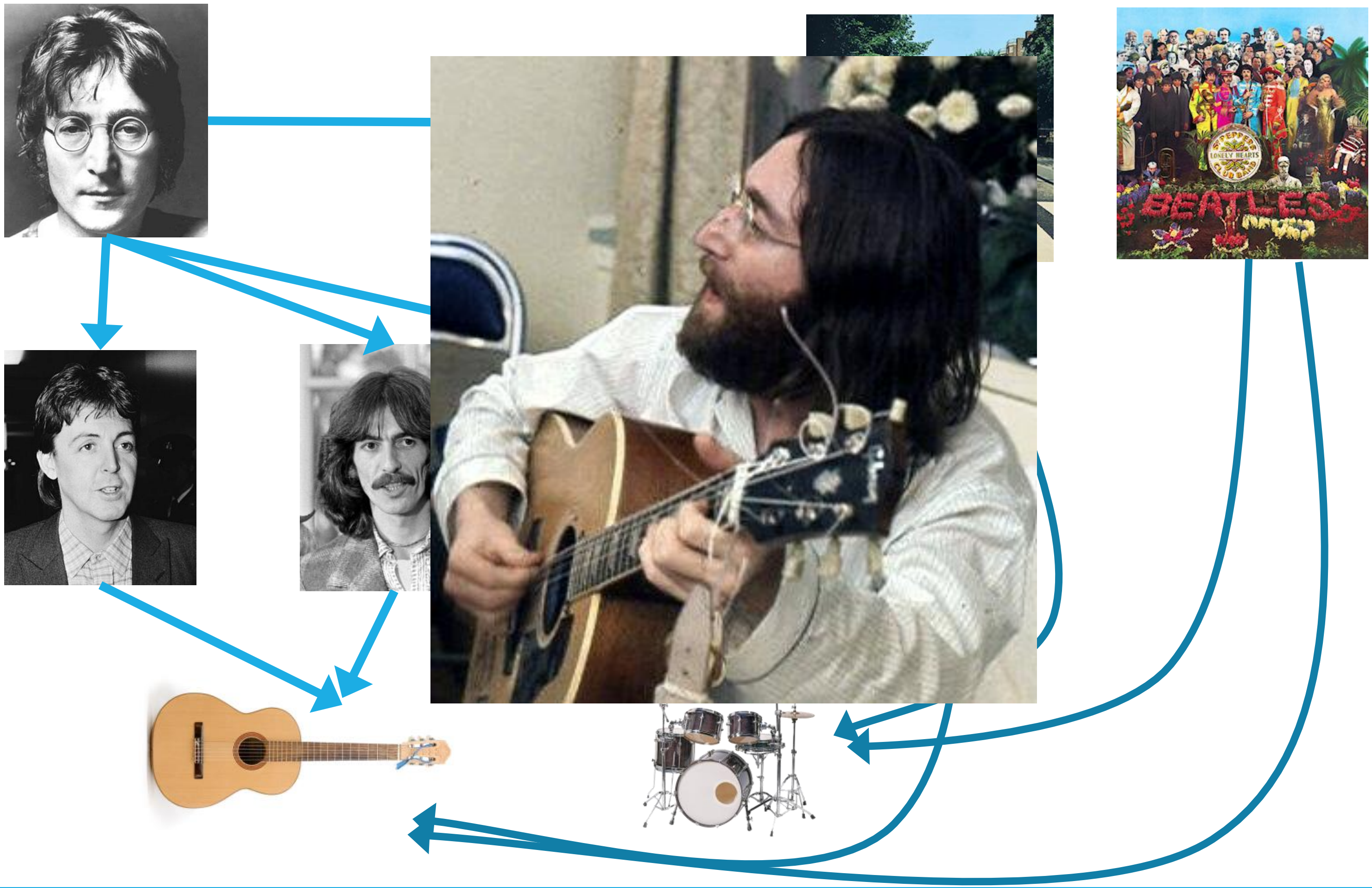
R(,PlaysInstrument,)

R(,AlbumArtist,)

R(,HasInstrument,)

Random Walk Illustration

Query: R(Lennon, PlaysInstrument, ?)



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