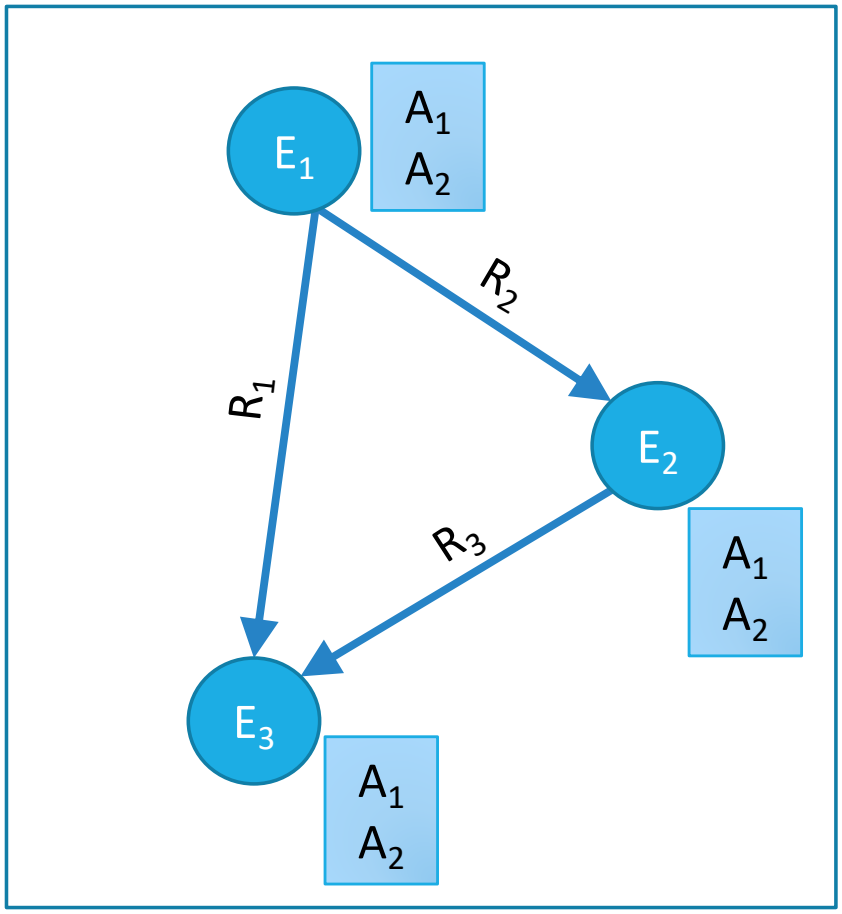
Probabilistic Models for KG Construction

DSCI 558 – 3/3/21

Jay Pujara

Reminder: Basic problems

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

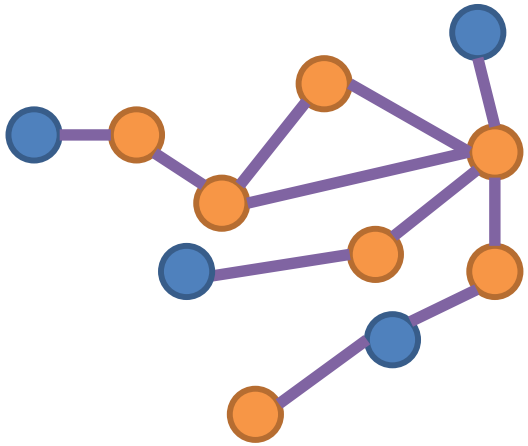


Motivating Problem: New Opportunities

Massive source of publicly available information

Extraction

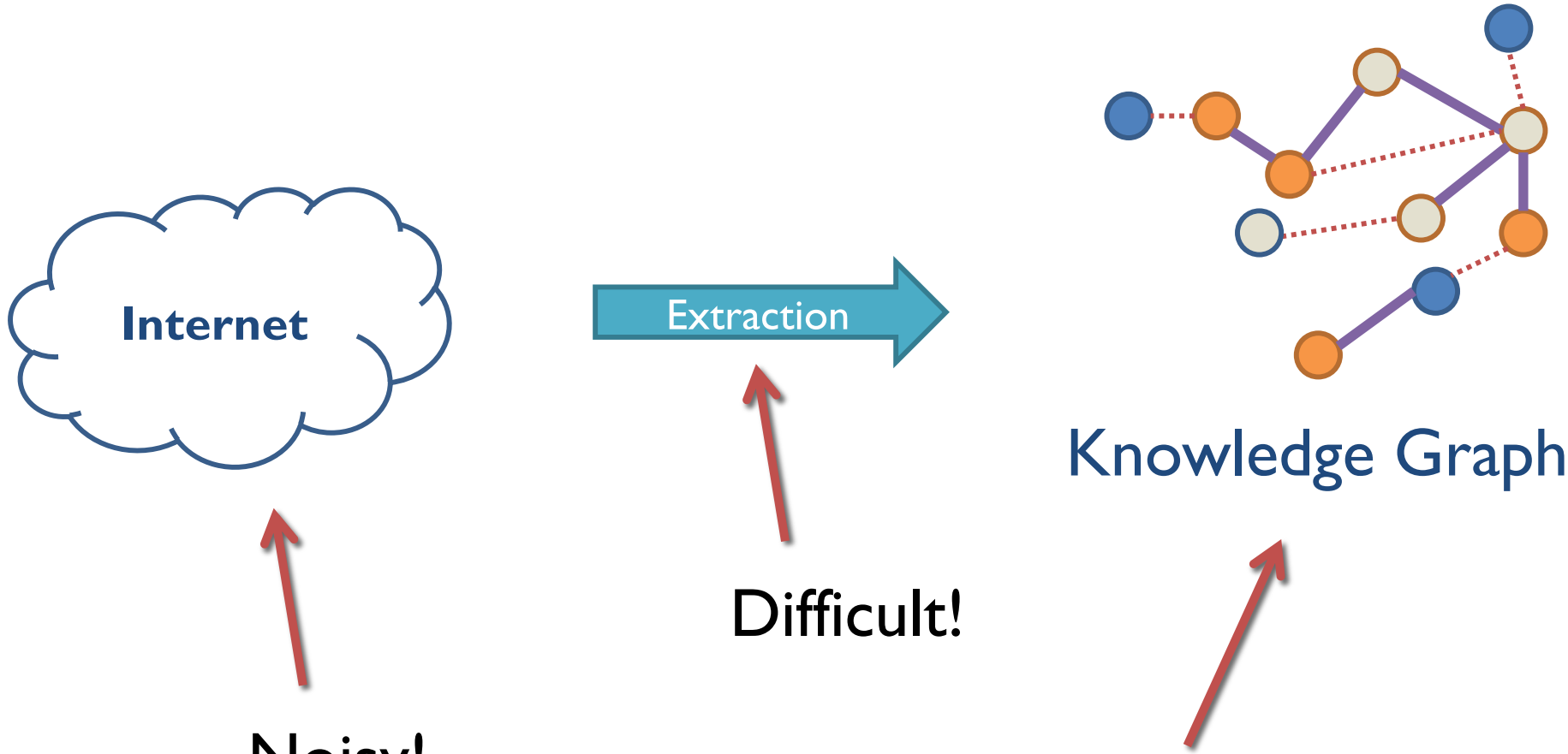
Cutting-edge IE methods



Knowledge Graph (KG)

Structured representation of entities, their labels and the relationships between them

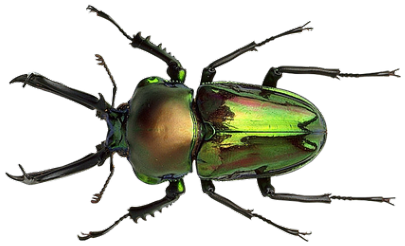
Motivating Problem: Real Challenges

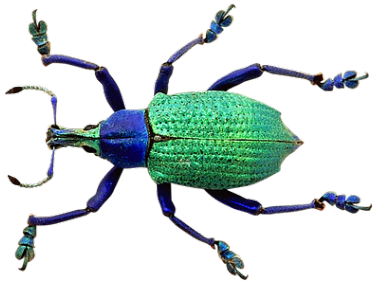


Graph Construction Issues

Extracted knowledge is:

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



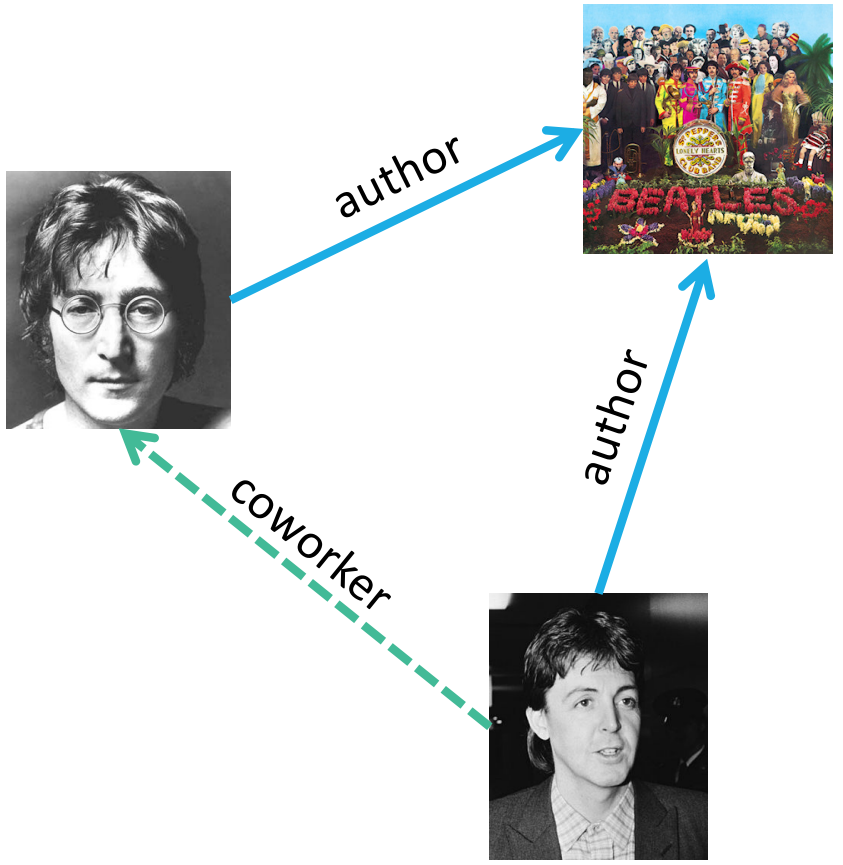


Graph Construction Issues

Extracted knowledge is:

- ambiguous

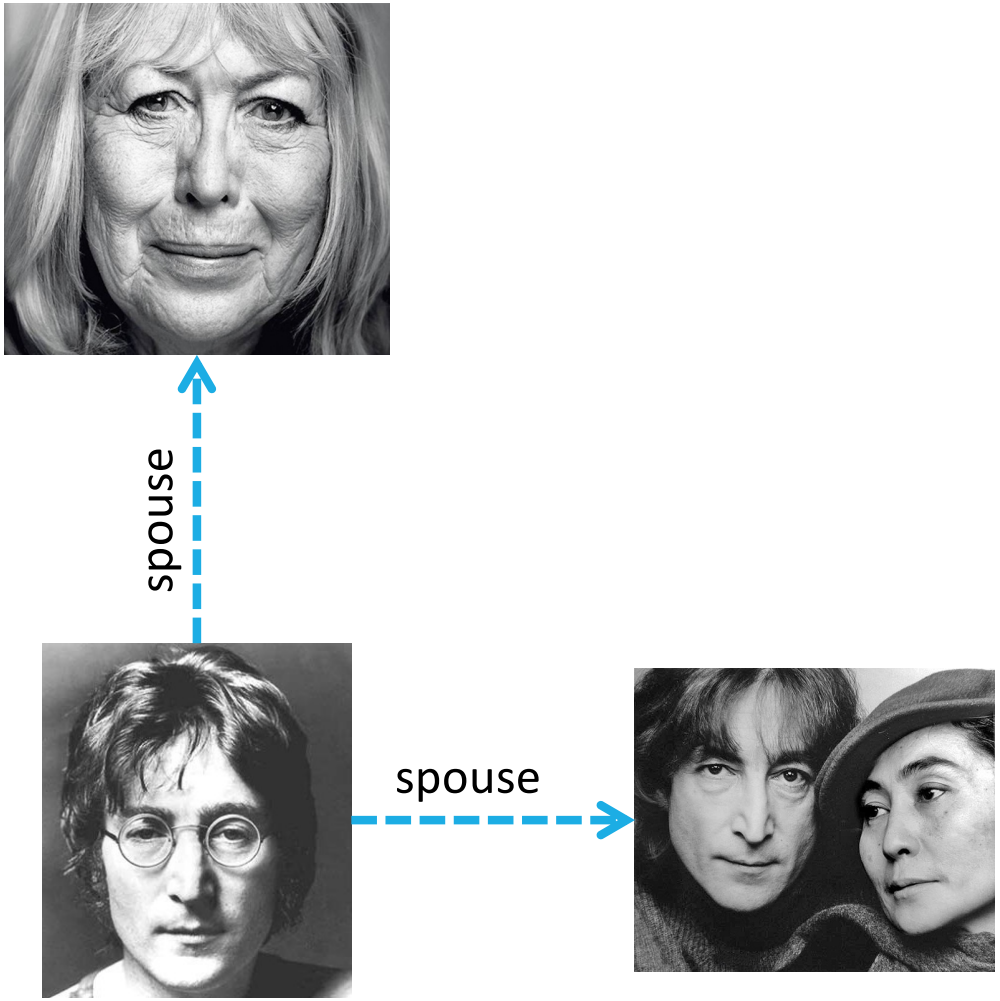
- incomplete
  - Ex: missing relationships
  - Ex: missing labels
  - Ex: missing entities



Graph Construction Issues

Extracted knowledge is:

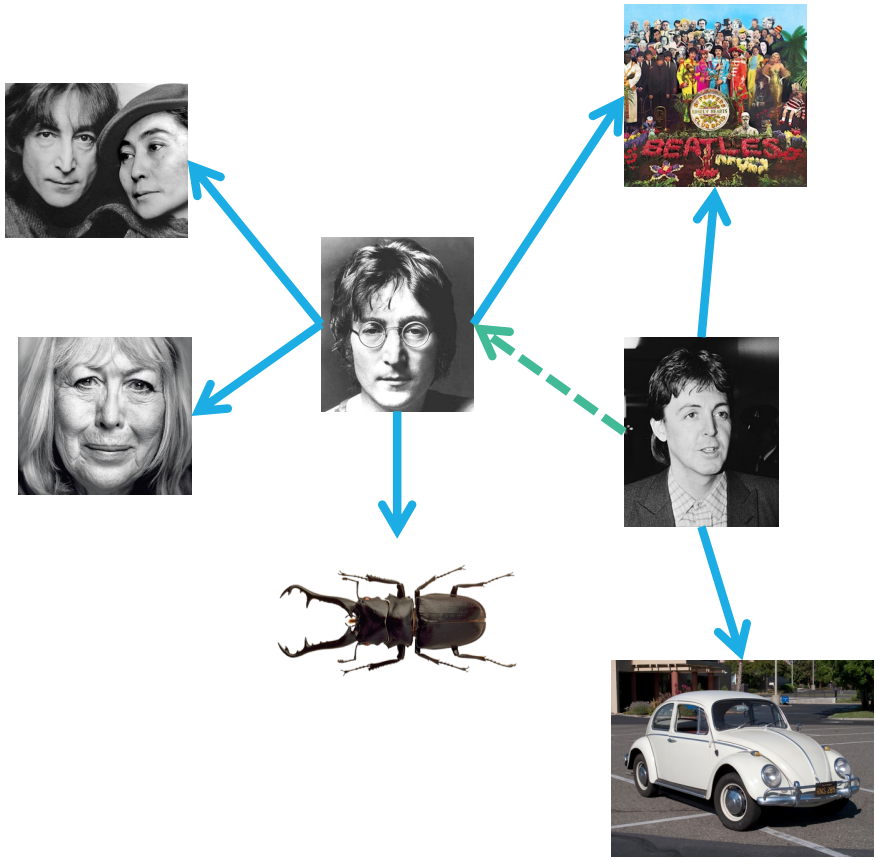
- ambiguous
- incomplete
- inconsistent
  - Ex: Cynthia Lennon, Yoko Ono
  - Ex: exclusive labels (alive, dead)
  - Ex: domain-range constraints



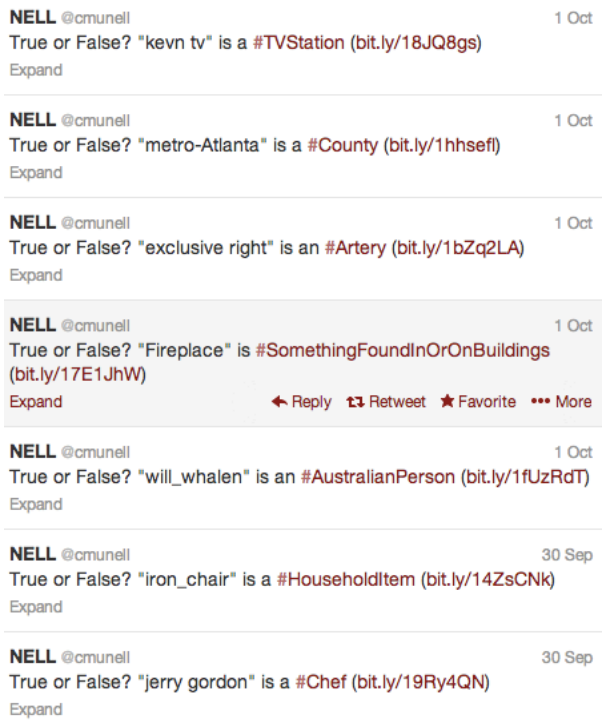
Graph Construction Issues

Extracted knowledge is:

- ambiguous
- incomplete
- inconsistent



NELL: The Never-Ending Language Learner



- Large-scale IE project (Carlson et al., 2010)
- Lifelong learning: aims to "read the web"
- Ontology of known labels and relations
- Knowledge base contains millions of facts

Examples of NELL errors

Entity co-reference errors

Kyrgyzstan has many variants:

- Kyrgystan
- Kyrgistan
- Kyrghyzstan
- Kyrgzstan
- Kyrgyz Republic

Saudi Cultural Days in the Kyrgyz Republic has concluded its activities in the capital Bishkek in the weekend in a special ceremony held on this occasion. The event was attended by Deputy Minister of Culture and Tourism of the Kyrgyz Republic Koulev Mirza; Kyrgyzstan's Ambassador to Saudi Arabia Jusupbek Sharipov; the Saudi Embassy Acting Chargé d'affaires to Kyrgyzstan, Mari bin Barakah Al-Derbas and members of the embassy staff, in the presence of a heavy turnout of Kyrgyz citizens.

The Days of Culture of Saudi Arabia in Kyrgyzstan will be held from 6 to 9 May.

Home > Holiday Destinations > Kyrghyzstan > Bishkek > Climate Profile

Refugees are often from areas where conflict is historically embedded and marked in ideology and injustice. The Tsarnaev family emigrated from the Chechen diaspora in Kyrgzstan, a region Stalin deported the Chechens to in 1943. After the fall of the Berlin Wall in 1991, Chechens engaged in a battle for independence from Russia that led to the Tsarnaevs' petition for refugee status in the early

Missing and spurious labels

Anssi Kullberg has sent along some great trip reports to unusual places, including Kyrgyzstan, Pakistan, Egypt/Jordan, and Afghanistan. I had to create a whole new country page for Afghanistan to hold that last one! Thanks so much, Anssi!

Erik Kleyheeg has just returned from Lesvos with some new bird images. Included here are: Common Scops-Owl, Wood Warbler, Spanish Sparrow, Red-throated Pipit, Eurasian Chiff-chaff, and Cretzschmar's Bunting.

Kyrgyzstan is labeled a bird and a country

Kyrgyzstan (/kɜrgɪ'stɑːn/ *kur-gi-stahn*;[5] Kyrgyz: Кыргызстан (IPA: [qɯrʁɯs'stɑn]); Russian: Киргизия), officially the **Kyrgyz Republic** (Kyrgyz: Кыргыз Республикасы; Russian: Кыргызская Республика), is a country located in Central Asia.[6] Landlocked and mountainous, Kyrgyzstan is bordered by Kazakhstan to the north, Uzbekistan to the west, Tajikistan to the southwest and China to the east. Its capital and largest city is Bishkek.

Missing and spurious relations

Guidance

Kazakhstan / Kyrgyzstan – Consular Fees

Organisation: Foreign & Commonwealth Office
Page history: Published 4 April 2013

Kyrgyzstan's location is ambiguous – Kazakhstan, Russia and US are included in possible locations

Kyrgyzstan U.S. Air Base Future Unclear

A Central Asian country of incredible natural beauty and proud nomadic traditions, most of Kyrgyzstan was formally annexed to Russia in 1876. The Kyrgyz staged a major revolt against the Tsarist Empire in 1916 in which almost one-sixth of the Kyrgyz population was killed. Kyrgyzstan became a Soviet republic in 1936 and

Violations of ontological knowledge

- Equivalence of co-referent entities (sameAs)
  - SameEntity(Kyrgyzstan, Kyrgyz Republic)
- Mutual exclusion (disjointWith) of labels
  - MUT(bird, country)
- Selectional preferences (domain/range) of relations
  - RNG(countryLocation, continent)

Enforcing these constraints require **jointly** considering multiple extractions

Graph Construction approach

- Graph construction **cleans** and **completes** extraction graph
- Incorporate ontological constraints and relational patterns
- Discover statistical relationships within knowledge graph

Graph Construction
Probabilistic Models

TOPICS:

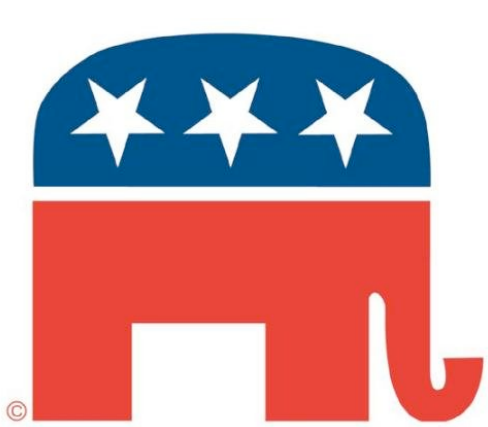
- Overview
- Graphical models
- Random Walk Methods

Graph Construction
Probabilistic Models

TOPICS:

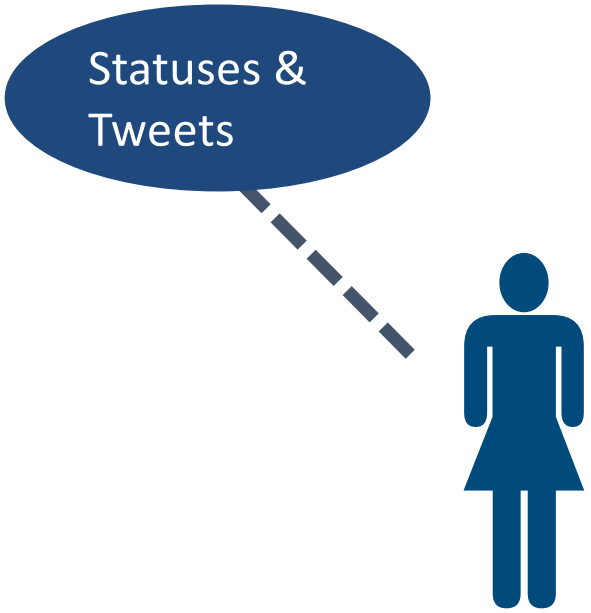
- OVERVIEW
- GRAPHICAL MODELS
- RANDOM WALK METHODS

Voter Party Classification



Voter Party Classification

Multiple Sources of Information



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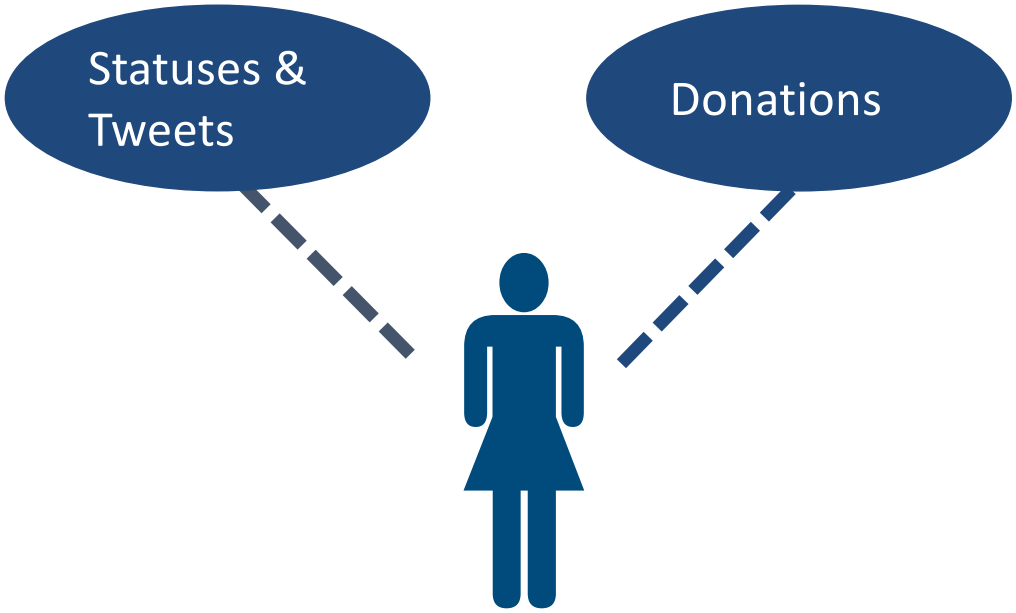

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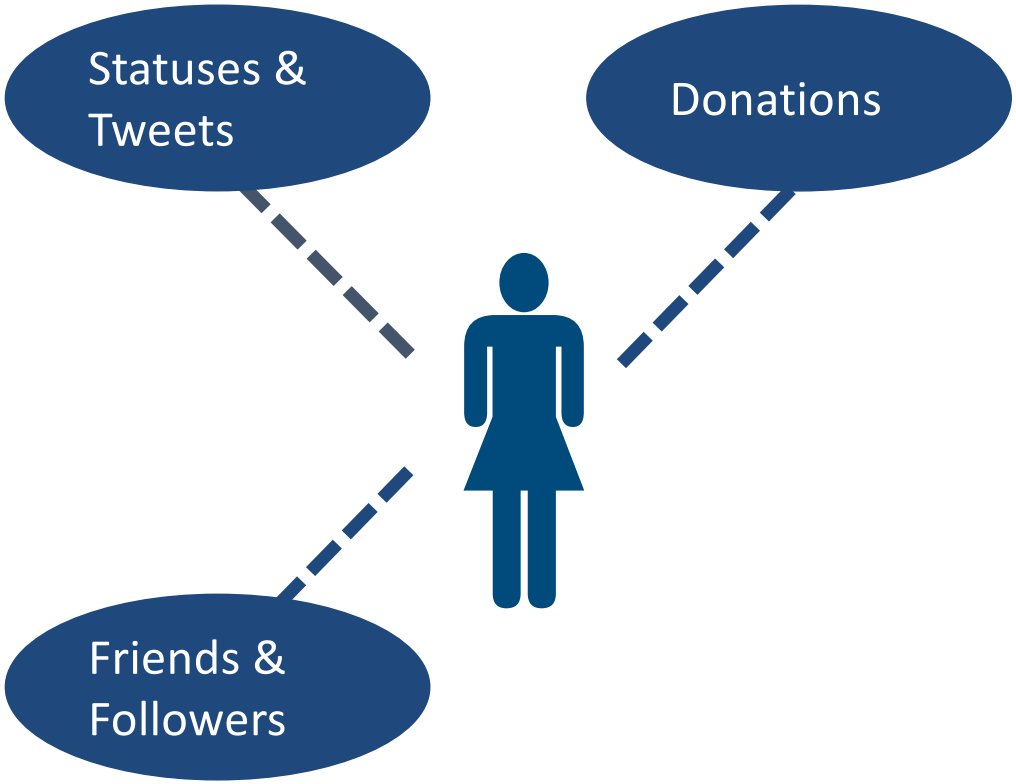

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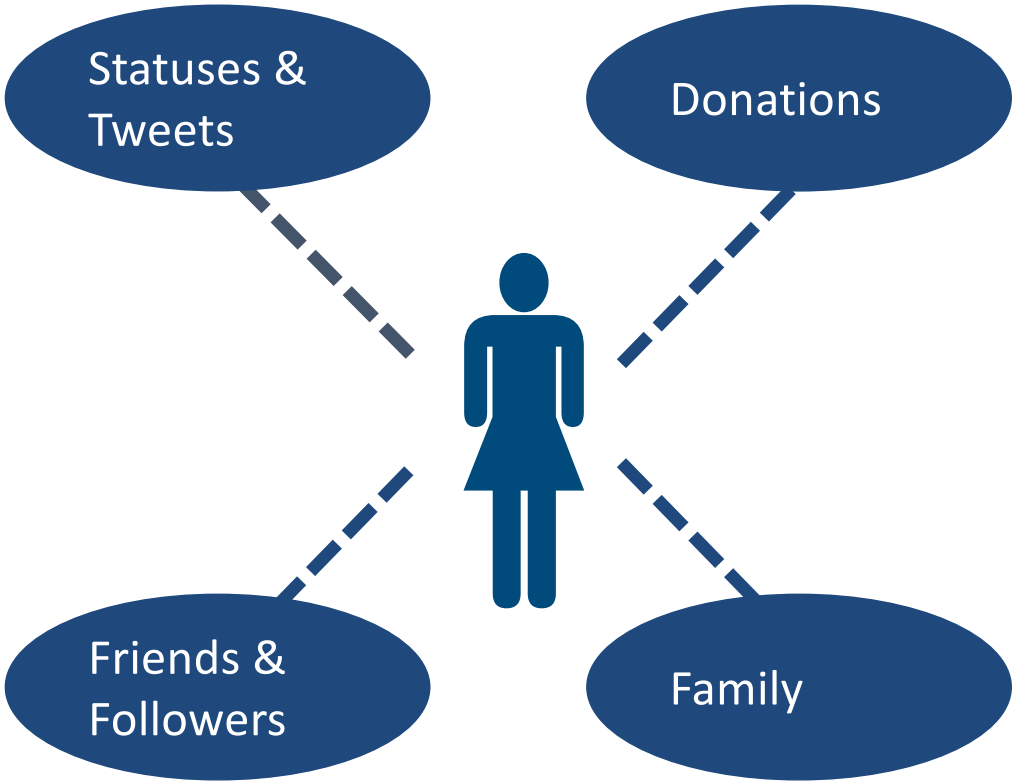

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Voter Party Classification

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Ca

Planned Parenthood
Planned Parenthood Action Fund

Donate to the Planned Parenthood Action Fund.

TELL YOUR FRIENDS AND FAMILY!

Voter Party Classification

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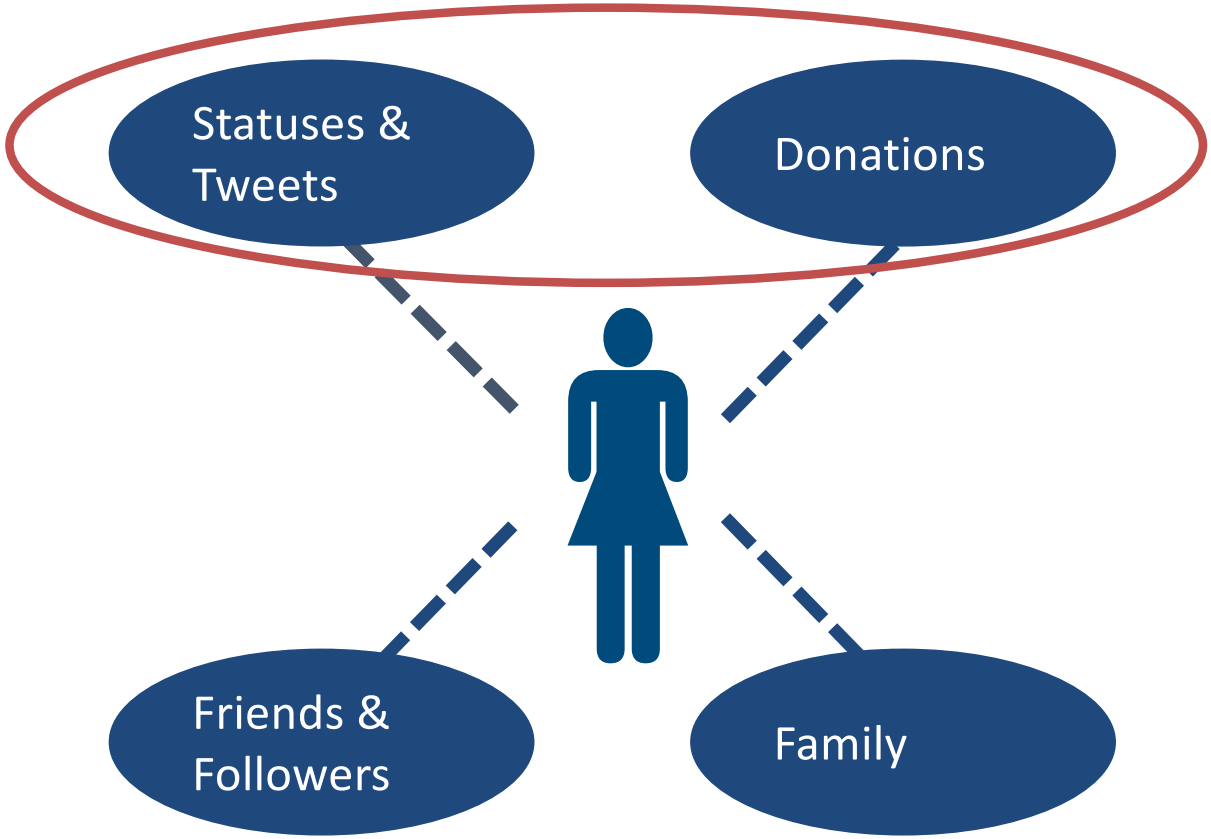

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↓ Bag-of-words features

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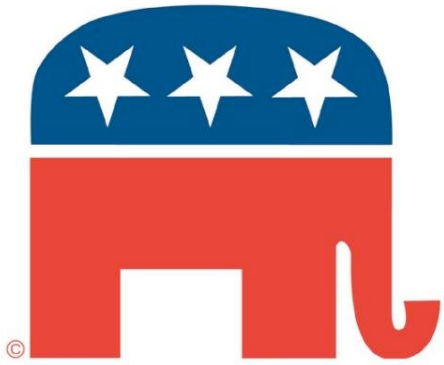

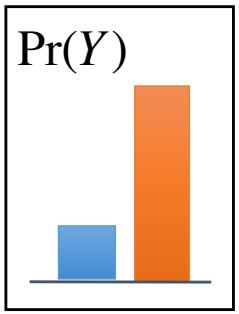

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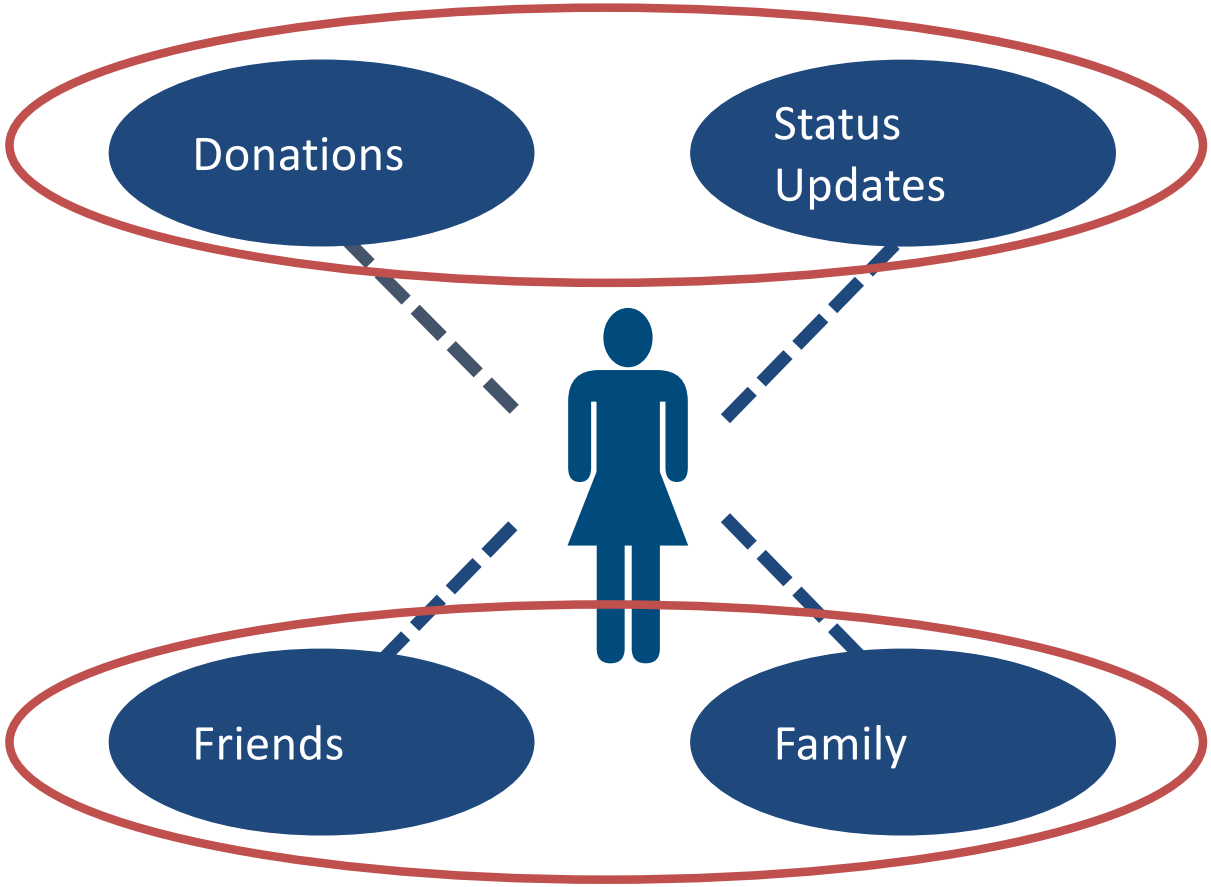

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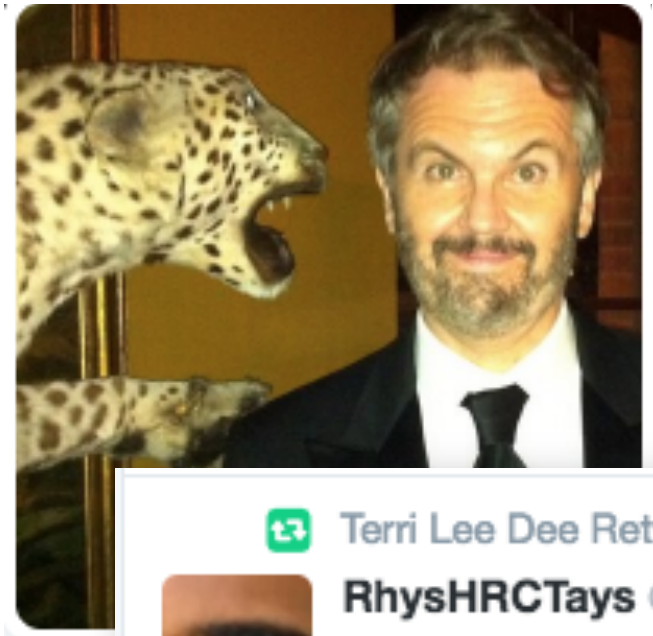

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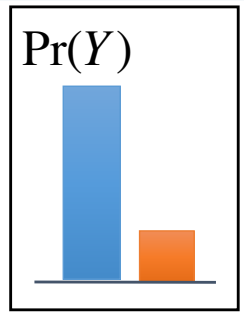

Collective Classification

Follows

My label is likely to match that of my follower

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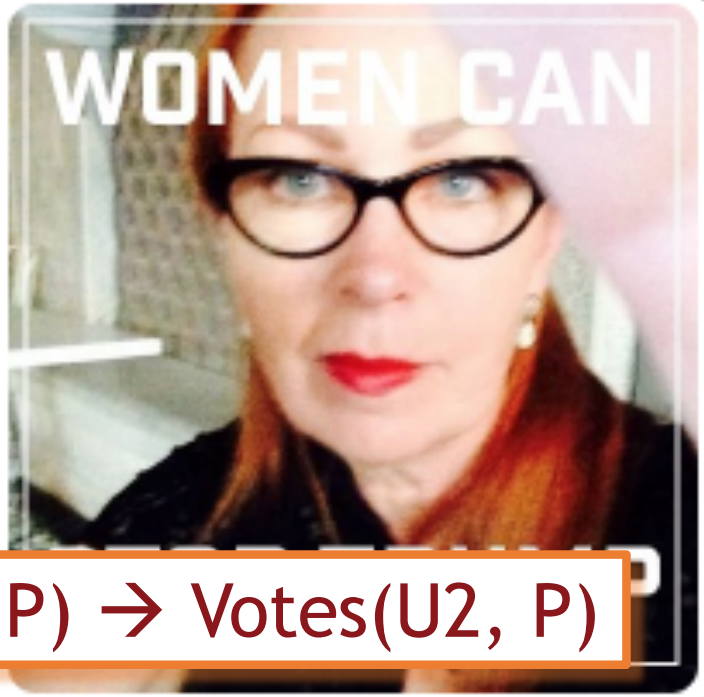
@terrileedee

Collective Classification

Follows



Follows(U1, U2) & Votes(U1, P) → Votes(U2, P)

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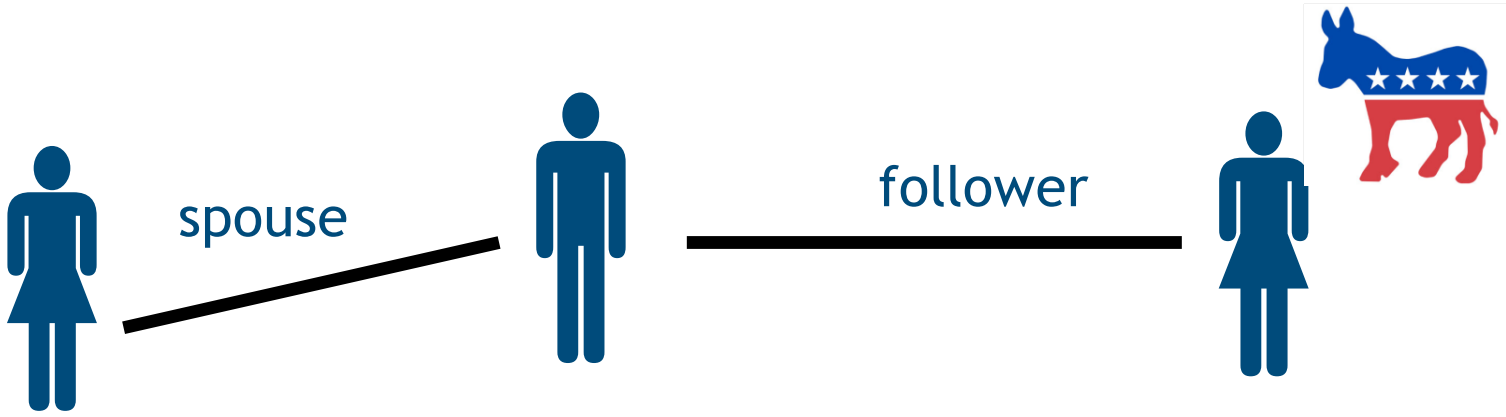

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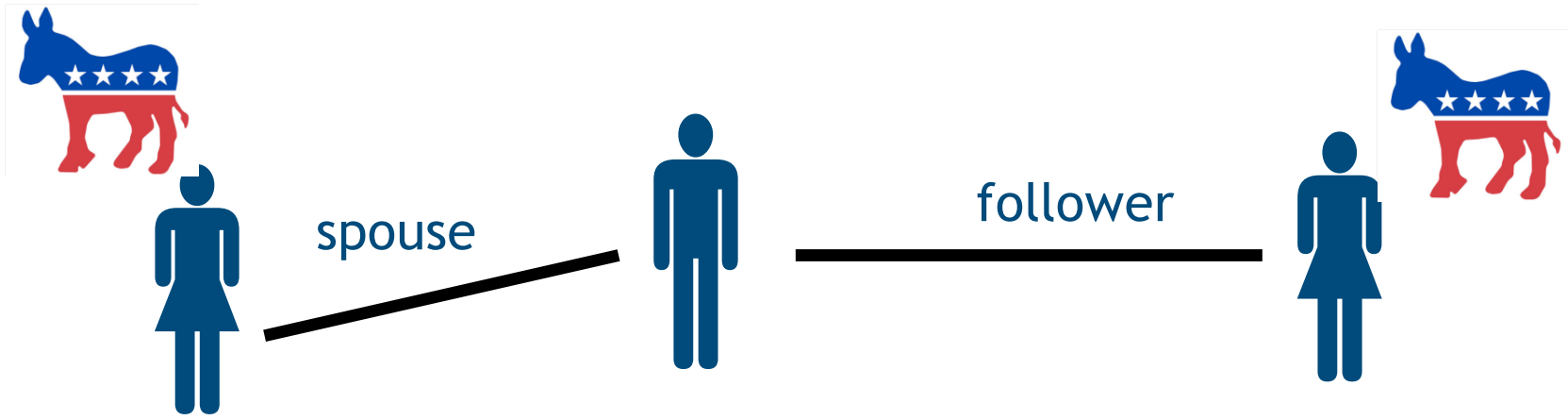

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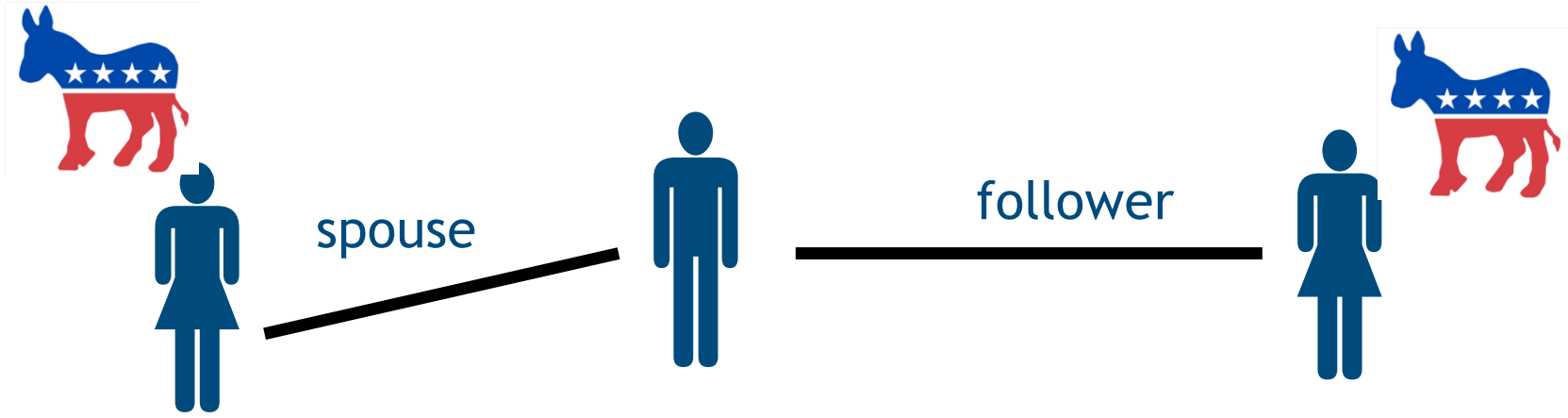
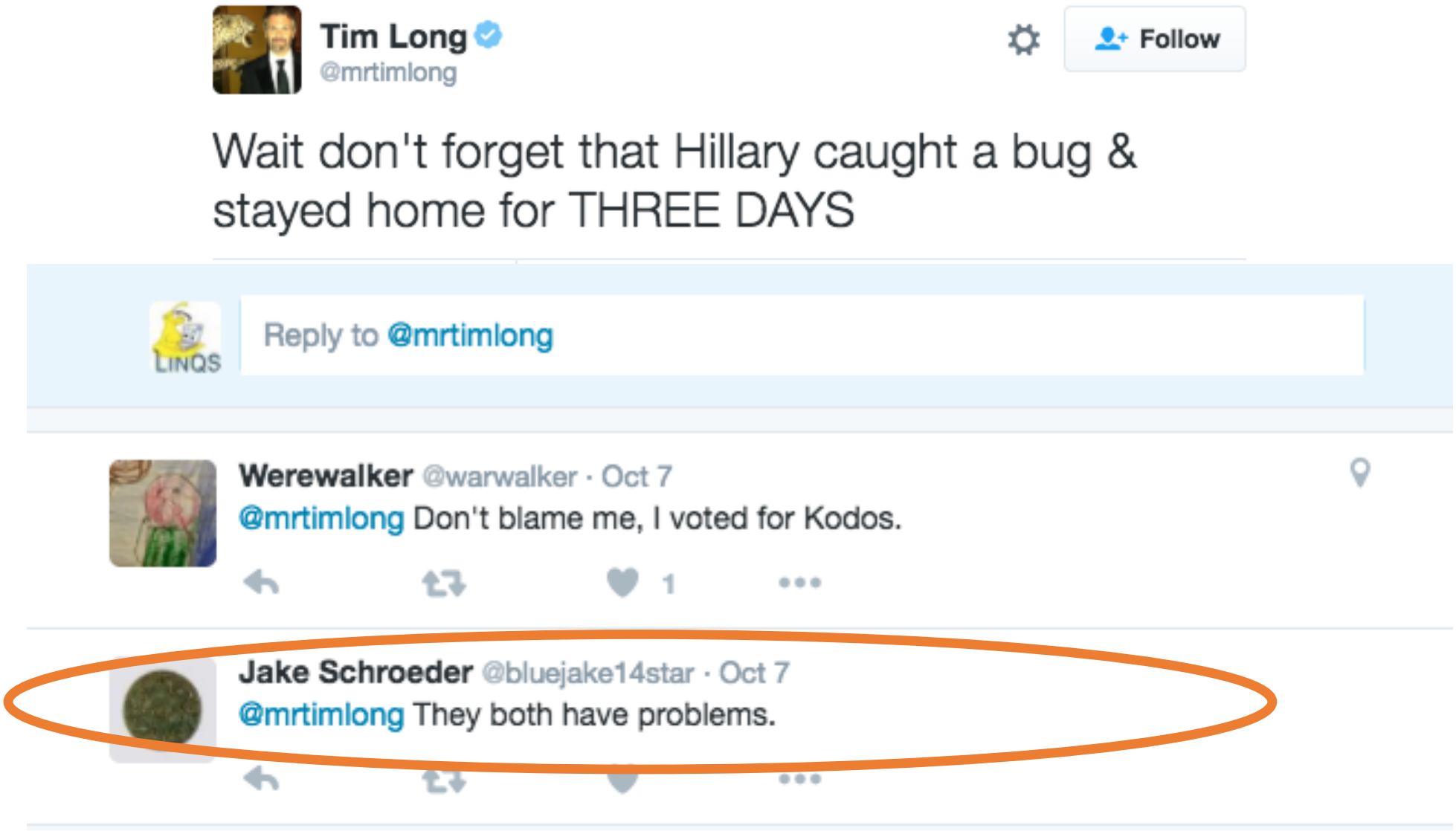


Spouse(U1, U2) & Votes(U1, P) → Votes(U2, P)

Follows(U1, U2) & Votes(U1, P) → Votes(U2, P)

Collective Classification



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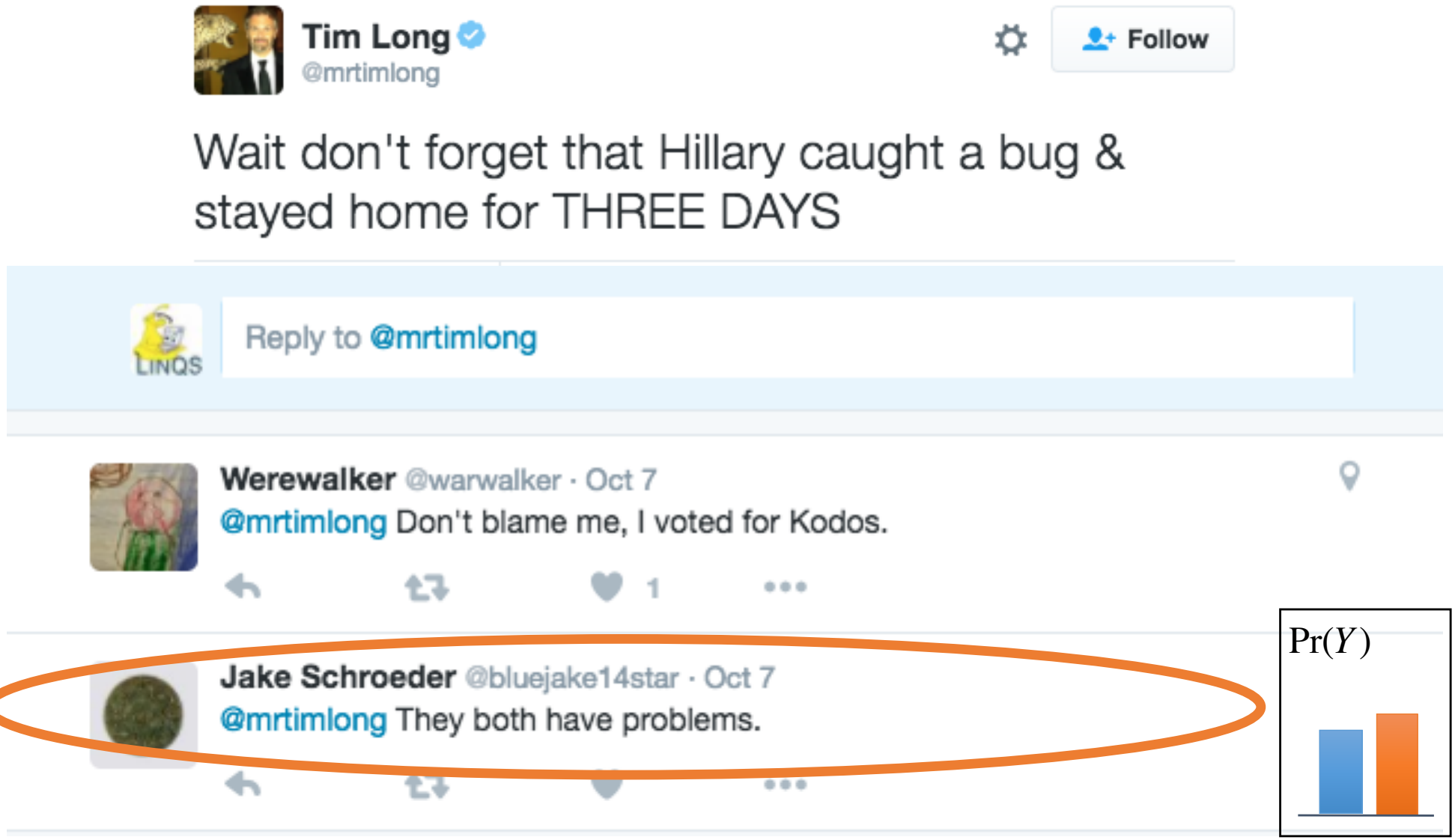

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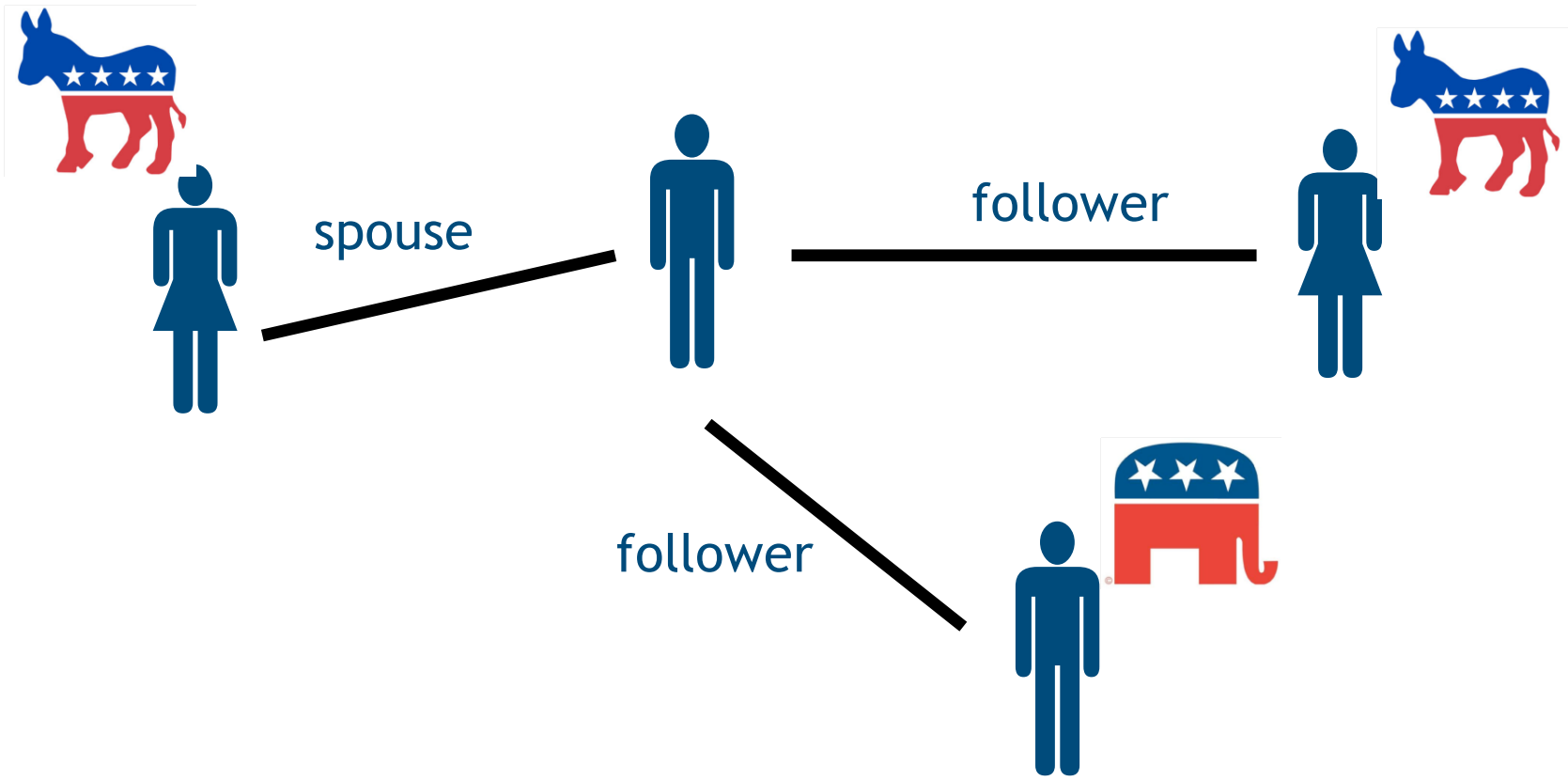
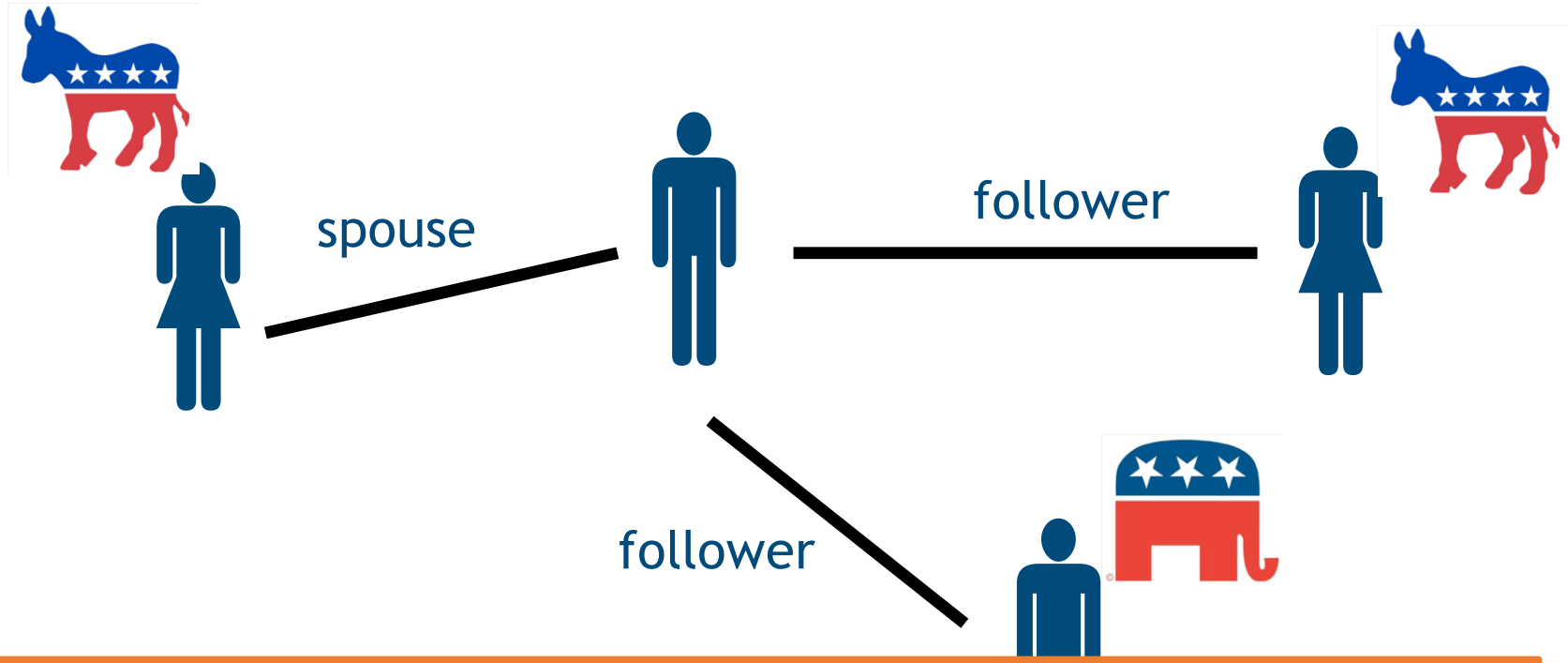


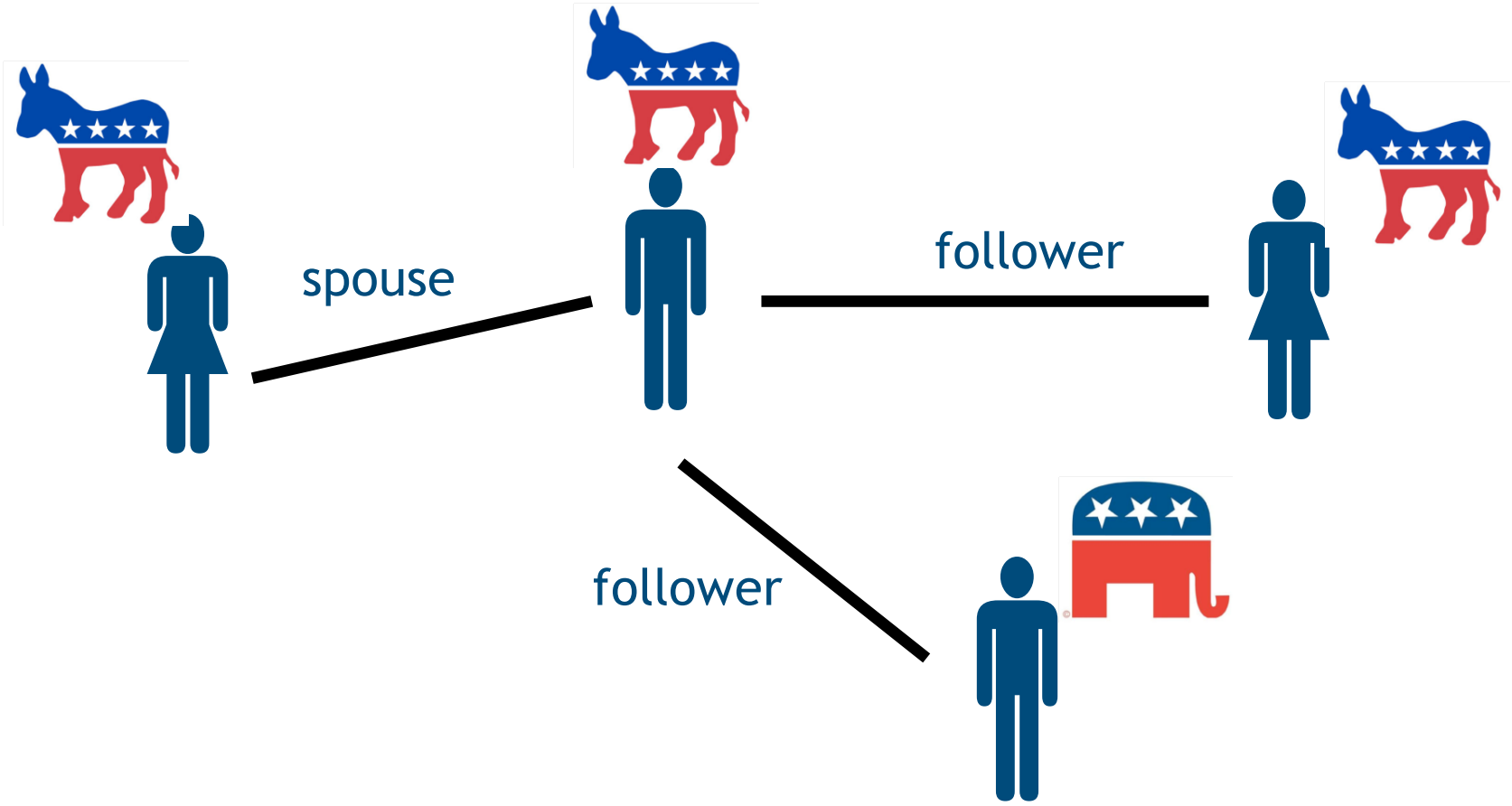
Collective Classification



5.0: Spouse(U1, U2) ^& Votes(U1, P) → Votes(U2, P)

2.0: Follows(U1, U2) & Votes(U1, P) → Votes(U2, P)

Collective Classification



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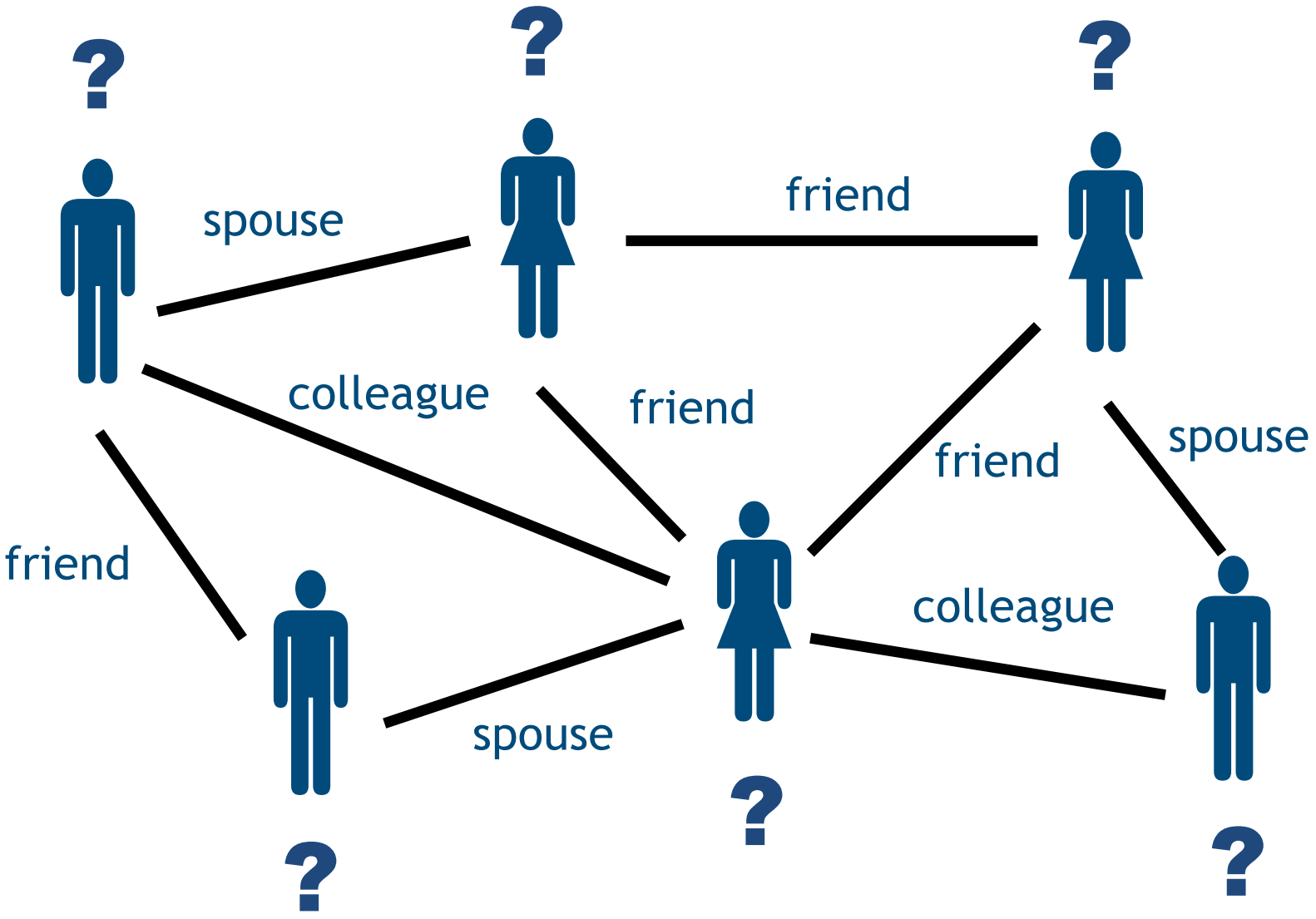
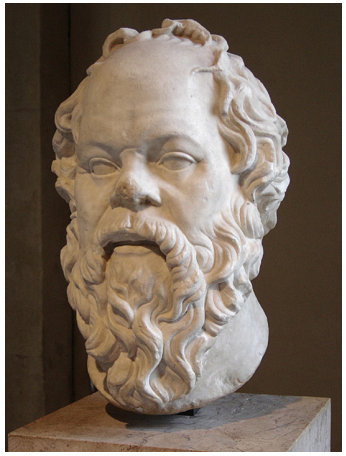


Collective Classification with PSL

```
/* Local rules */
5.0: Donates(A, P) -> Votes(A, P)
0.3: Mentions(A, “Affordable Health”) -> Votes(A, “Democrat”)
0.3: Mentions(A, “Tax Cuts”) -> Votes(A, “Republican”)

/* Relational rules */
1.0: Votes(A,P) & Spouse(B,A) -> Votes(B,P)
0.3: Votes(A,P) & Friend(B,A) -> Votes(B,P)
0.1: Votes(A,P) & Colleague(B,A) -> Votes(B,P)

/* Range constraint */
Votes(A, “Republican”) + Votes(A, “Democrat”) = 1.0 .
```

Beyond Pure Reasoning



- Classical AI approach to knowledge: reasoning

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

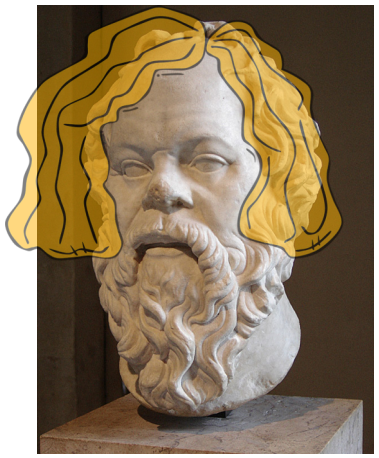
Beyond Pure Reasoning

- Classical AI approach to knowledge: reasoning

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

- Reasoning difficult when extracted knowledge has errors

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)

Logic Refresher: Satisfaction

```
/* Model Snippet */
Mentions(A, “Affordable Health”) -> Votes(A, “Democrat”)
```

Affordable Health	Democrat	Logical Satisfaction
TRUE	TRUE	☺
TRUE	FALSE	☹
FALSE	TRUE	☺
FALSE	FALSE	☺

Logic and Noisy Data

```
/* Model Snippet */
[1] Mentions(A, “Affordable Health”) ->  Votes(A, “Democrat”)
[2] Mentions(A, “Tax Cuts”)          -> !Votes(A, “Democrat”)
```

Affordable Health	Tax Cuts	Democrat	[1] Logical Satisfaction	[2] Logical Satisfaction
TRUE	TRUE	TRUE	☺	☹
TRUE	TRUE	FALSE	☹	☺

Logic and Noisy Data

```
/* Model Snippet */
[1] Mentions(A, “Affordable Health”) ->  Votes(A, “Democrat”)
[2] Mentions(A, “Tax Cuts”)          -> !Votes(A, “Democrat”)
```

Affordable Health	Tax Cuts	Democrat	[1] Logical Satisfaction	[2] Logical Satisfaction
TRUE	TRUE	TRUE	☺	☹
TRUE	TRUE	FALSE	☹	☺

In logic, much as in politics, it is hard to satisfy everyone

Soft Logic to the Rescue!

```
/* Model Snippet */
[1] Mentions(A, “Affordable Health”) ->  Votes(A, “Democrat”)
[2] Mentions(A, “Tax Cuts”)          -> !Votes(A, “Democrat”)
```

Affordable Health	Tax Cuts	Democrat	[1] Logical Satisfaction	[2] Logical Satisfaction
TRUE	TRUE	0.5	😐	😐
TRUE	TRUE	0.5	😐	😐

What does 0.5 MEAN?

What does 0.5 mean?

- Rounding probability:
  - Flip a coin with bias 0.5
  - Heads = **TRUE**
  - Tails = **FALSE**

- **Using this method is a ¾ optimal solution to the NP hard weighted MAX SAT problem** [Goemans&Williams, 94]

What does  MEAN?

What does 😐 mean?

```
P -> Q
```

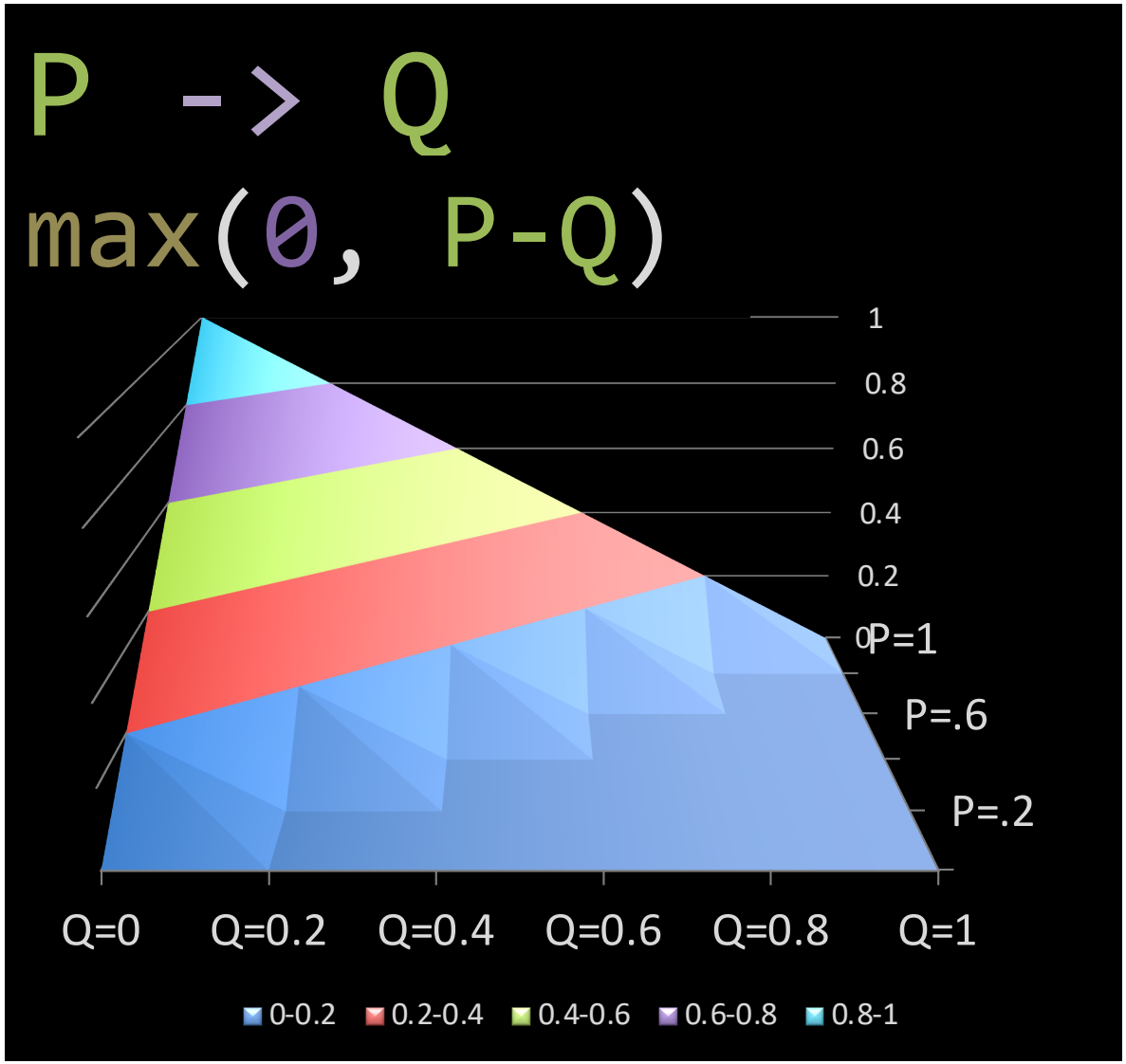
```
• /* Soft Logic Penalty */

• if P < Q
      return ☺
• else:
•     return P-Q
```

😐: Closed Form

```
P -> Q
```

- `max(0, P-Q)`

😐: Closed Form


P -> Q
max(0, P-Q)
1
0.8
0.6
0.4
0.2
0
P=1
P=.6
P=.2
Q=0
Q=0.2
Q=0.4
Q=0.6
Q=0.8
Q=1
0-0.2
0.2-0.4
0.4-0.6
0.6-0.8
0.8-1

What does 😐 mean?

```
/* Model Snippet */
[1] Mentions(A, “Affordable Health”) ->  Votes(A, “Democrat”)
[2] Mentions(A, “Tax Cuts”)          -> !Votes(A, “Democrat”)
```

```
/* Soft Logic Penalty */

if Mentions(A, “Tax Cuts”) < !Votes(A, “Democrat”):
      return 0
else:
      return Mentions(A, “Tax Cuts”) - !Votes(A, “Democrat”)
```

Computing 😐

```
/* Model Snippet */
[1] Mentions(A, “Affordable Health”) ->  Votes(A, “Democrat”)
[2] Mentions(A, “Tax Cuts”)          -> !Votes(A, “Democrat”)
```

Affordable Health	Tax Cuts	Democrat	[1] Penalty	[2] Penalty
1	1	0.7		
1	1	0.2		

```
!Q = 1-Q
 P -> Q = max(0, P-Q)
```

Computing 😐

```
/* Model Snippet */
[1] Mentions(A, “Affordable Health”) ->  Votes(A, “Democrat”)
[2] Mentions(A, “Tax Cuts”)          -> !Votes(A, “Democrat”)
```

Affordable Health	Tax Cuts	Democrat	[1] Penalty	[2] Penalty
1	1	0.7	0.3	0.7
1	1	0.2	0.8	0.2

```
!Q = 1-Q
 P -> Q = max(0, P-Q)
```

Computing 😐 with soft evidence

```
/* Model Snippet */
[1] Supports(A, “Affordable Health”) ->  Votes(A, “Democrat”)
[2] Supports(A, “Tax Cuts”)          -> !Votes(A, “Democrat”)
```

Affordable Health	Tax Cuts	Democrat	[1] Penalty	[2] Penalty
0.4	0.1	0.65		
0.4	0.1	0.2		
0.4	0.1	0.9		

```
!Q = 1-Q
 P -> Q = max(0, P-Q)
```

Computing 😐 with soft evidence

```
/* Model Snippet */
[1] Supports(A, “Affordable Health”) ->  Votes(A, “Democrat”)
[2] Supports(A, “Tax Cuts”)          -> !Votes(A, “Democrat”)
```

Affordable Health	Tax Cuts	Democrat	[1] Penalty	[2] Penalty
0.4	0.1	0.65	0	0
0.4	0.1	0.2	0.2	0
0.4	0.1	0.9	0.5	0

```
!Q = 1-Q
 P -> Q = max(0, P-Q)
```

Computing 😐 for arbitrary formulas

```
!Q = 1-Q
P -> Q = max(0, P-Q)
P &  Q = max(0, P+Q-1)
P |  Q = min(1, P+Q)
```

Underlying Probability Distribution

$$p(\mathbf{Y}|\mathbf{X}) = \frac{1}{Z(w,\mathbf{X})} \exp\left[-\sum_{j=1}^{m} w_j \left[\max\{\ell_j(\mathbf{Y},\mathbf{X}),0\}\right]^{\{1,2\}}\right]$$

Joint probability over soft-truth assignments

Sum over rule penalties

Optimizing PSL models

- PSL finds optimal assignment for all unknowns
- Optimal = minimizes the soft-logic penalty
- **Fast,** joint convex optimization using ADMM
- Supports learning rule weights and latent variables

Graph Construction
Probabilistic Models

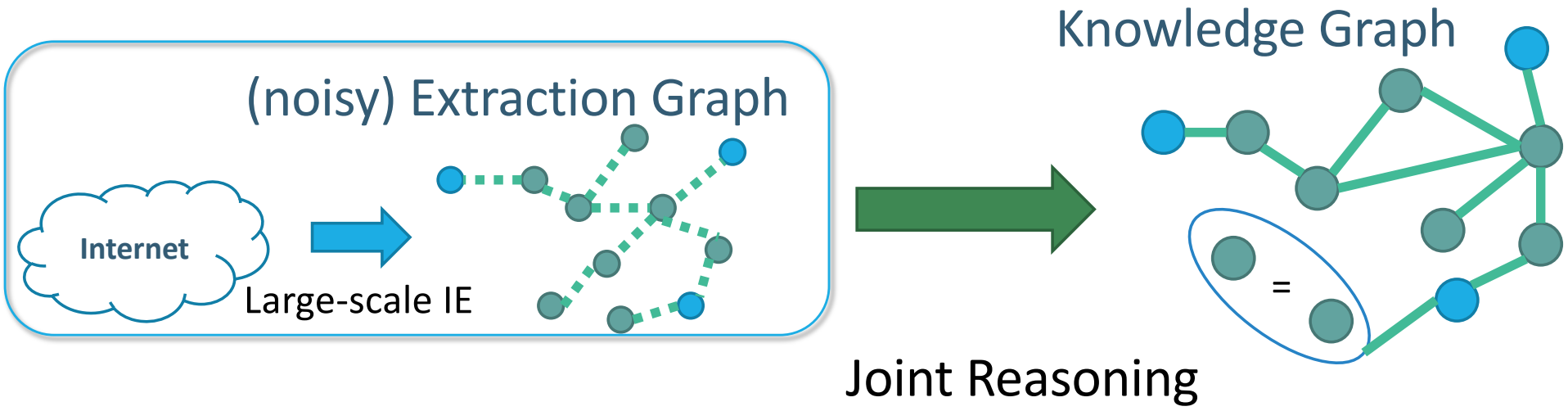
TOPICS:

- OVERVIEW
- GRAPHICAL MODELS
- RANDOM WALK METHODS

Graphical Models: Overview

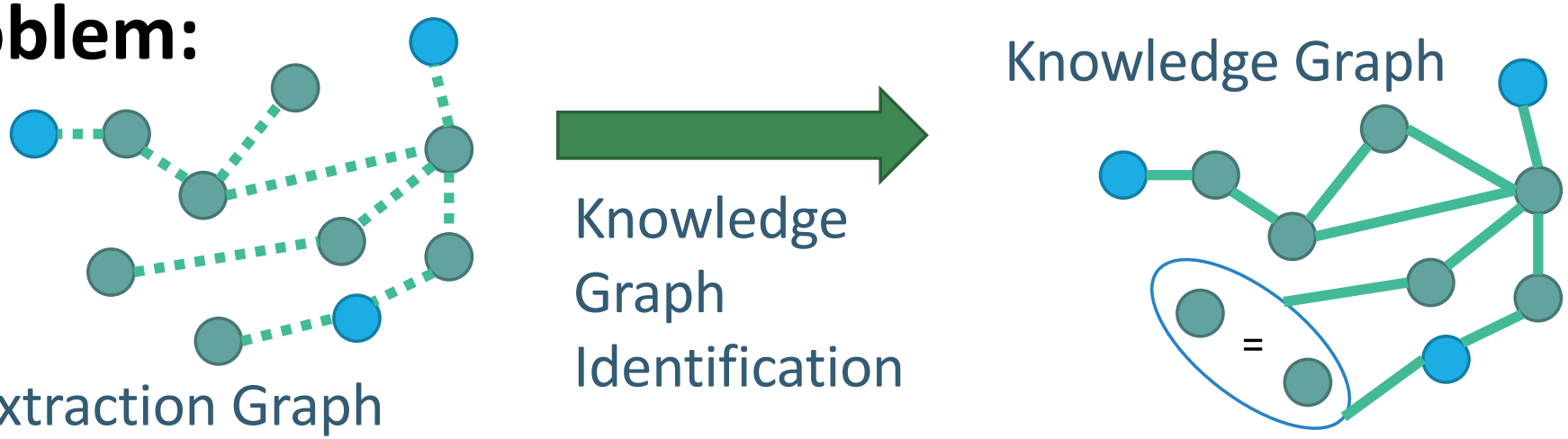
- Define **joint probability distribution** on knowledge graphs
- Each candidate fact in the knowledge graph is a **variable**
- Statistical signals, ontological knowledge and rules parameterize the **dependencies** between variables
- Find most likely knowledge graph by **optimization/sampling**

Motivating Problem (revised)



Knowledge Graph Identification

Problem:



Solution: *Knowledge Graph Identification* (KGI)

Performs *graph identification*:

- entity resolution
- collective classification
- link prediction

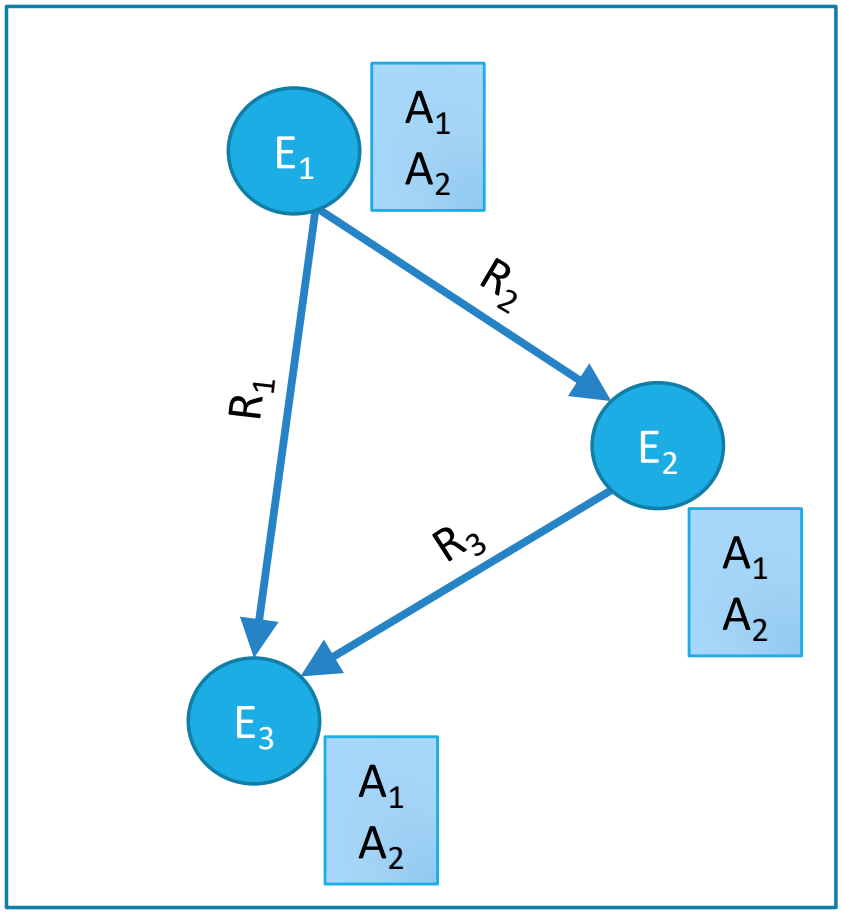
Enforces *ontological constraints*

Incorporates *multiple uncertain sources*

Knowledge Graph Identification

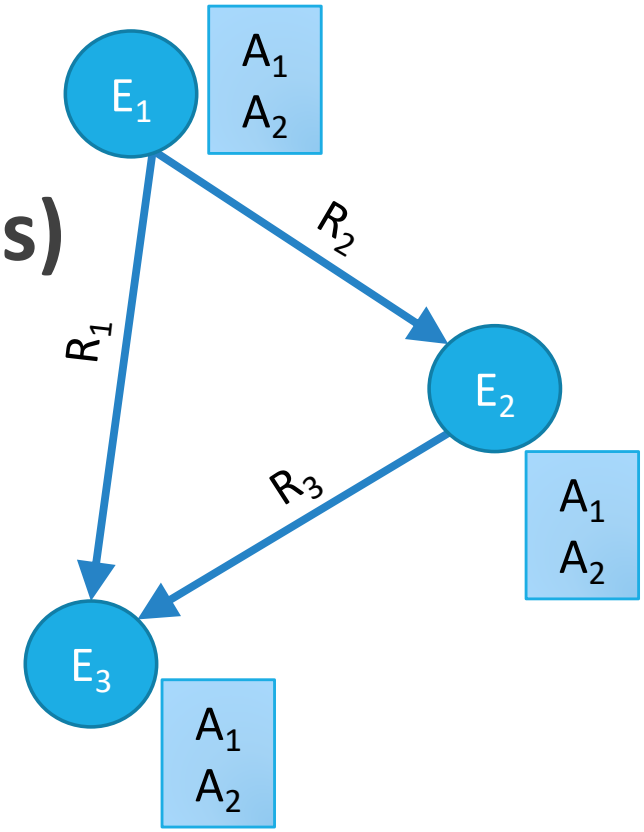
Define a graphical model to perform all three of these tasks simultaneously!

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



Knowledge Graph Identification

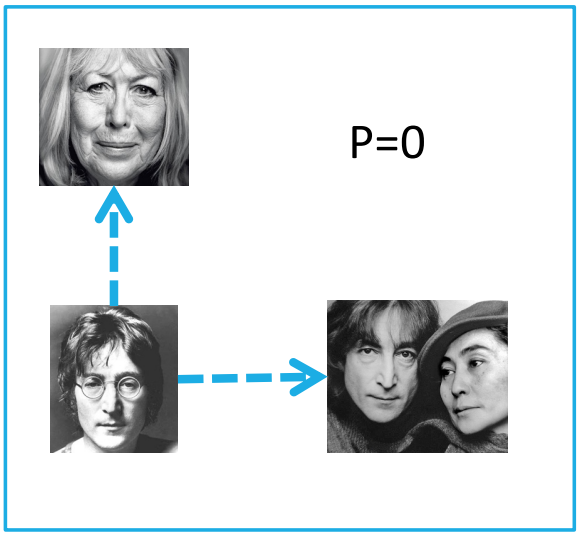
P(Who, What, How | Extractions)

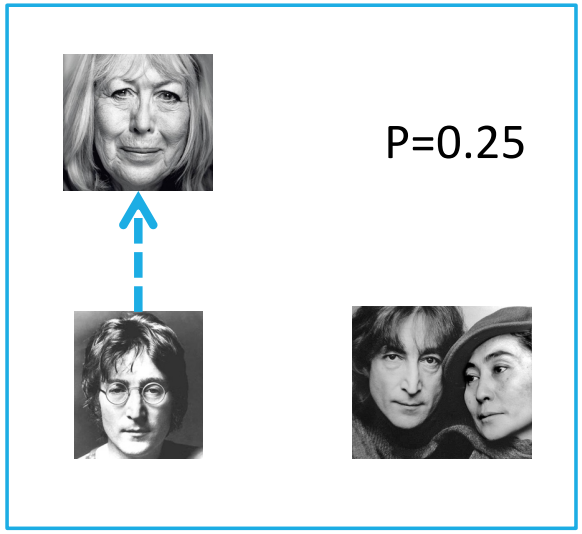


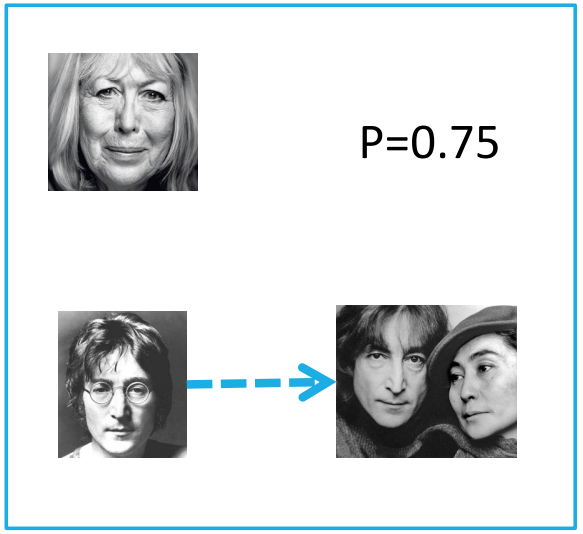
Probabilistic Models

- Use dependencies between facts in KG

- Probability defined *jointly* over facts







What determines probability?

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

What determines probability?

- **Statistical signals from text extractors and classifiers**
  - P(R(John,Spouse,Yoko))=0.75; P(R(John,Spouse,Cynthia))=0.25
  - LevenshteinSimilarity(Beatles, Beetles) = 0.9

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- Statistical signals from text extractors and classifiers

- **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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- **Statistical signals from text extractors and classifiers**
- **Ontological knowledge about domain**
- **Rules and patterns mined from data**
  - 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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- **Rules and patterns mined from data**
  - R(A, Spouse, B) & R(A, Lives, L) -> R(B, Lives, L)
  - 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

Uncertain Extractions:

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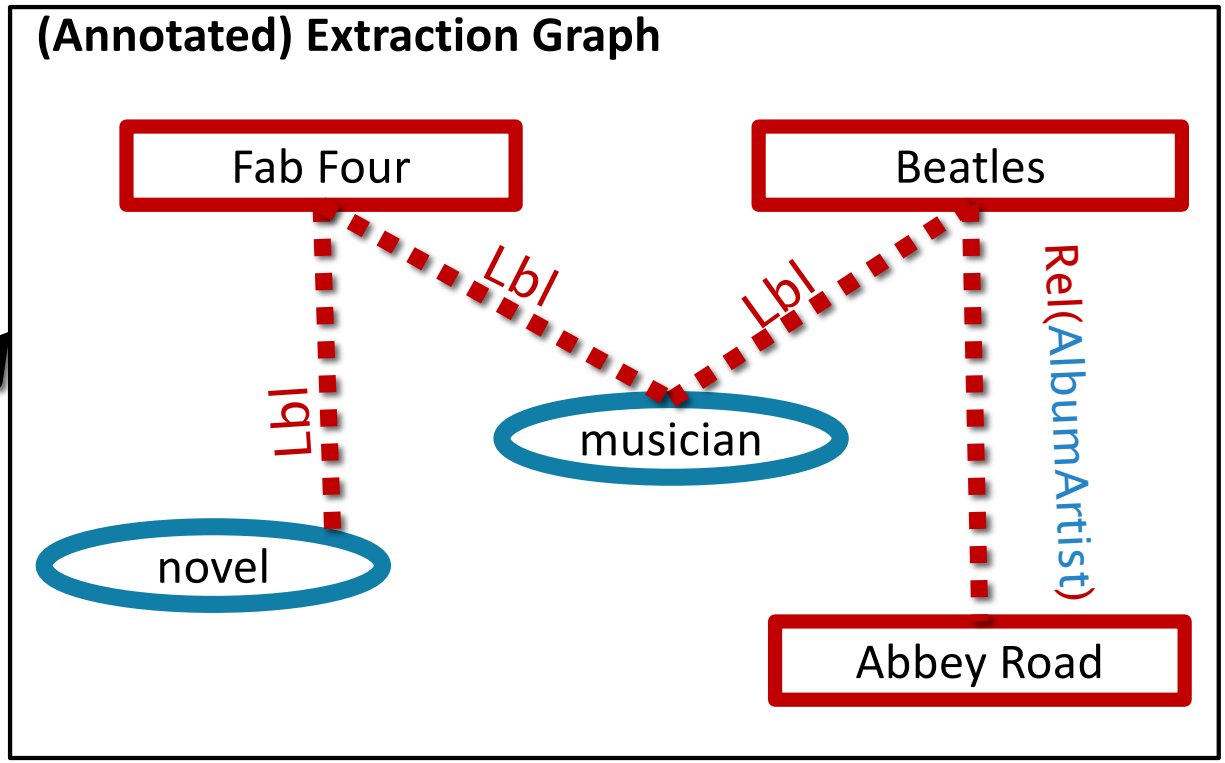

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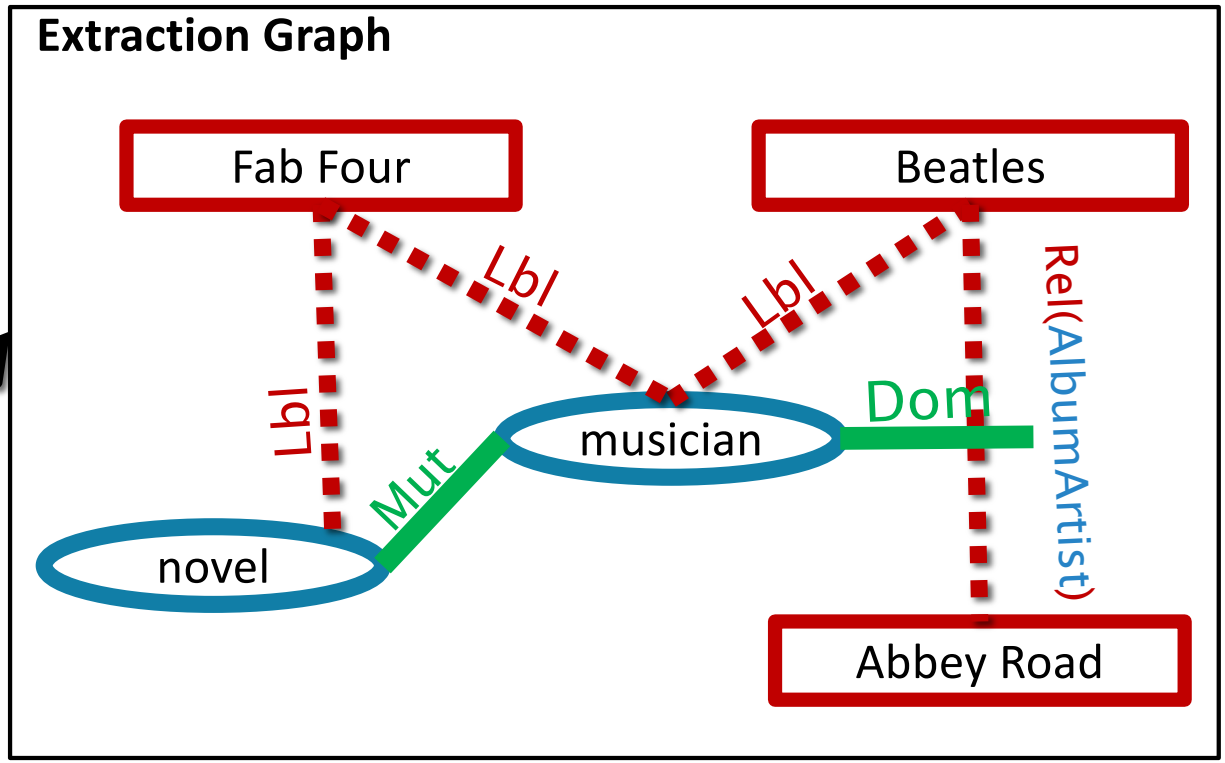
Ontology:

Dom(albumArtist, musician)

Mut(novel, musician)



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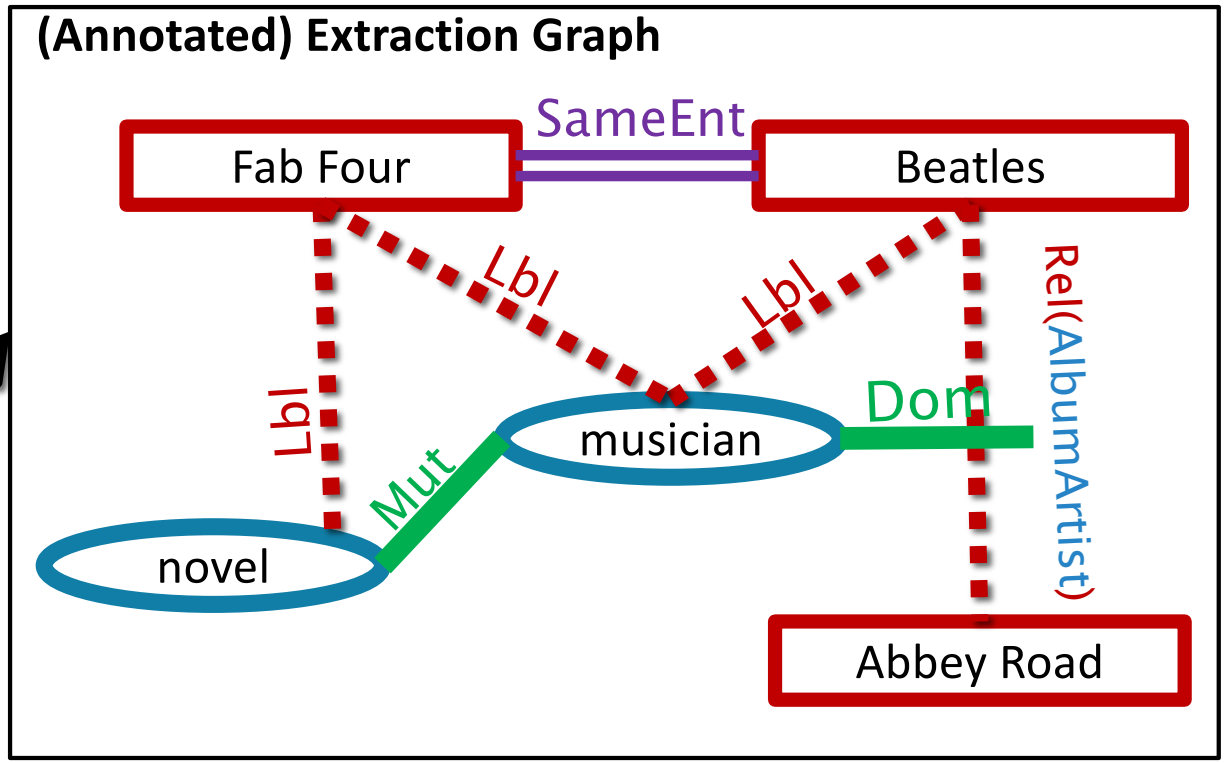
Entity Resolution:

SameEnt(Fab Four, Beatles)



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Entity Resolution:
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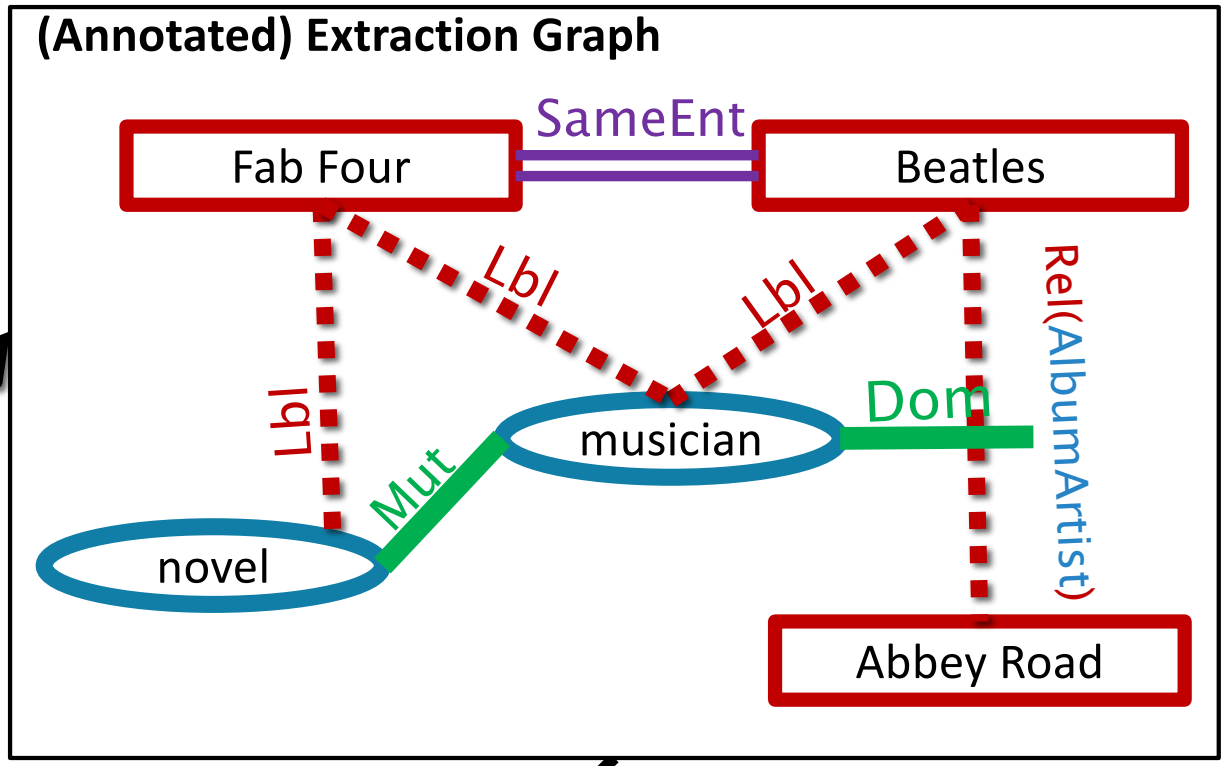
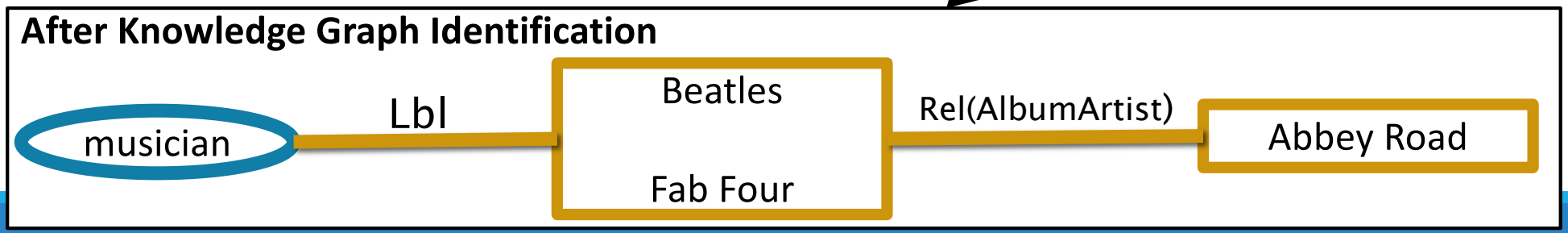
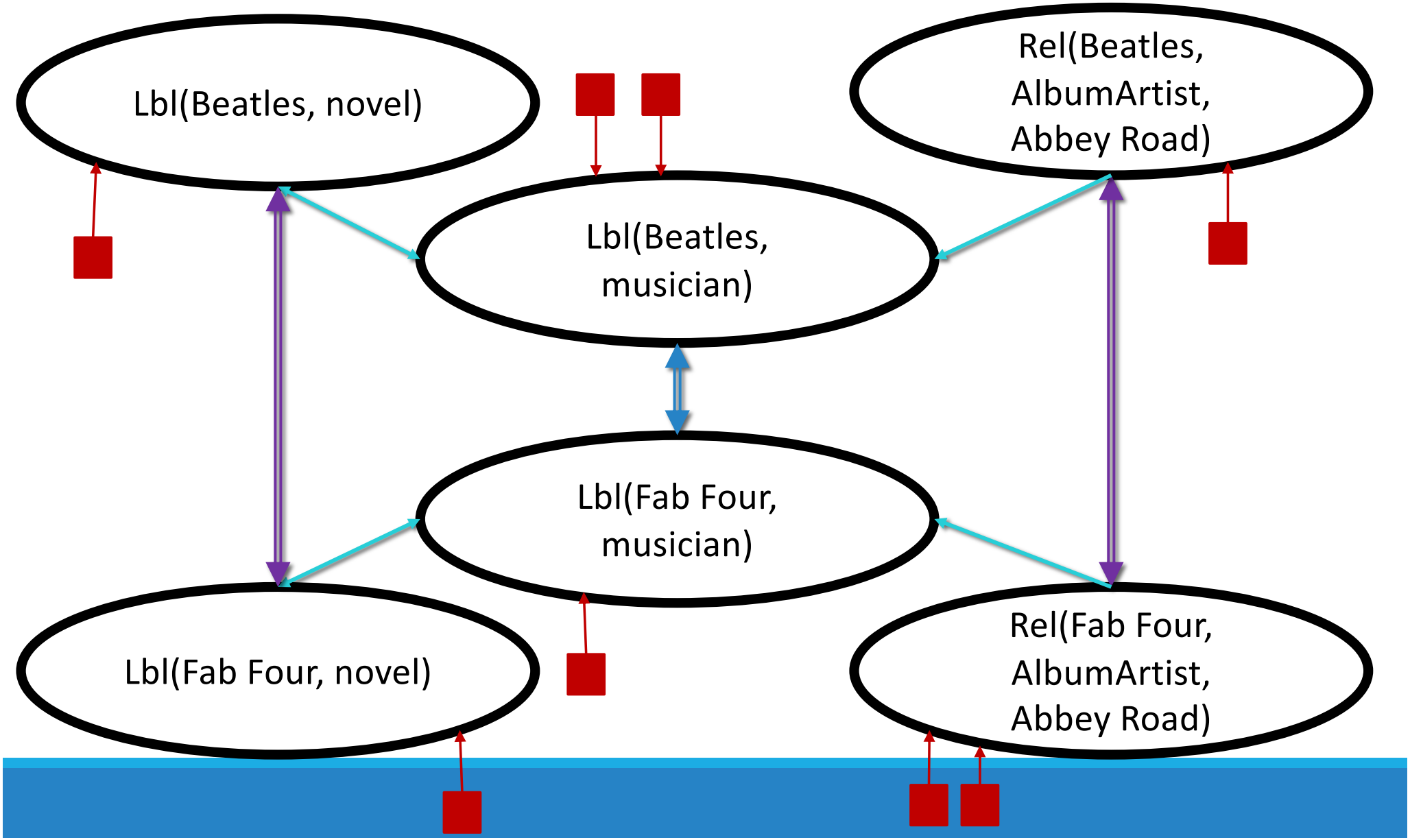




Probabilistic graphical model for KG



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_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

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

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

Probability Distribution over KGs

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

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

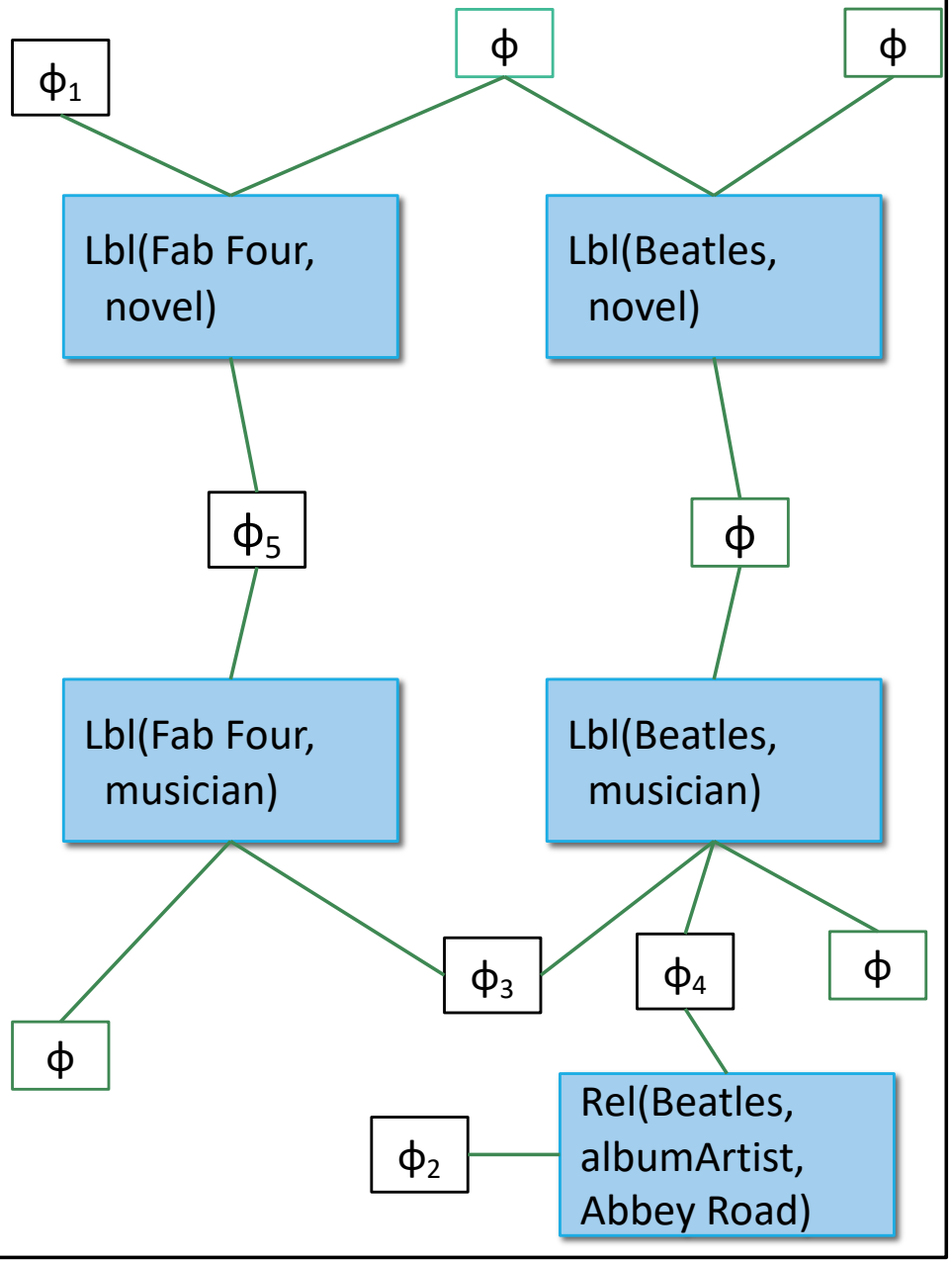
$[\phi_1]$ $\text{CandLbl}_{\text{struct}}(\texttt{FabFour}, \texttt{novel})$
$\Rightarrow$ $\text{Lbl}(\texttt{FabFour}, \texttt{novel})$

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

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

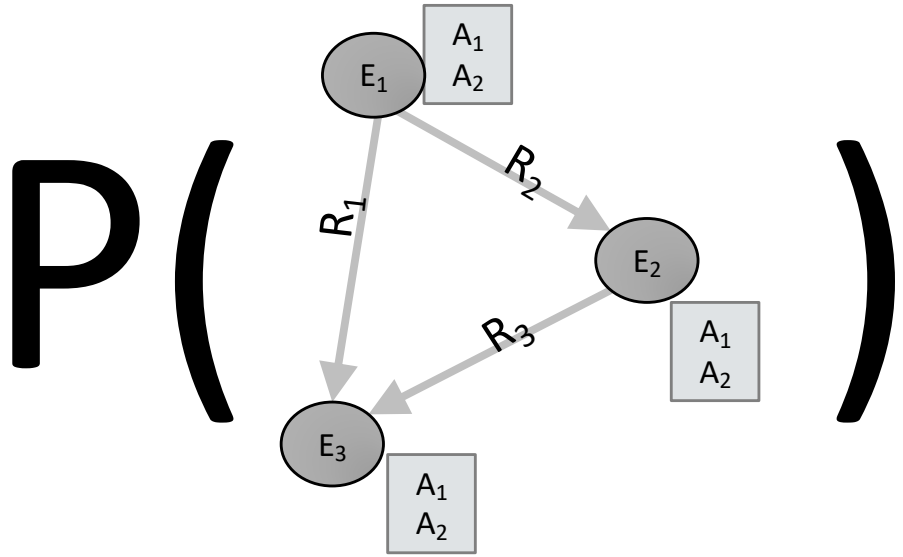
$[\phi_4]$ $\text{Dom}(\texttt{AlbumArtist}, \texttt{musician})$
$\wedge$ $\text{Rel}(\texttt{Beatles}, \texttt{AlbumArtist}, \texttt{AbbeyRoad})$
$\Rightarrow$ $\text{Lbl}(\texttt{Beatles}, \texttt{musician})$

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

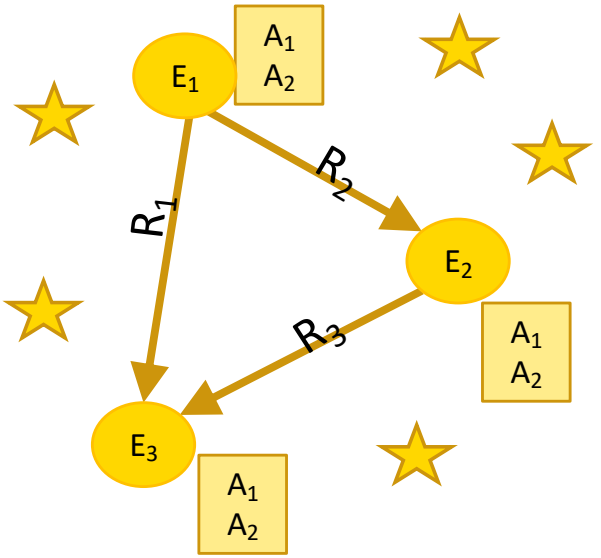


How do we get a knowledge graph?

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

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