
THE 18TH EUROPEAN CONFERENCE ON MACHINE LEARNING
AND
THE 11TH EUROPEAN CONFERENCE ON PRINCIPLES AND PRACTICE
OF KNOWLEDGE DISCOVERY IN DATABASES

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# STATISTICAL RELATIONAL LEARNING

# TUTORIAL NOTES

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**presented by**

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# Statistical Relational Learning: A Tutorial

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ECML/PKDD 2007 Tutorial

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## Roadmap

- SRL: What is it?
- SRL Tasks & Challenges
- 4 SRL Approaches
- Applications and Future directions

## Why SRL?

- Traditional statistical machine learning approaches assume:
  - A random sample of homogeneous objects from single relation
- Traditional ILP/relational learning approaches assume:
  - No noise or uncertainty in data
- Real world data sets:
  - Multi-relational, heterogeneous and semi-structured
  - Noisy and uncertain
- Statistical Relational Learning:
  - newly emerging research area at the intersection of research in social network and link analysis, hypertext and web mining, graph mining, relational learning and inductive logic programming
- Sample Domains:
  - web data, bibliographic data, epidemiological data, communication data, customer networks, collaborative filtering, trust networks, biological data, natural language, vision

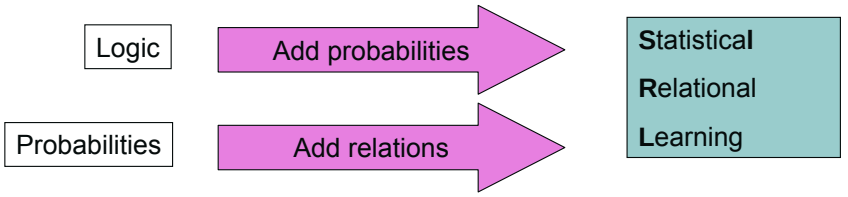
## What is SRL?

- Three views…

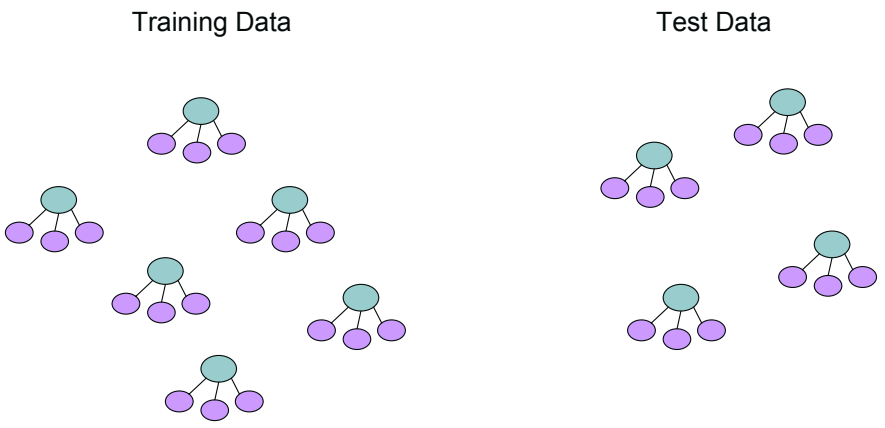
## View 1: Alphabet Soup

## View 2: Representation Soup

- Hierarchical Bayesian Model + Relational Representation



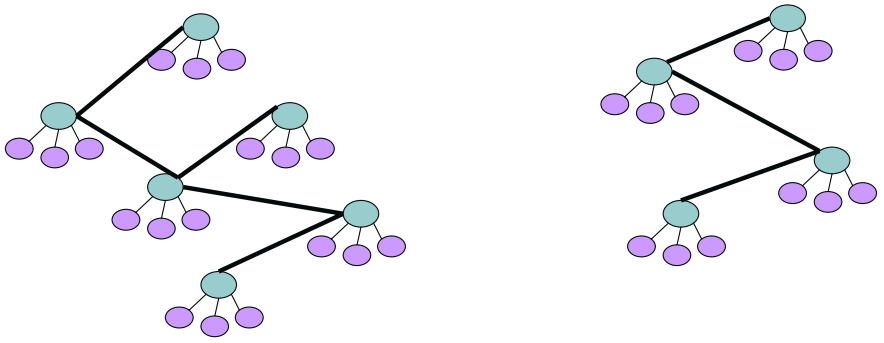

## View 3: Data Soup



# View 3: Data Soup

Training Data

Test Data



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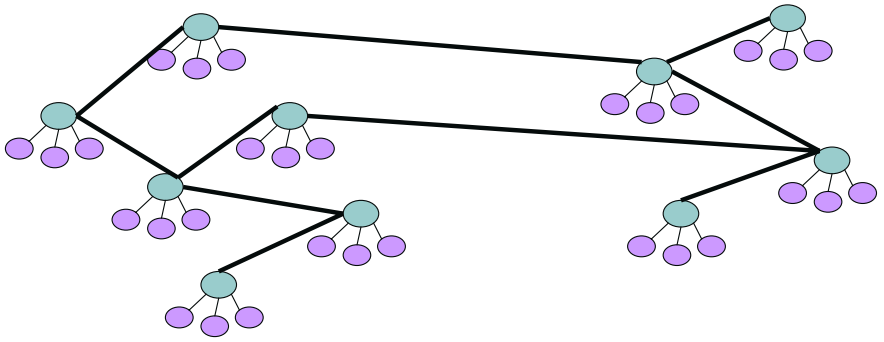
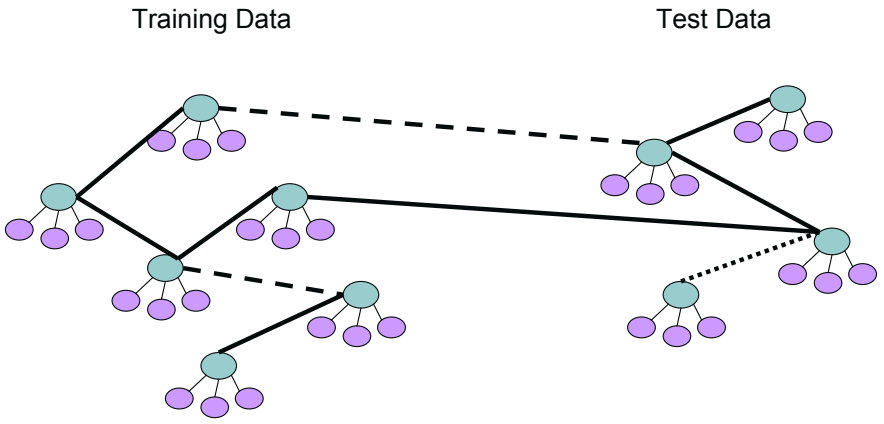
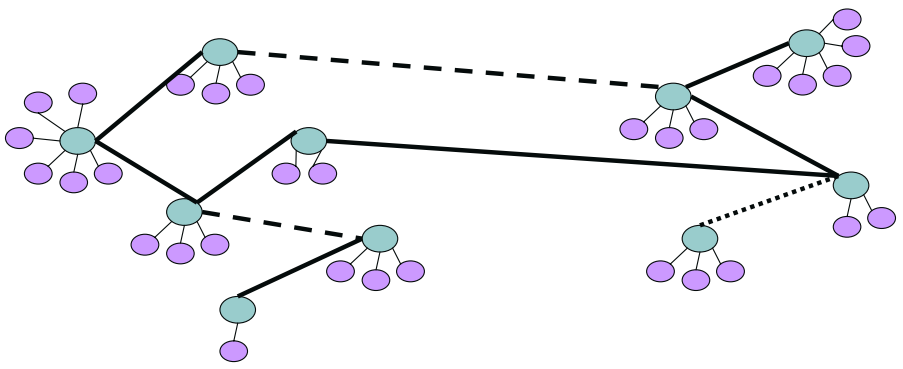


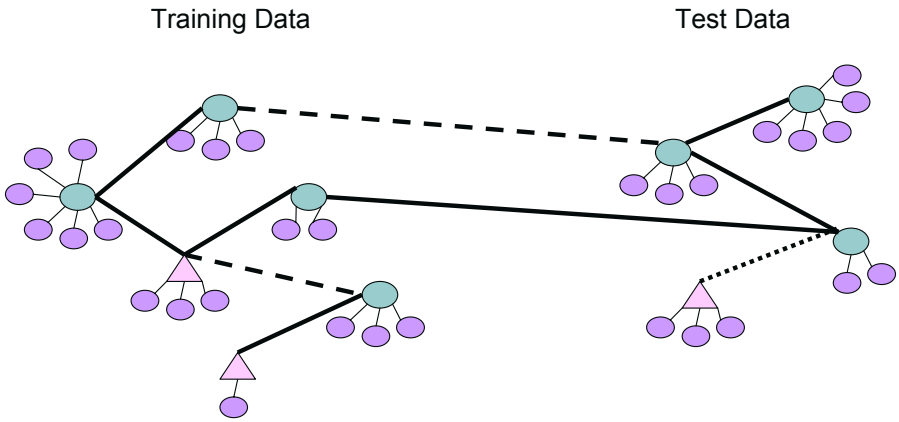
# View 3: Data Soup




# View 3: Data Soup



## View 3: Data Soup




## Goals

- By the end of this tutorial, hopefully, you will be:
  1. able to distinguish among different SRL tasks
  2. able to represent a problem in one of several SRL representations
  3. excited about SRL research problems and practical applications

## Roadmap

- SRL: What is it?
- **SRL Tasks & Challenges**
- 4 SRL Approaches
- Applications and Future directions

## SRL Tasks

- Tasks
  - Object Classification
  - Object Type Prediction
  - Link Type Prediction
  - Predicting Link Existence
  - Link Cardinality Estimation
  - Entity Resolution
  - Group Detection
  - Subgraph Discovery
  - Metadata Mining

# Object Prediction

- **Object Classification**
  - Predicting the category of an object based on its attributes *and* its links *and* attributes of linked objects
  - e.g., predicting the topic of a paper based on the words used in the paper, the topics of papers it cites, the research interests of the author
- **Object Type Prediction**
  - Predicting the type of an object based on its attributes and its links and attributes of linked objects
  - e.g., predict the venue type of a publication (conference, journal, workshop) based on properties of the paper

# Link Prediction

- **Link Classification**
  - Predicting type or purpose of link based on properties of the participating objects
  - e.g., predict whether a citation is to foundational work, background material, gratuitous PC reference
- **Predicting Link Existence**
  - Predicting whether a link exists between two objects
  - e.g. predicting whether a paper will cite another paper
- **Link Cardinality Estimation**
  - Predicting the number of links to an object or predicting the number of objects reached along a path from an object
  - e.g., predict the number of citations of a paper

## More complex prediction tasks

- **Group Detection**
  - Predicting when a set of entities belong to the same group based on clustering both object attribute values and link structure
  - e.g., identifying research communities
- **Entity Resolution**
  - Predicting when a collection of objects are the same, based on their attributes *and* their links (aka: record linkage, identity uncertainty)
  - e.g., predicting when two citations are referring to the same paper.
- **Predicate Invention**
  - Induce a new general relation/link from existing links and paths
  - e.g., propose concept of advisor from co-author and financial support
- **Subgraph Identification, Metadata Mapping**

## SRL Challenges

- Collective Classification
- Collective Consolidation
- Logical vs. Statistical dependencies
- Feature Construction – aggregation, selection
- Flexible and Decomposable Combining Rules
- Instances vs. Classes
- Effective Use of Labeled & Unlabeled Data
- Link Prediction
- Closed vs. Open World

**Challenges common to any SRL approach!**
Bayesian Logic Programs, Markov Logic Networks, Probabilistic Relational Models, Relational Markov Networks, Relational Probability Trees, Stochastic Logic Programming to name a few

## Roadmap

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## Four SRL Approaches

- Directed Approaches
  - Rule-based Directed Models
  - Frame-based Directed Models
- Undirected Approaches
  - Frame-based Undirected Models
  - Rule-based Undirected Models
- Programming Language Approaches (oops, five!)

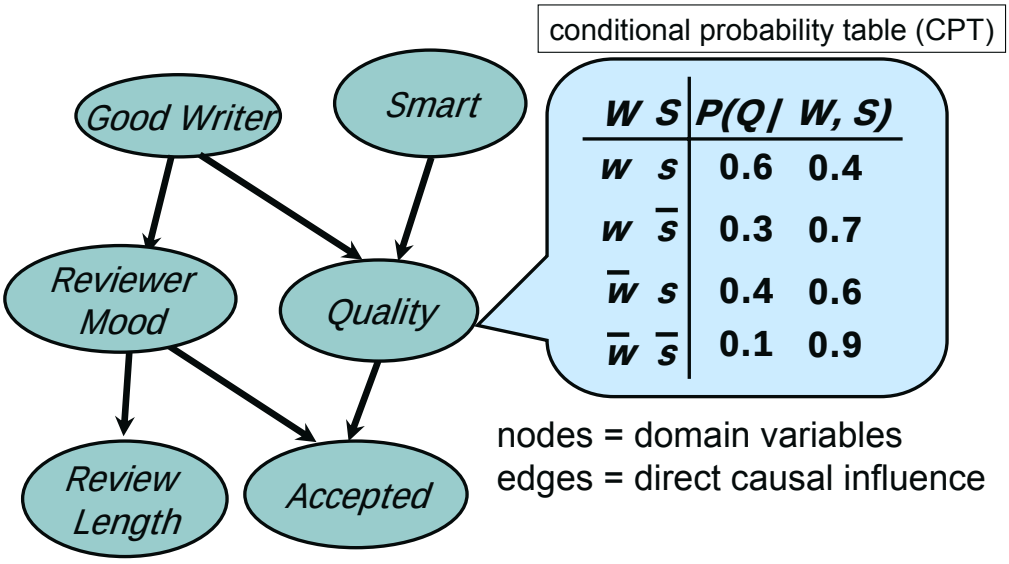
## Emphasis in Different Approaches

- Rule-based approaches focus on facts
  - what is true in the world?
  - what facts do other facts depend on?
- Frame-based approaches focus on objects and relationships
  - what types of objects are there, and how are they related to each other?
  - how does a property of an object depend on other properties (of the same or other objects)?
- Directed approaches focus on causal interactions
- Undirected approaches focus on symmetric, non-causal interactions
- Programming language approaches focus on processes
  - how is the world generated?
  - how does one event influence another event?

## Four SRL Approaches

- Directed Approaches
  - **BN Tutorial**
  - Rule-based Directed Models
  - Frame-based Directed Models
- Undirected Approaches
  - Markov Network Tutorial
  - Rule-based Undirected Models
  - Frame-based Undirected Models

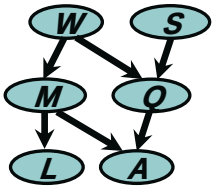
## Bayesian Networks




Network structure encodes conditional independencies:

$I$(*Review-Length* , *Good-Writer* | *Reviewer-Mood*)

## BN Semantics




conditional independencies in BN structure + local CPTs = full joint distribution over domain

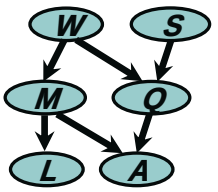
$$P(\bar{w},s,m,q,\bar{l},a) =$$

$$P(\bar{w})P(s)P(m|\bar{w})P(q|\bar{w},s)P(\bar{l}|m)P(a|m,q)$$

- Compact & natural representation:
  - nodes $\leq k$ parents $\Rightarrow$ $O(2^k n)$ vs. $O(2^n)$ params
  - natural parameters

# Reasoning in BNs

- Full joint distribution answers any query
  - *P(event | evidence)*
- Allows combination of different types of reasoning:
  - Causal: *P(Reviewer-Mood | Good-Writer)*
  - Evidential: *P(Reviewer-Mood | not Accepted)*
  - Intercausal: *P(Reviewer-Mood | not Accepted, Quality)*




# Variable Elimination

- To compute $P(a) = \sum_{w,s,m,q,l} P(w,s,m,q,l,a)$

factors

$$\sum_{w,s,m,q,l} P(w)P(s)P(m \mid w)P(q \mid w,s)P(l \mid m)P(a \mid m,q)$$

| mood | good writer | |
|---|---|---|
| pissy | false | 1 |
| pissy | true | 0 |
| good | false | 0.7 |
| good | true | 0.3 |

A factor is a function from values of variables to positive real numbers

## Variable Elimination

- To compute $P(a) = \sum_{w,s,m,q,l} P(w,s,m,q,l,a)$

$$\sum_{w,s,m,q} \sum_{l} P(w)P(s)P(m|w)P(q|w,s)P(l|m)P(a|m,q)$$

## Variable Elimination

- To compute $P(a) = \sum_{w,s,m,q,l} P(w,s,m,q,l,a)$

$$\sum_{w,s,m,q} P(w)P(s)P(m|w)P(q|w,s)P(a|m,q)\sum_{l} P(l|m)$$

sum out $l$

## Variable Elimination

- To compute $P(a) = \sum_{w,s,m,q,l} P(w,s,m,q,l,a)$

$$\sum_{w,s,m,q} P(w)P(s)P(m \mid w)P(q \mid w,s)P(a \mid m,q)f_1(m)$$

new factor

## Variable Elimination

- To compute $P(a) = \sum_{w,s,m,q,l} P(w,s,m,q,l,a)$

$$\sum_{s,m,q} P(s)P(a \mid m,q)f_1(m)\sum_{w} P(w)P(m \mid w)P(q \mid w,s)$$

multiply factors together
then sum out $w$

## Variable Elimination

- To compute $P(a) = \sum_{w,s,m,q,l} P(w,s,m,q,l,a)$

$$\sum_{s,m,q} P(s)P(a \mid m,q)f_1(m)f_2(m,q,s)$$

new factor

## Variable Elimination

- To compute $P(a) = \sum_{w,s,m,q,l} P(w,s,m,q,l,a)$

$$P(a)$$

## Other Inference Algorithms

- Exact
  - Junction Tree [Lauritzen & Spiegelhalter 88]
  - Cutset Conditioning [Pearl 87]
- Approximate
  - Loopy Belief Propagation [McEliece et al 98]
  - Likelihood Weighting [Shwe & Cooper 91]
  - Markov Chain Monte Carlo [eg MacKay 98]
    - Gibbs Sampling [Geman & Geman 84]
    - Metropolis-Hastings [Metropolis et al 53, Hastings 70]
  - Variational Methods [Jordan et al 98]

## Learning BNs

| | Parameters only | Structure and Parameters |
|---|---|---|
| Complete Data | Easy: counting | Structure search |
| Incomplete Data | EM [Dempster et al 77] or gradient descent [Russell et al 95] | Structural EM [Friedman 97] |

See [Heckerman 98] for a general introduction

## BN Parameter Estimation

- Assume known dependency structure $G$
- Goal: estimate BN parameters $\theta$
  - entries in local probability models,

$$\theta_{x,u} = P(X = x \mid \text{Pa}[X] = u)$$

- $\theta$ is good if it's likely to generate observed data.

$$l(\theta : D, G) = \log P(D \mid \theta, G)$$

- MLE Principle: Choose $\theta^*$ so as to maximize $l$
- Alternative: incorporate a prior

## Learning With Complete Data

- Fully observed data: data consists of set of instances, each with a value for all BN variables
- With fully observed data, we can compute $N_{q,\overline{w},s}$ = number of instances with $q$, $\overline{w}$ and $s$
  - and similarly for other counts
- We then estimate

$$\theta_{q,\overline{w},s} = P(q \mid \overline{w}, s) = \frac{N_{q,\overline{w},s}}{N_{\overline{w},s}}$$

## Dealing w/ missing values

- Can't compute $N_{q,\overline{w},s}$
- But can use Expectation Maximization (EM)
  1. Given parameter values, can compute expected counts: $E[N_{q,\overline{w},s}] = \sum_{\text{instances } i} P(q^i, \overline{w}^i, s^i \mid \text{evidence}^i)$

     this requires BN inference
  2. Given expected counts, estimate parameters:

$$\theta_{q,\overline{w},s} = P(q \mid \overline{w}, s) = \frac{E[N_{q,\overline{w},s}]}{E[N_{\overline{w},s}]}$$

- Begin with arbitrary parameter values
- Iterate these two steps
- Converges to local maximum of likelihood

## Structure search

- Begin with an empty network
- Consider all neighbors reached by a search operator that are acyclic
  - add an edge
  - remove an edge
  - reverse an edge
- For each neighbor
  - compute ML parameter values $\theta_s^*$
  - compute score($s$) = $\log P(D \mid s, \theta_s^*) + \log P(s)$
- Choose the neighbor with the highest score
- Continue until reach a local maximum

## Mini-BN Tutorial Summary

- Representation – probability distribution factored according to the BN DAG
- Inference – exact + approximate
- Learning – parameters + structure

## Four SRL Approaches

- Directed Approaches
  - BN Tutorial
  - **Rule-based Directed Models**
  - Frame-based Directed Models
- Undirected Approaches
  - Markov Network Tutorial
  - Frame-based Undirected Models
  - Rule-based Undirected Models

## Directed Rule-based Flavors

- Goldman & Charniak [93]
- Breese [92]
- Probabilistic Horn Abduction [Poole 93]
- Probabilistic Logic Programming [Ngo & Haddawy 96]
- Relational Bayesian Networks [Jaeger 97]
- Bayesian Logic Programs [Kersting & de Raedt 00]
- Stochastic Logic Programs [Muggleton 96]
- PRISM [Sato & Kameya 97]
- CLP(BN) [Costa et al. 03]
- Logical Bayesian Networks [Fierens et al 04, 05]
- etc.

## Intuitive Approach

In logic programming,

```
accepted(P) :- author(P,A), famous(A).
```

means

For all P,A if A is the author of P and A is famous, then P is accepted

This is a categorical inference

But this may not be true in all cases

## Fudge Factors

Use

accepted(P) :- author(P,A), famous(A). (0.6)

This means

For all P,A if A is the author of P and A is famous, then P is accepted with probability 0.6

But what does this mean when there are other possible causes of a paper being accepted?

e.g. accepted(P) :- high_quality(P). (0.8)

## Intuitive Meaning

accepted(P) :- author(P,A), famous(A). (0.6)

means

For all P,A if A is the author of P and A is famous, then P is accepted with probability 0.6, *provided no other possible cause of the paper being accepted holds*

If more than one possible cause holds, a combining rule is needed to combine the probabilities

## Meaning of Disjunction

In logic programming

accepted(P) :- author(P,A), famous(A).

accepted(P) :- high_quality(P).

means

For all P,A if A is the author of P and A is famous, or if P is high quality, then P is accepted

## Probabilistic Disjunction

Now

accepted(P) :- author(P,A), famous(A). (0.6)

accepted(P) :- high_quality(P). (0.8)

means

For all P,A, if (A is the author of P and A is famous *successfully* cause P to be accepted) or (P is high quality *successfully* causes P to be accepted), then P is accepted.

If A is the author of P and A is famous, they successfully cause P to be accepted with probability 0.6.

If P is high quality, it successfully causes P to be accepted with probability 0.8.

- All causes act independently to produce effect (*causal independence)*
- Leak probability: effect may happen with no cause
  - e.g. accepted(P). (0.1)

## Computing Probabilities

- What is *P*(**accepted(p1)**) given that Alice is an author and Alice is famous, and that the paper is high quality, but no other possible cause is true?

$$
\begin{aligned}
P &= \text{P(at least one true cause succeeds)} \\
&= 1 - P(\text{all true possible causes fail}) \\
&= 1 - \prod_{\text{true possible causes } i} (1 - p_{\text{success}}(i)) \\
&= 1 - (1-0.6)(1-0.8)(1-0.1) = 0.928
\end{aligned}
$$

leak

## Combination Rules

- Other combination rules are possible
- e.g., max

$$P(\text{effect}) = \max_{\text{true possible causes } i} p_{\text{success}}(i)$$

- In our case,
  *P*(**accepted(p1)**) = max {0.6,0.8,0.1} = 0.8
- Harder to interpret in terms of logic program

## KBMC

- Knowledge-Based Model Construction (KBMC) [Wellman et al. 92, Ngo & Haddawy 95]
- Method for computing more complex probabilities
- Construct a Bayesian network, given a query *Q* and evidence *E*
  - query and evidence are sets of ground atoms, i.e., predicates with no variable symbols
    - e.g. **author(p1,alice)**
- Construct network by searching for possible proofs of the query and the variables
- Use standard BN inference techniques on constructed network

## KBMC Example

**smart(alice).** (0.8)
**smart(bob).** (0.9)
**author(p1,alice).** (0.7)
**author(p1,bob).** (0.3)
**high_quality(P) :- author(P,A), smart(A).** (0.5)
**high_quality(P).** (0.1)
**accepted(P) :- high_quality(P).** (0.9)

Query is **accepted(p1).**
Evidence is **smart(bob).**

## Backward Chaining

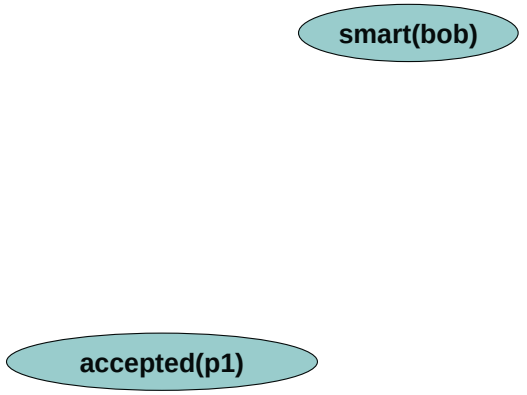
Start with evidence variable **smart(bob)**


## Backward Chaining

Rule for **smart(bob)** has no antecedents – stop backward chaining

## Backward Chaining

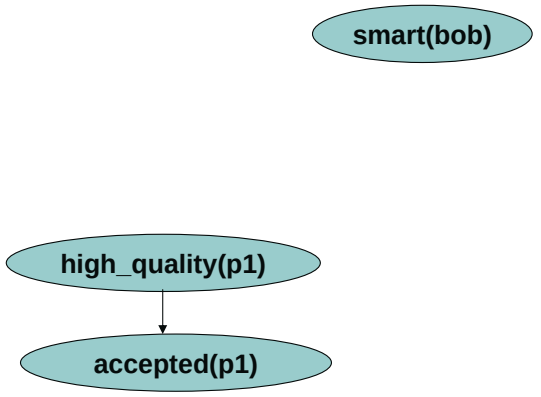
Begin with query variable **accepted(p1)**




## Backward Chaining

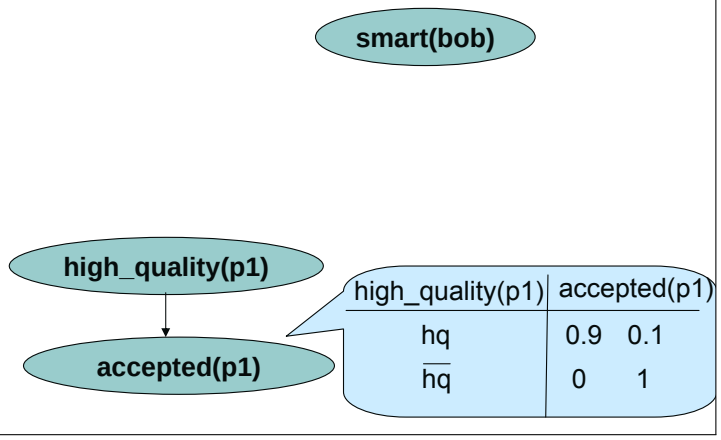
Rule for **accepted(p1)** has antecedent **high_quality(p1)**

add **high_quality(p1)** to network, and make parent of **accepted(p1)**



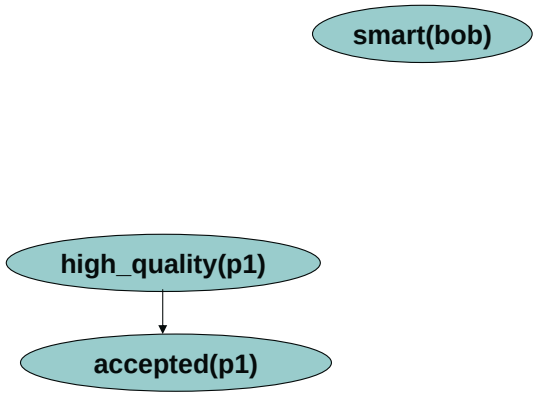
## Backward Chaining

All of **accepted(p1)**'s parents have been found – create its conditional probability table (CPT)



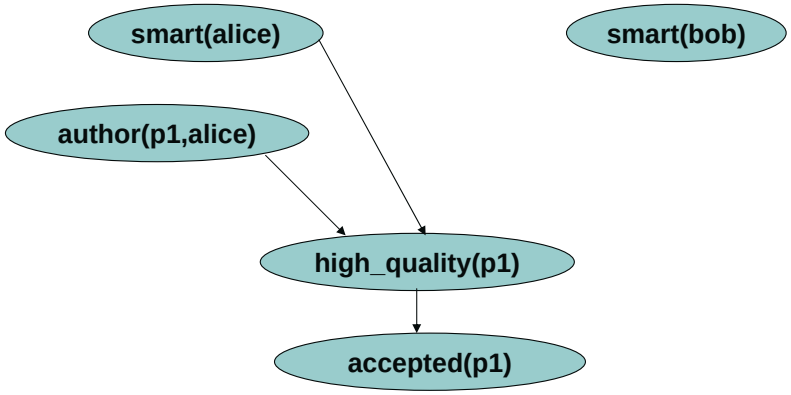

## Backward Chaining

**high_quality(p1) :- author(p1,A), smart(A)** has two groundings: **A=alice** and **A=bob**



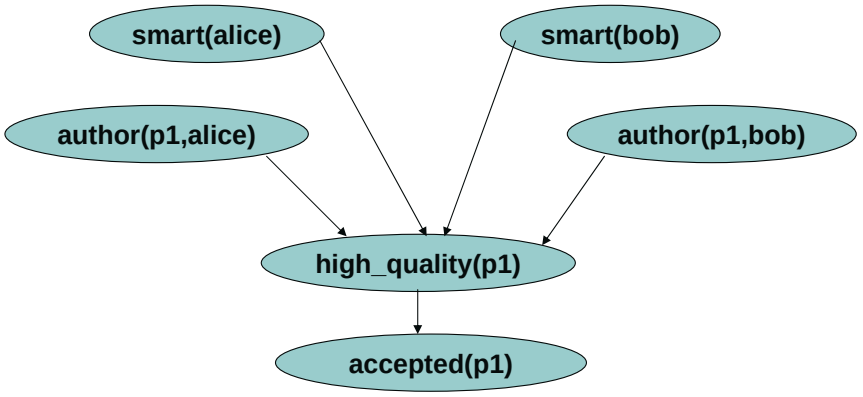
## Backward Chaining

For grounding **A=alice,** add **author(p1,alice)** and **smart(alice**) to network, and make parents of **high_quality(p1)**



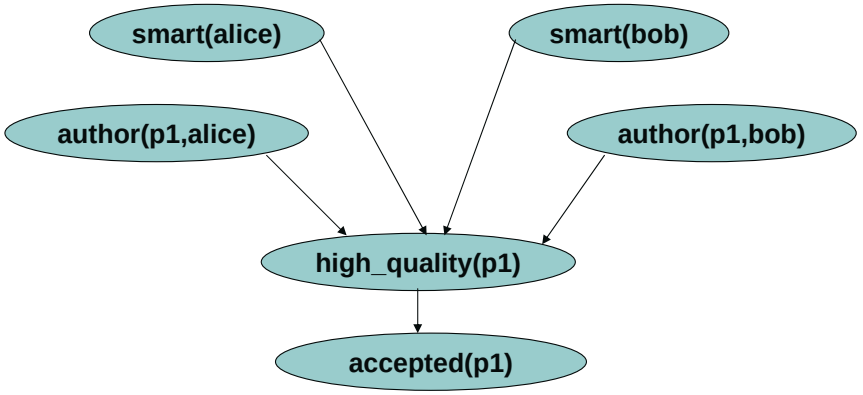

## Backward Chaining

For grounding **A=bob**, add **author(p1,bob)** to network. **smart(bob)** is already in network. Make both parents of **high_quality(p1)**



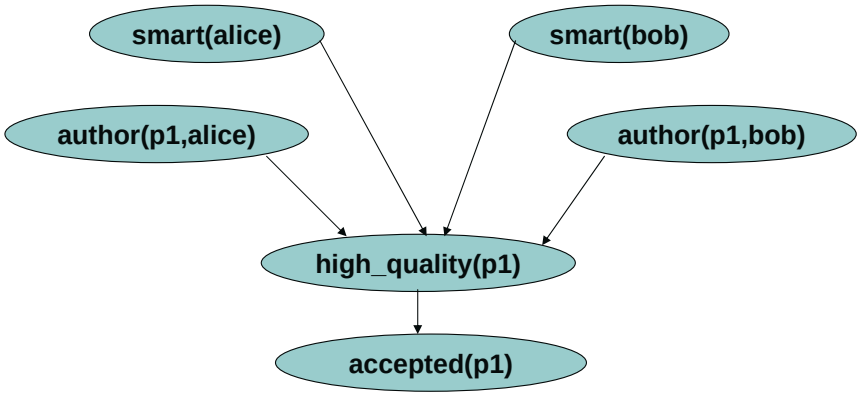
## Backward Chaining

Create CPT for **high_quality(p1)** – make noisy-or



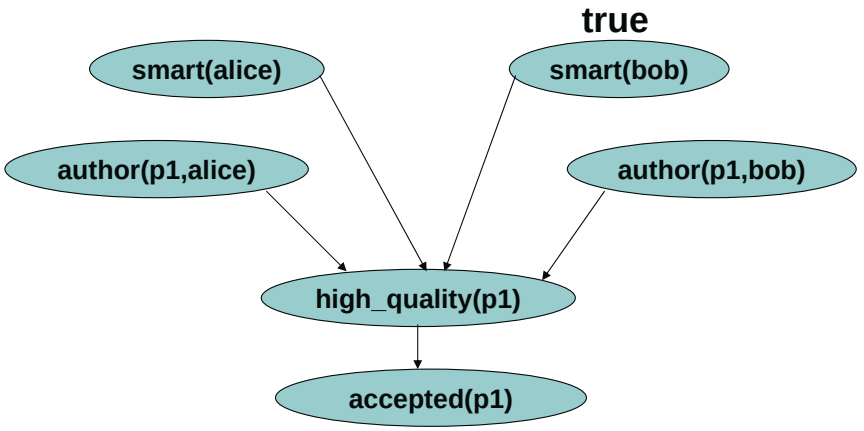

## Backward Chaining

**author(p1,alice), smart(alice)** and **author(p1,bob)** have no antecedents – stop backward chaining



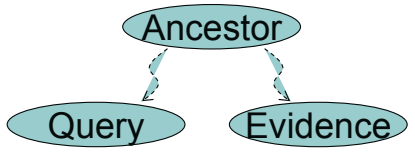
## Backward Chaining

- assert evidence **smart(bob) = true**, and compute ***P*(accepted(p1) | smart(bob) = true)**




## Backward Chaining on Both Query and Evidence

- Necessary, if query and evidence have common ancestor




- Sufficient. *P*(Query | Evidence) can be computed using only ancestors of query and evidence nodes
  - unobserved descendants are irrelevant

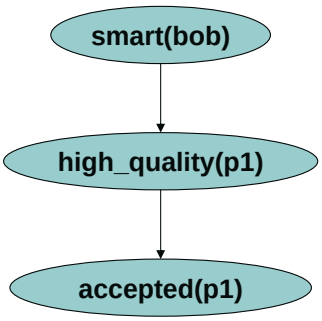
## The Role of Context

- Context is deterministic knowledge known prior to the network being constructed
  - May be defined by its own logic program
  - Is not a random variable in the BN
- Used to determine structure of the constructed BN
  - If a context predicate P appears in the body of a rule R, only backward chain on R if P is true

## Context example

Suppose **author(P,A)** is a context predicate, **author(p1,bob)** is true, and **author(p1,alice)** cannot be proven from deterministic KB (and is therefore false by assumption)

Network is




No **author(p1,bob)** node because it is a context predicate

No **smart(alice)** node because **author(p1,alice)** is false

## Semantics

- Assumption: no cycles in resulting BN
  - If there are cycles, cannot interpret BN as definition of joint probability distribution
- Assuming BN construction process terminates, conditional probability of any query given any evidence is defined by the BN.
- Somewhat unsatisfying because
  1. meaning of program is query dependent (depends on constructed BN)
  2. meaning is not stated declaratively in terms of program but in terms of constructed network instead

## Disadvantages of Approach

- Up until now, ground logical atoms have been random variables ranging over T,F
  - cumbersome to have a different random variable for **lead_author(p1,alice), lead_author(p1,bob)** and all possible values of **lead_author(p1,A)**
  - worse, since **lead_author(p1,alice)** and **lead_author(p1,bob)** are different random variables, it is possible for both to be true at the same time

## Bayesian Logic Programs [Kersting and de Raedt]

- Now, ground atoms are random variables with any range (not necessarily Boolean)
  - now **quality** is a random variable, with values **high, medium, low**
- Any probabilistic relationship is allowed
  - expressed in CPT
- Semantics of program given once and for all
  - not query dependent

## Meaning of Rules in BLPs

**accepted(P) :- quality(P).**

means

"For all P, *if* **quality(P)** is a random variable, then **accepted(P)** is a random variable"

Associated with this rule is a conditional probability table (CPT) that specifies the probability distribution over **accepted(P)** for any possible value of **quality(P)**

## Combining Rules for BLPs

accepted(P) :- quality(P).
accepted(P) :- author(P,A), fame(A).

- Before, combining rules combined individual probabilities with each other
  - noisy-or and max rules easy to interpret
- Now, combining rules combine entire CPTs

## Semantics of BLPs

- Random variables are all ground atoms that have finite proofs in logic programs
  - assumes acyclicity
  - assumes no function symbols
- Can construct BN over all random variables
  - parents derived from rules
  - CPTs derived using combining rules
- Semantics of BLP: joint probability distribution over all random variables
  - does not depend on query
- Inference in BLP by KBMC

## An Issue

- How to specify uncertainty over single-valued relations?
- Approach 1: make **lead_author(P)** a random variable taking values **bob**, **alice** etc.
  - we can't say **accepted(P) :- lead_author(P), famous(A)** because **A** does not appear in the rule head or in a previous term in the body
- Approach 2: make **lead_author(P,A)** a random variable with values **true, false**
  - we run into the same problems as with the intuitive approach (may have zero or many lead authors)
- Approach 3: make **lead_author** a function
  - say **accepted(P) :- famous(lead_author(P))**
  - need to specify how to deal with function symbols and uncertainty over them

## First-Order Variable Elimination

- [Poole 03, Braz et al 05]
- Generalization of variable elimination to first order domains
- Reasons directly about first-order variables, instead of at the ground level
- Assumes that the size of the population for each type of entity is known

## Learning Rule Parameters

- [Koller & Pfeffer 97, Sato & Kameya 01]
- Problem definition:
  - Given a skeleton rule base consisting of rules without uncertainty parameters
  - and a set of instances, each with
    - a set of context predicates
    - observations about some random variables
  - Goal: learn parameter values for the rules that maximize the likelihood of the data

## Basic Approach

1. Construct a network $BN^i$ for each instance *i* using KBMC, backward chaining on all the observed variables
2. Expectation Maximization (EM)
   - exploit parameter sharing

## Parameter Sharing

- In BNs, all random variables have distinct CPTs
  - only share parameters between different instances, not different random variables
- In logical approaches, an instance may contain many objects of the same kind
  - multiple papers, multiple authors, multiple citations
- Parameters are shared within instances
  - same parameters used across different papers, authors, citations
- Parameter sharing allows faster learning, and learning from a single instance

## Rule Parameters & CPT Entries

- In principle, combining rules produce complicated relationship between model parameters and CPT entries
- With a *decomposable* combining rule, each node is derived from a single rule
  - Most natural combining rules are decomposable
    - e.g. noisy-or decomposes into set of *and*s followed by *or*

## Parameters and Counts

- Each time a node is derived from a rule *r*, it provides one experiment to learn about the parameters associated with *r*
- Each such node should therefore make a separate contribution to the count for those parameters
- $\theta^r_{x,u}$: the parameter associated with $P(X=x|\text{Parents}[X]=u)$ when rule *r* applies
- $N^r_{x,u}$: the number of times a node has value *x* and its parents have value *u* when rule *r* applies

## EM With Parameter Sharing

- Given parameter values, compute expected counts:

$$E[N^r_{x,u}] = \sum_{\text{instances } i} \sum_X P(X = x, \text{Parents}[X] = u \mid \text{evidence}^i)$$

where the inner sum is over all nodes derived from rule *r* in $BN^i$

- Given expected counts, estimate:

$$\theta^r_{x,u} = \frac{E[N^r_{x,u}]}{E[N^r_u]}$$

- Iterate these two steps

## Learning Rule Structure

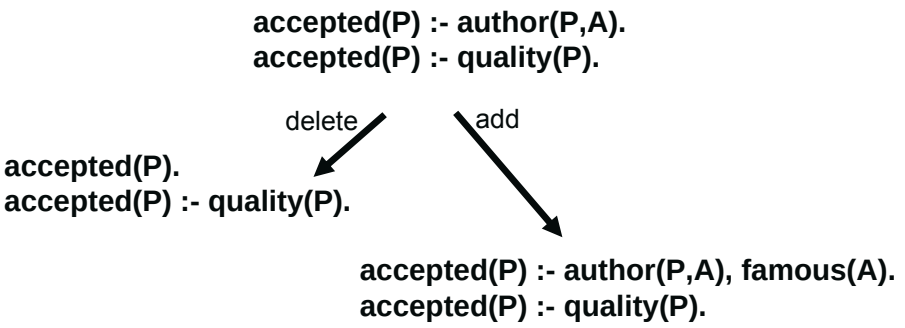
- [Kersting and De Raedt 02]
- Problem definition:
  - Given a set of instances, each with
    - context predicates
    - observations about some random variables
  - Goal: learn
    - a skeleton rule base consisting of rules and parameter values for the rules
- Generalizes BN structure learning
  - define legal models
  - scoring function same as for BN
  - define search operators

## Legal Models

- Hypothesis space consists of all rule sets using given predicates, together with parameter values
- A legal hypothesis:
  - is logically valid: rule set does not draw false conclusions for any data cases
  - the constructed BN is acyclic for every instance

## Search operators

- Add a constant-free atom to the body of a single clause
- Remove a constant-free atom from the body of a single clause




## Summary: Directed Rule-based Approaches

- Provide an intuitive way to describe how one fact depends on other facts
- Incorporate relationships between entities
- Generalizes to many different situations
  - Constructed BN for a domain depends on which objects exist and what the known relationships are between them (context)
- Inference at the ground level via KBMC
  - or lifted inference via FOVE
- Both parameters and structure are learnable

## Four SRL Approaches

- Directed Approaches
  - BN Tutorial
  - Rule-based Directed Models
  - **Frame-based Directed Models**
- Undirected Approaches
  - Markov Network Tutorial
  - Frame-based Undirected Models
  - Rule-based Undirected Models

## Frame-based Approaches

- Probabilistic Relational Models (PRMs)
  - Representation & Inference [Koller & Pfeffer 98, Pfeffer, Koller, Milch &Takusagawa 99, Pfeffer 00]
  - Learning [Friedman et al. 99, Getoor, Friedman, Koller & Taskar 01 & 02, Getoor 01]
- Probabilistic Entity Relation Models (PERs)
  - Representation [Heckerman, Meek & Koller 04]

# Four SRL Approaches

- Directed Approaches
  - BN Tutorial
  - Rule-based Directed Models
  - **Frame-based Directed Models**
    - PRMs w/ Attribute Uncertainty
    - Inference in PRMs
    - Learning in PRMs
    - PRMs w/ Structural Uncertainty
    - PRMs w/ Class Hierarchies
- Undirected Approaches
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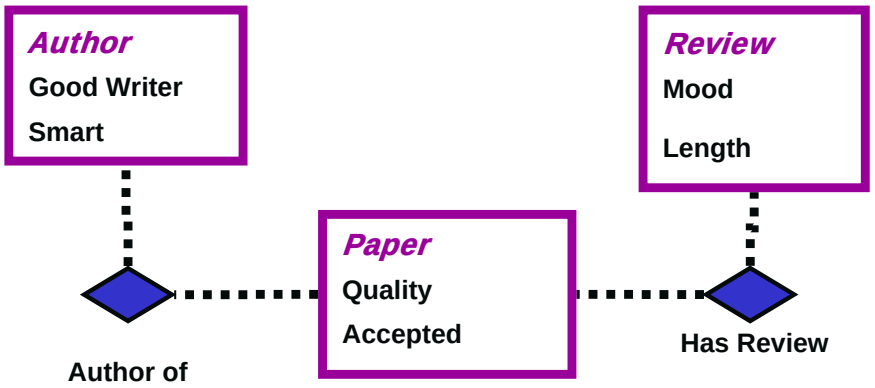
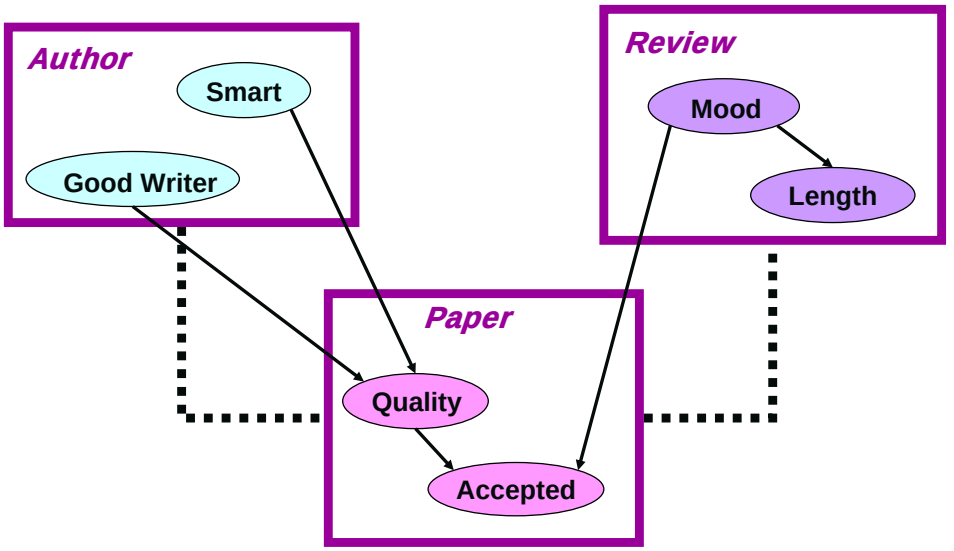
  - Frame-based Undirected Models
  - Rule-based Undirected Models

# Relational Schema

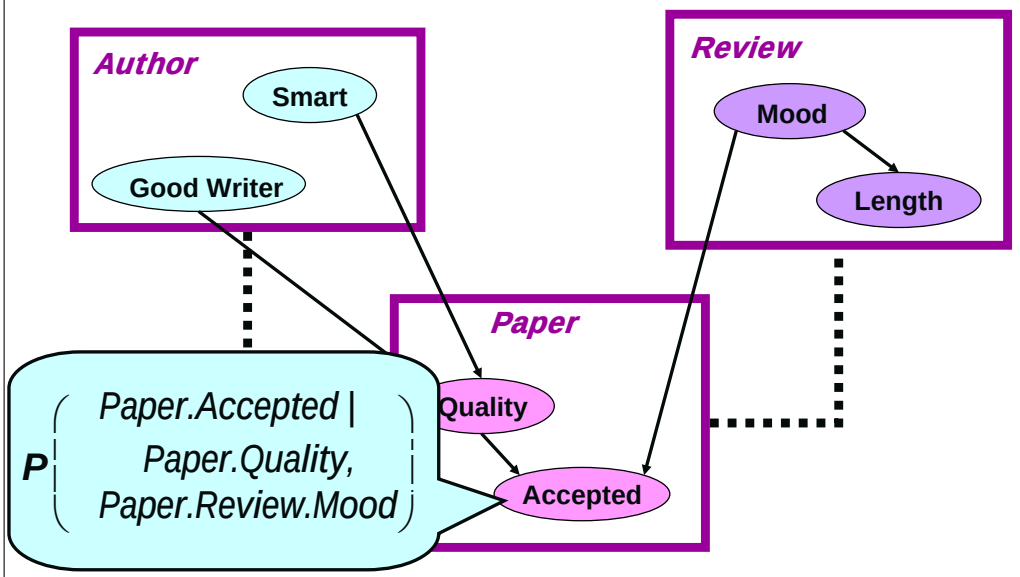



- Describes the types of objects and relations in the database

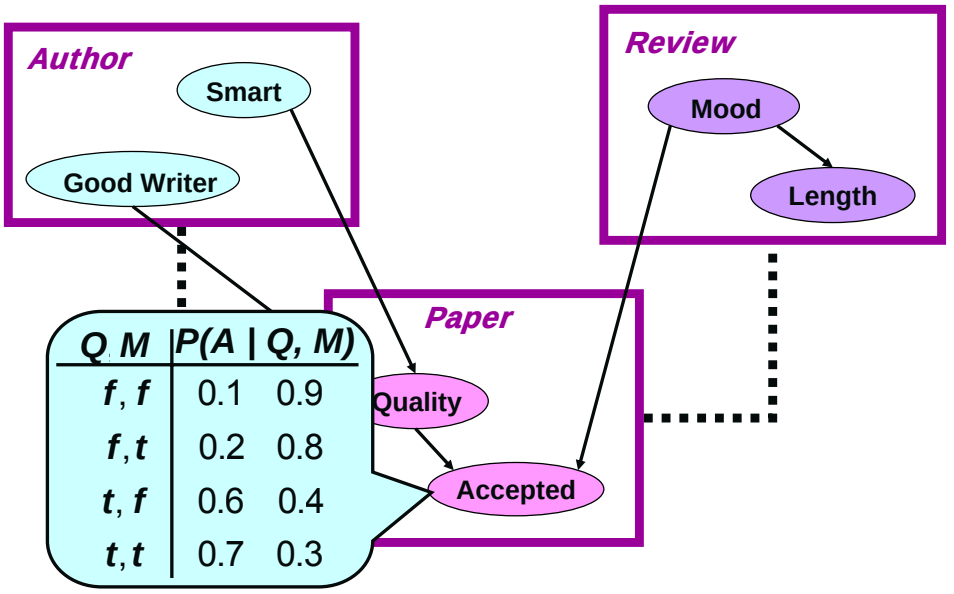
## Probabilistic Relational Model



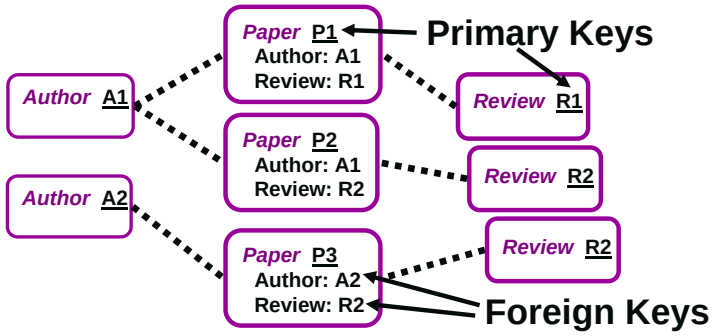

## Probabilistic Relational Model



# Probabilistic Relational Model



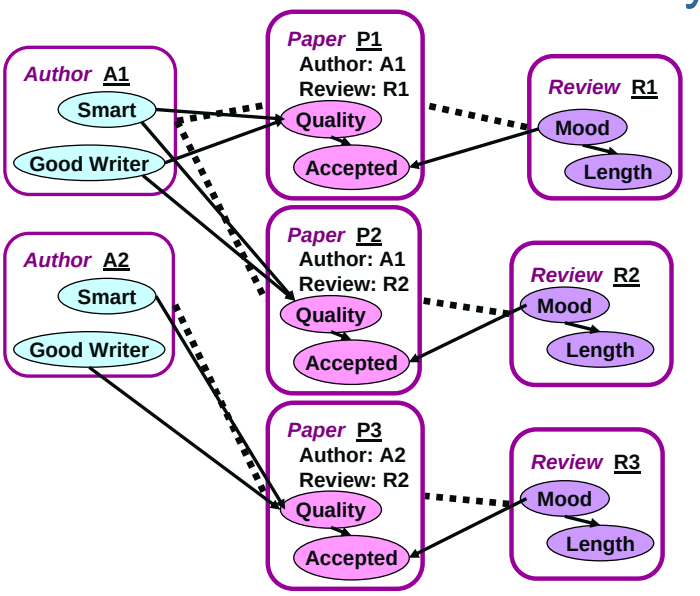

# Relational Skeleton




Fixed relational skeleton σ:

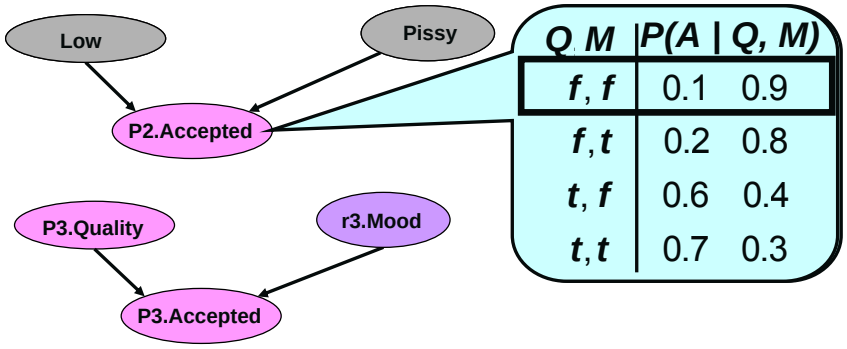
- set of objects in each class
- relations between them

# PRM w/ Attribute Uncertainty

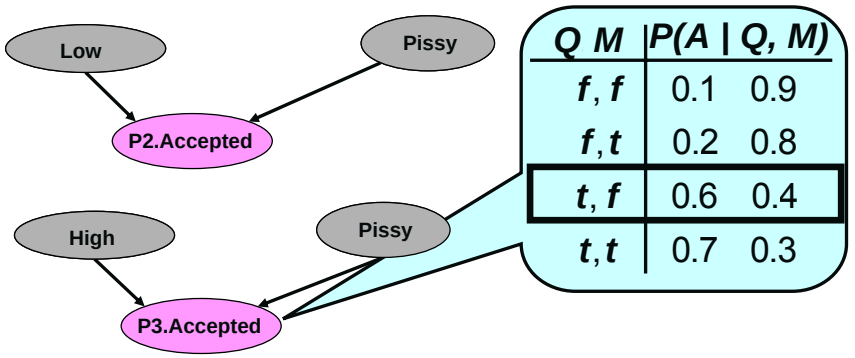



PRM defines distribution over instantiations of attributes

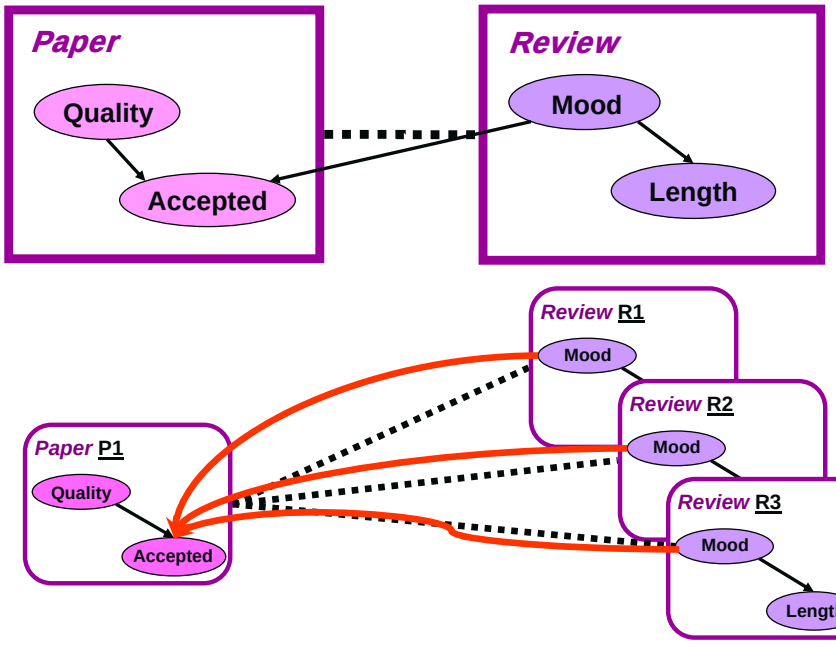
# A Portion of the BN



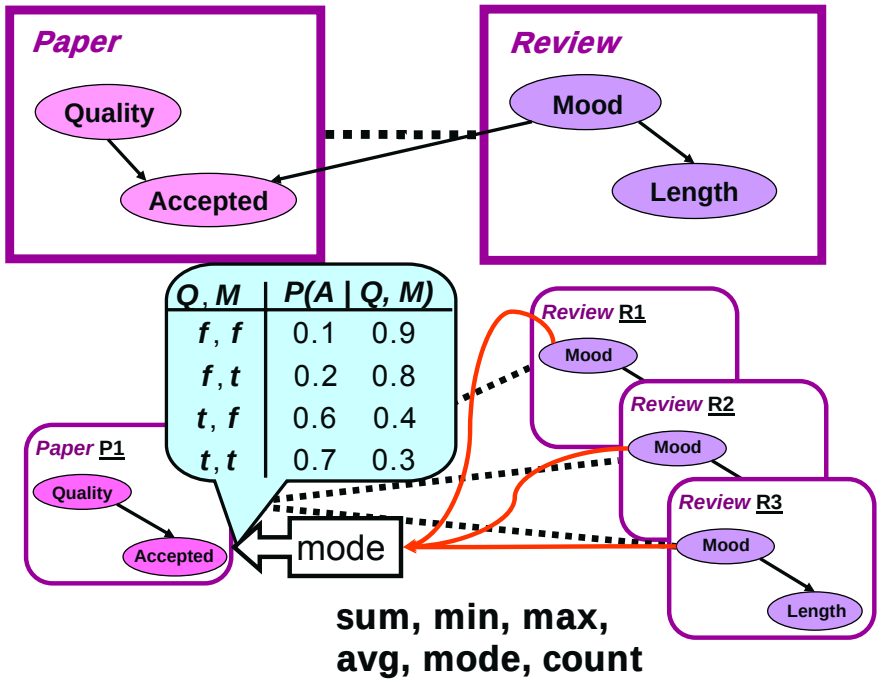
## A Portion of the BN



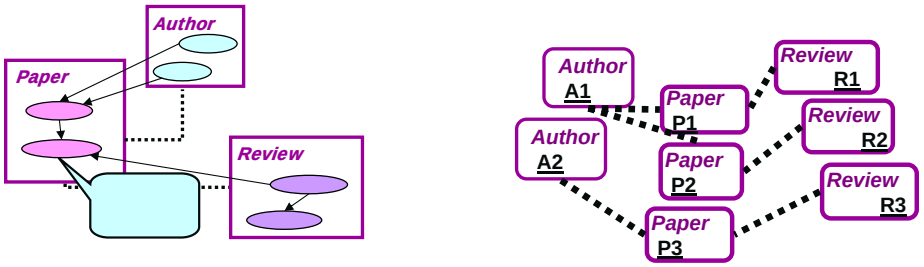

## PRM: Aggregate Dependencies



## PRM: Aggregate Dependencies




## PRM with AU Semantics




PRM + relational skeleton $\sigma$ =

probability distribution over completions I:

$$P(I \mid \sigma, S, \Theta) = \prod_{x \in \sigma} \prod_{x.A} P(x.A \mid parents_{S,\sigma}(x.A))$$

Objects Attributes

# Four SRL Approaches

- Directed Approaches
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    - PRMs w/ Attribute Uncertainty
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    - Learning in PRMs
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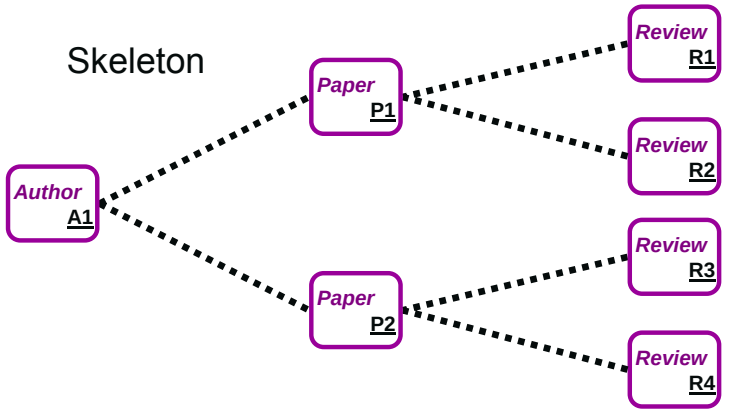
  - Rule-based Undirected Models

# PRM Inference

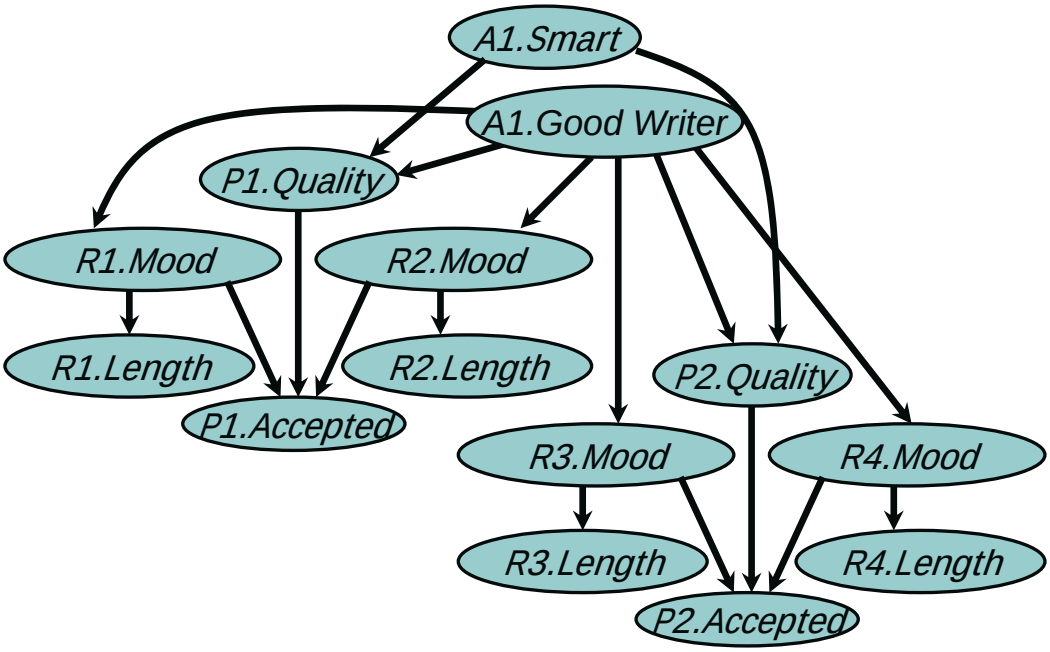
- Simple idea: enumerate all attributes of all objects
- Construct a Bayesian network over all the attributes

## Inference Example




Query is ***P*(A1.good-writer)**
Evidence is **P1.accepted = T, P2.accepted = T**

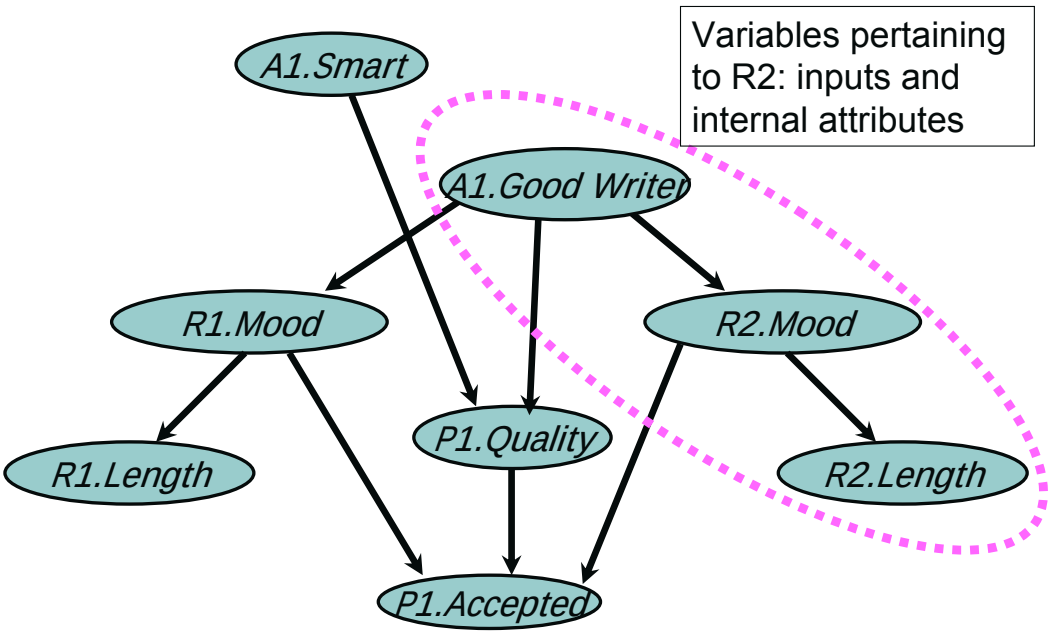
## PRM Inference: Constructed BN



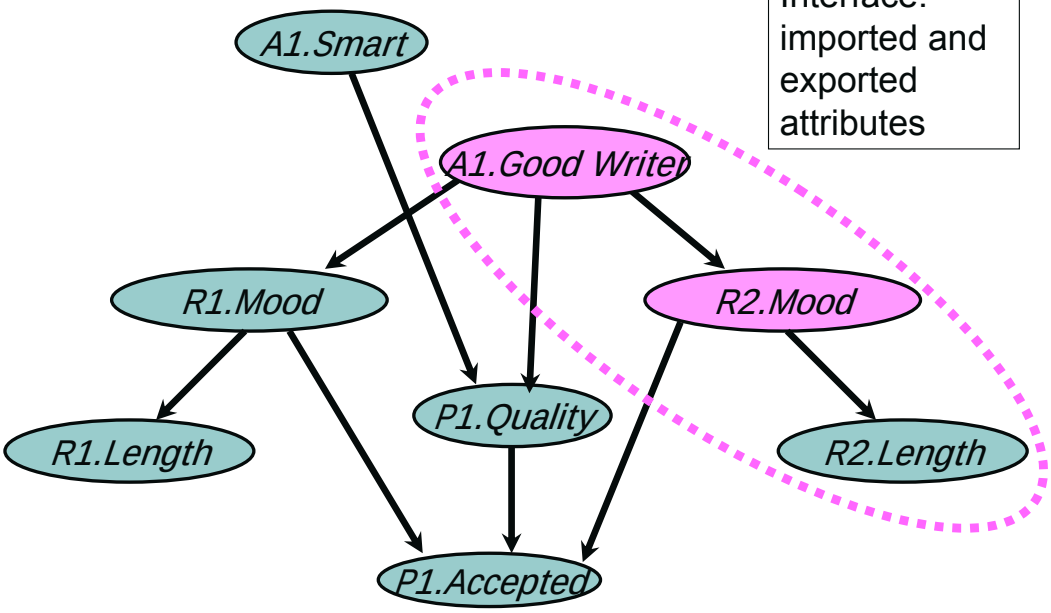
## PRM Inference

- Problems with this approach:
  - constructed BN may be very large
  - doesn't exploit object structure
- Better approach:
  - reason about objects themselves
  - reason about whole classes of objects
- In particular, exploit:
  - reuse of inference
  - encapsulation of objects

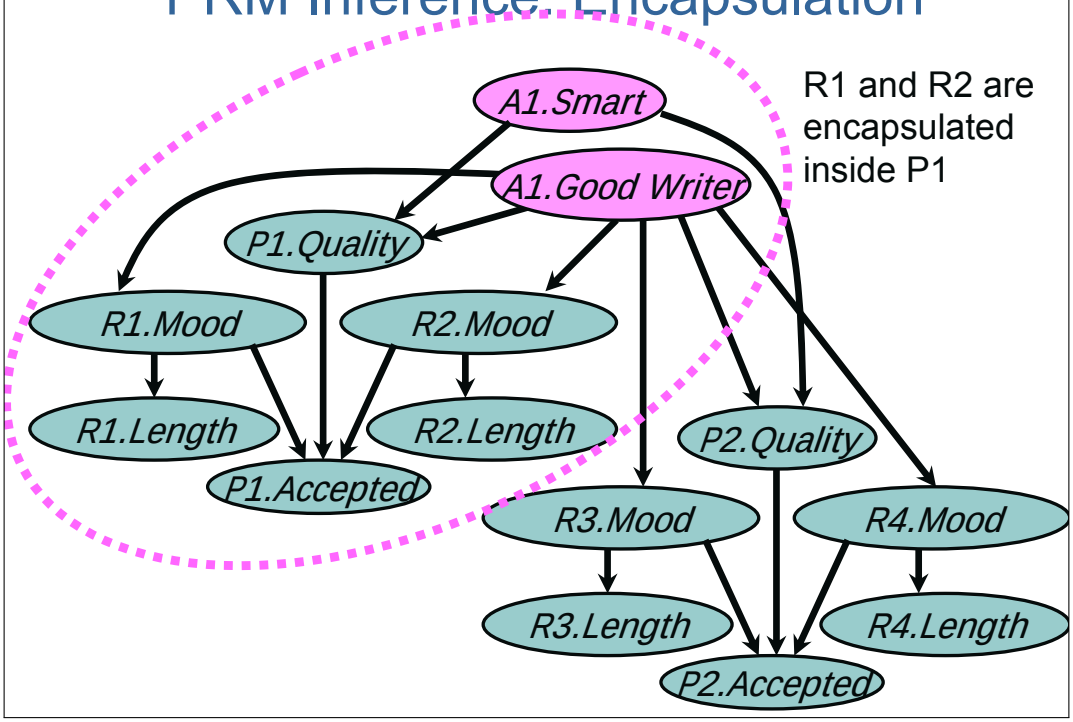
## PRM Inference: Interfaces



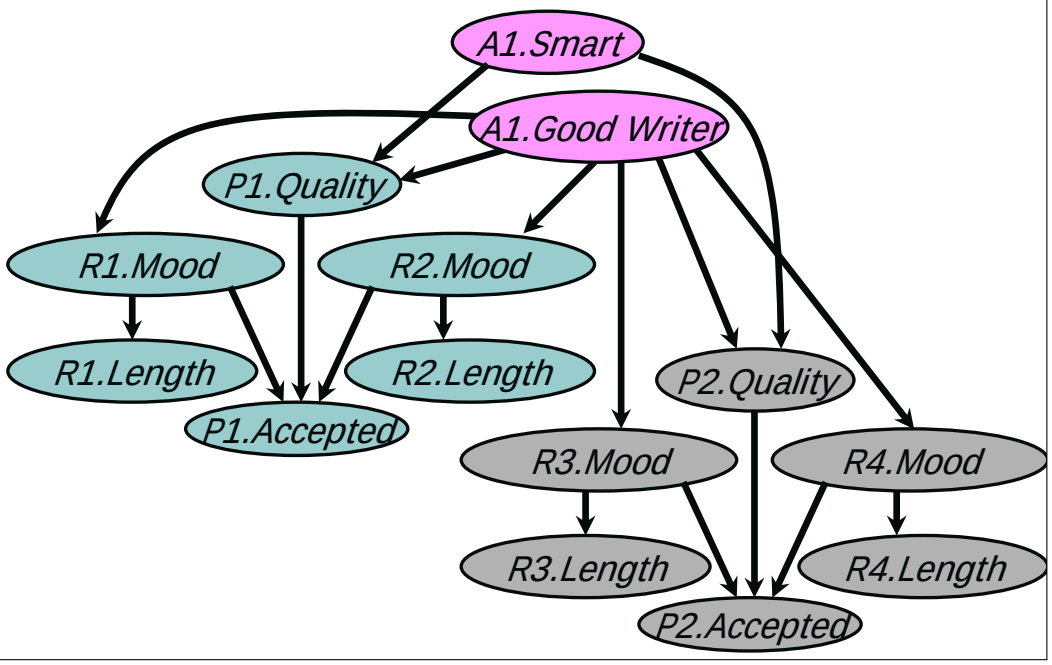
## PRM Inference: Interfaces



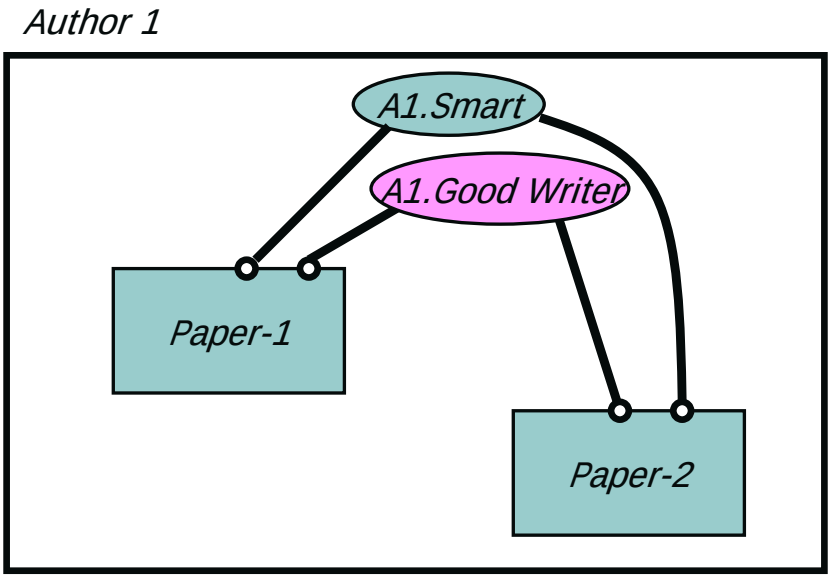

## PRM Inference: Encapsulation



## PRM Inference: Reuse




## Structured Variable Elimination



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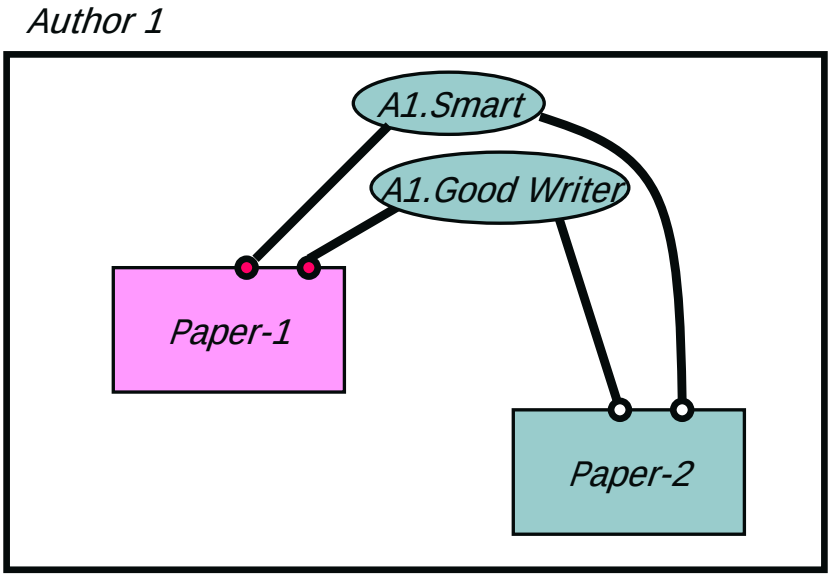


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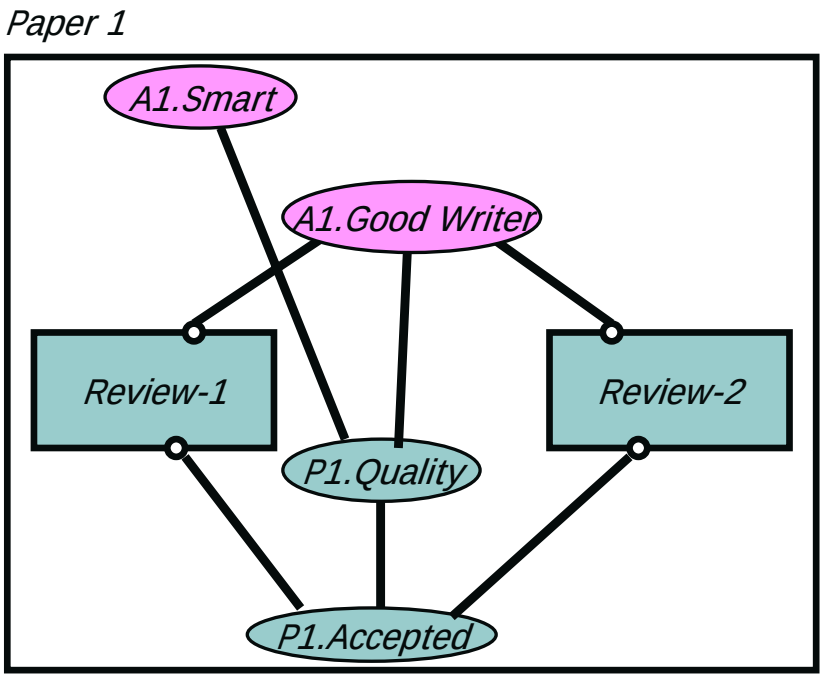
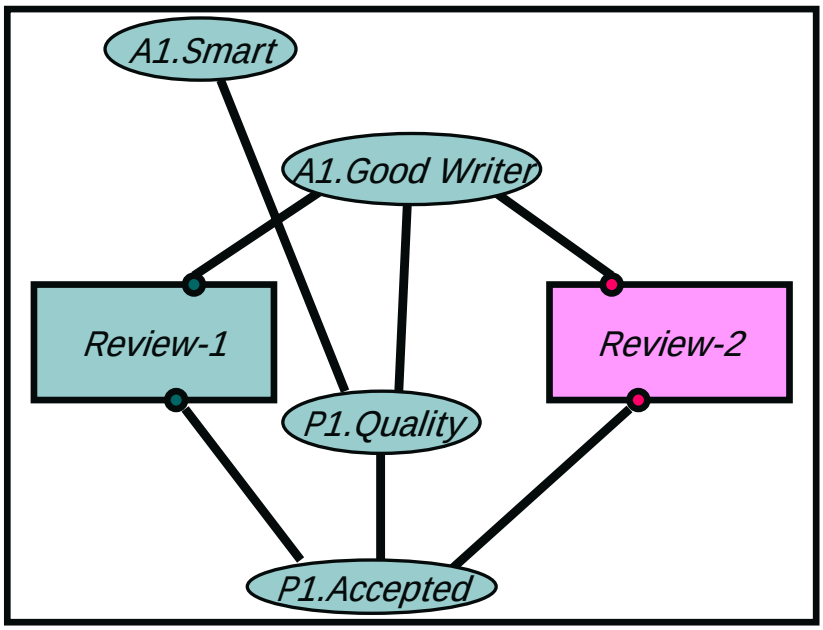


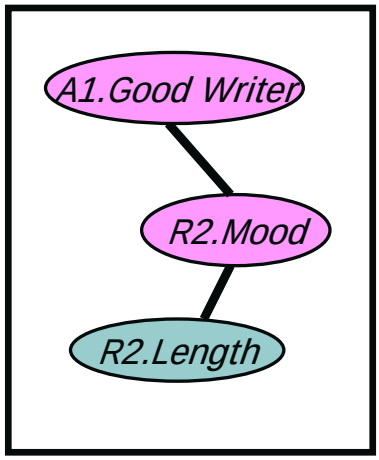
## Structured Variable Elimination

*Paper 1*




## Structured Variable Elimination

*Review 2*

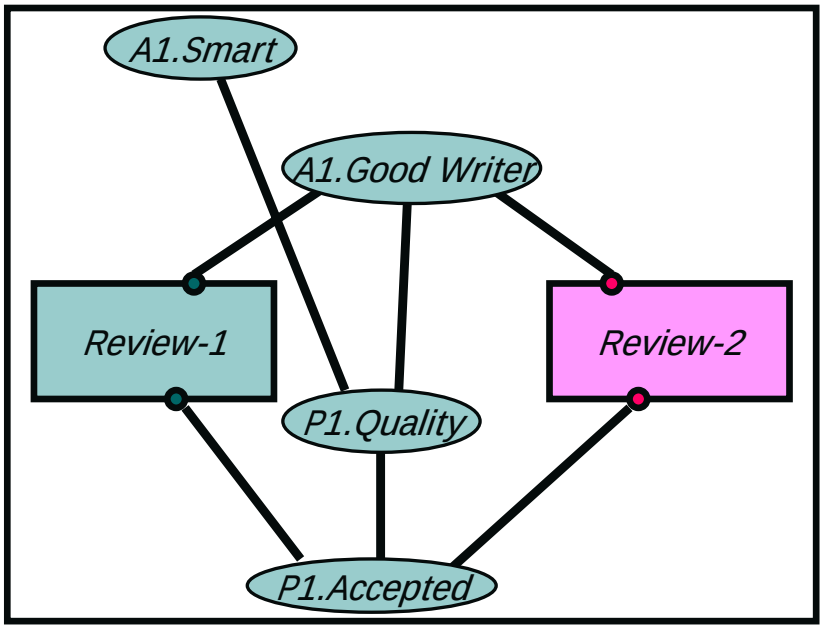


## Structured Variable Elimination

*Review 2*

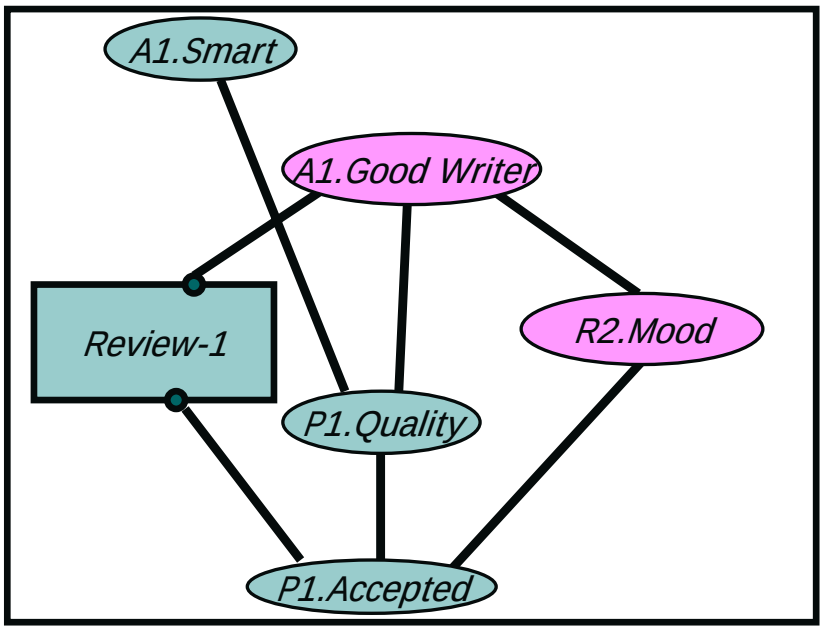

## Structured Variable Elimination

*Paper 1*



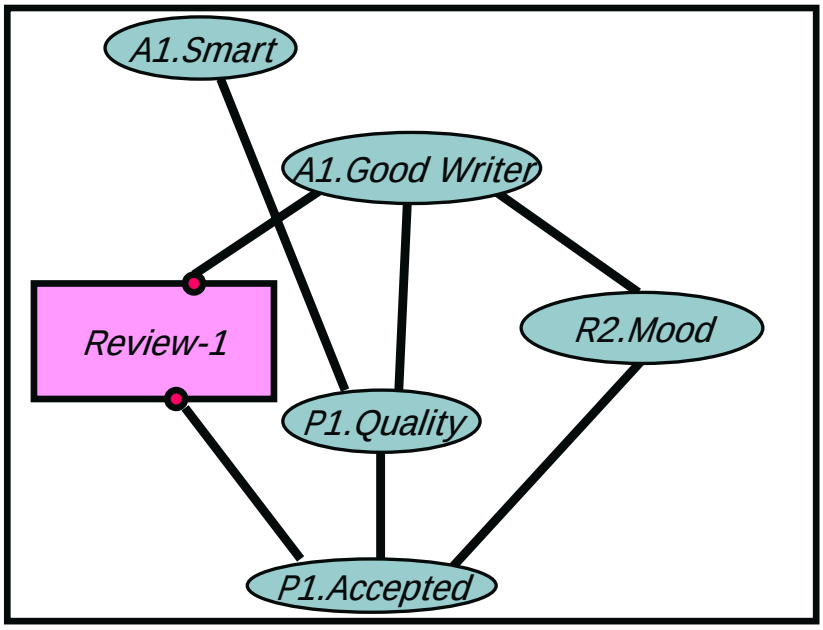
## Structured Variable Elimination

*Paper 1*



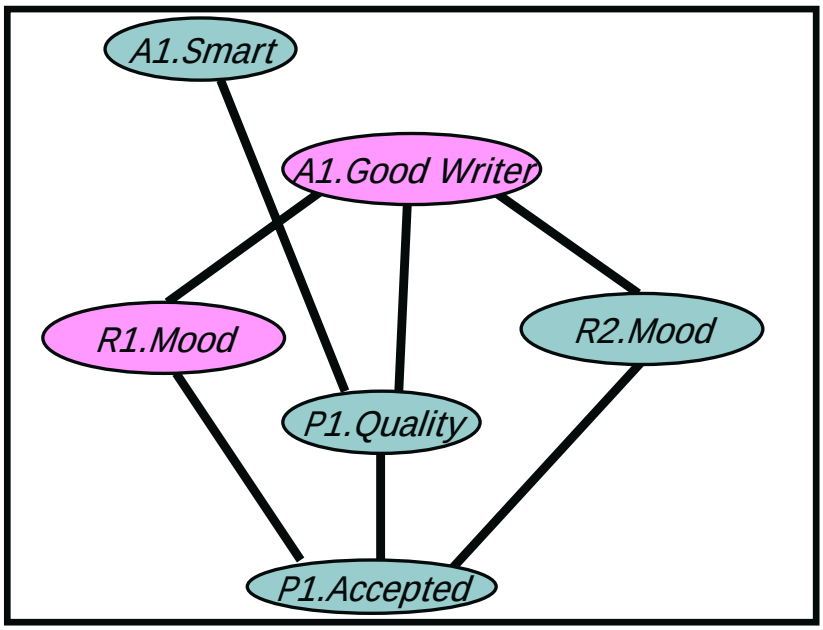

## Structured Variable Elimination

*Paper 1*



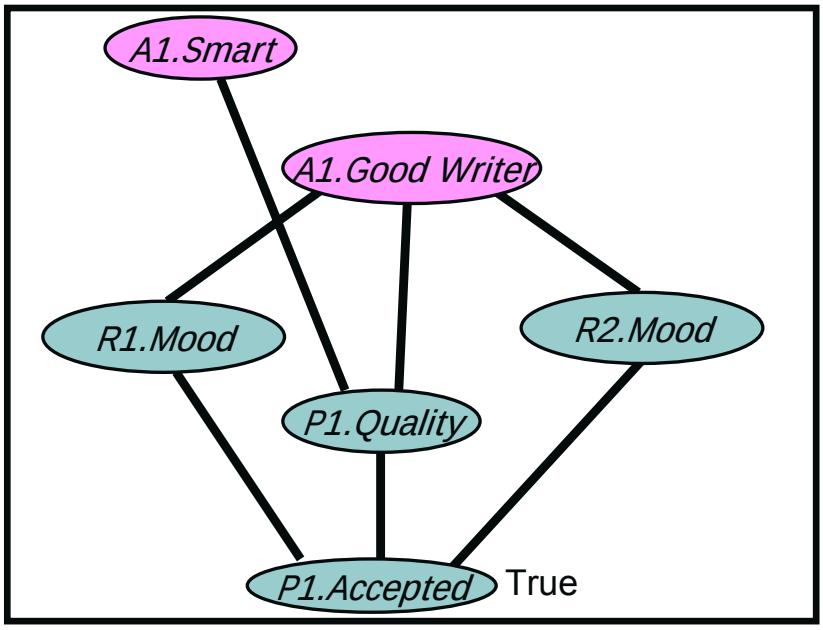
## Structured Variable Elimination

*Paper 1*



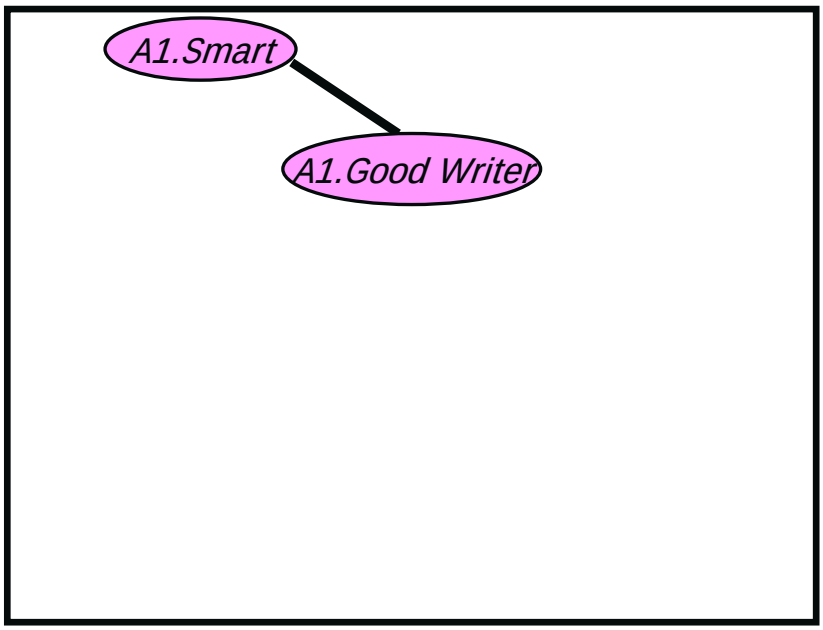

## Structured Variable Elimination

*Paper 1*



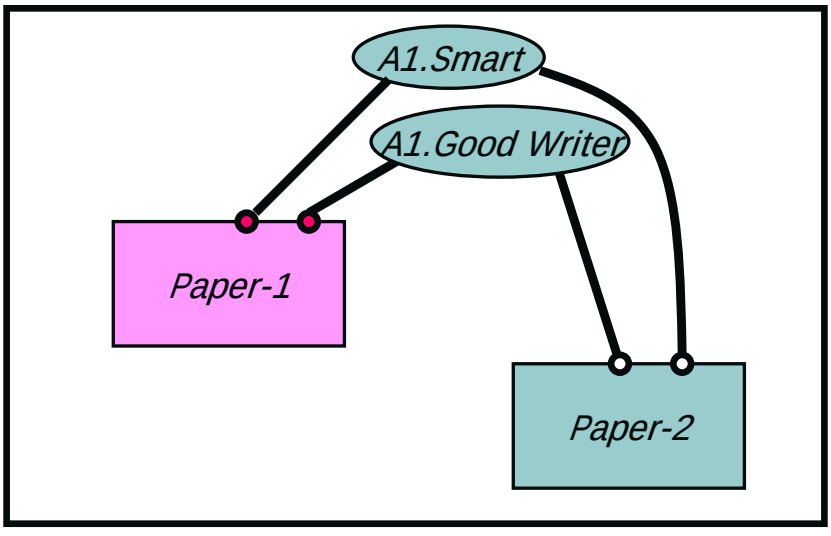
## Structured Variable Elimination

*Paper 1*




## Structured Variable Elimination

*Author 1*



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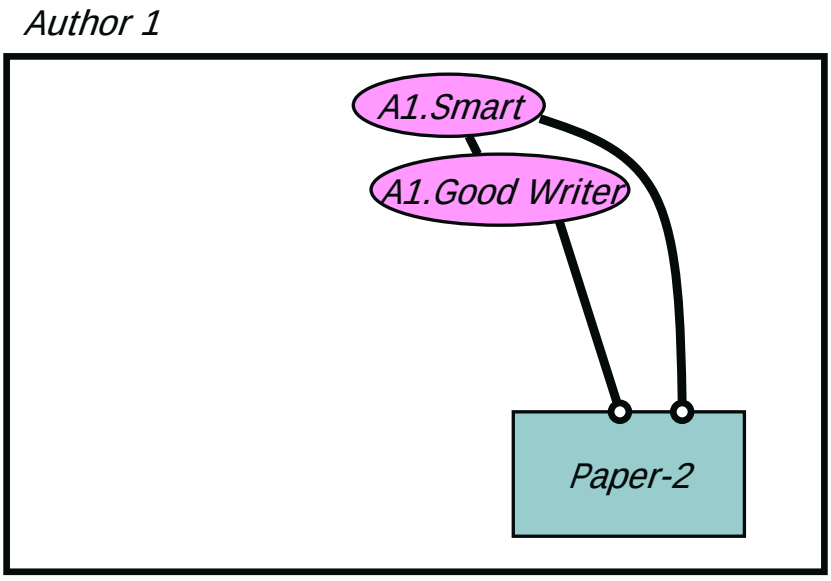


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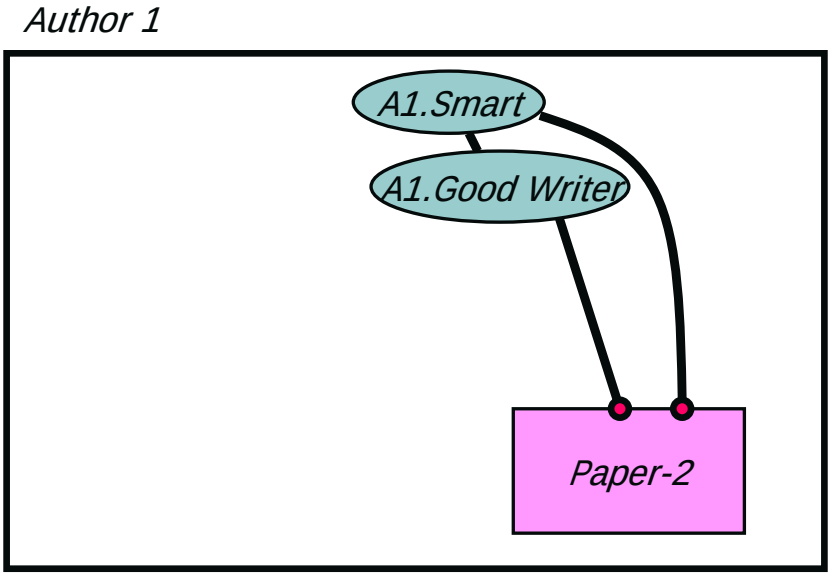

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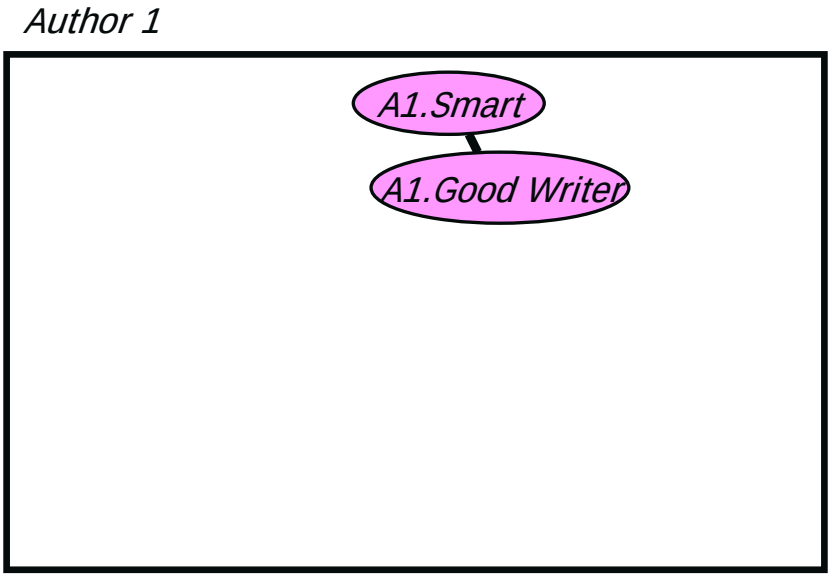


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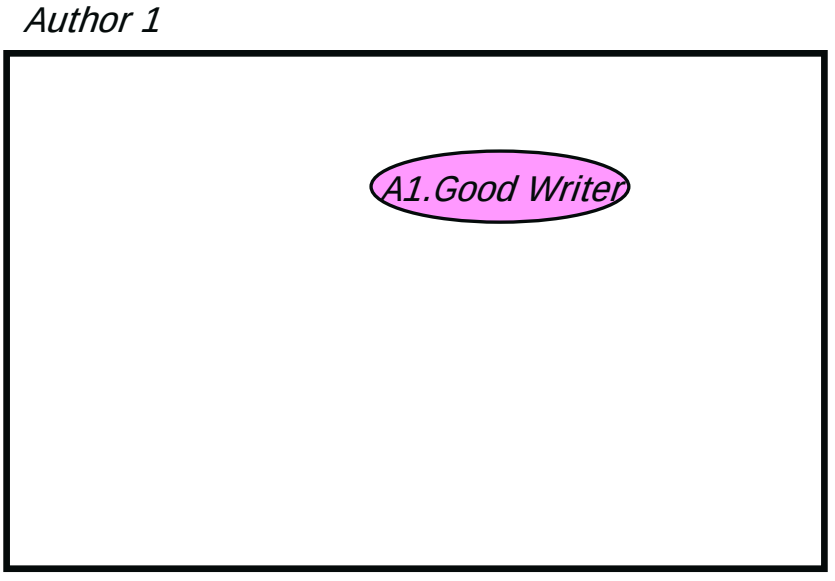
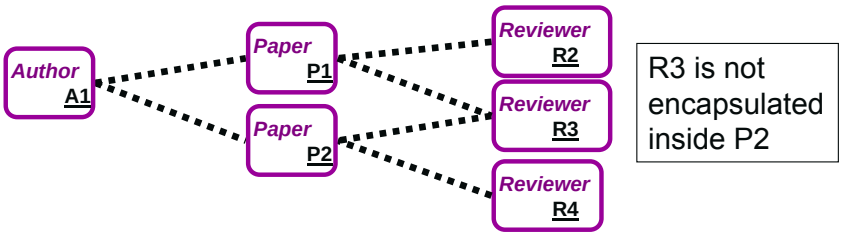


# Benefits of SVE

- Structured inference leads to good elimination orderings for VE
  - interfaces are separators
    - finding good separators for large BNs is very hard
  - therefore cheaper BN inference
- Reuses computation wherever possible

# Limitations of SVE

- Does not work when encapsulation breaks down




- But when we don't have specific information about the connections between objects, we can assume that encapsulation holds
  - i.e., if we know P1 has two reviewers R1 and R2 but they are not named instances, we assume R1 and R2 are encapsulated
- Cannot reuse computation when different objects have different evidence

# Four SRL Approaches

- Directed Approaches
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  - Rule-based Directed Models
  - **Frame-based Directed Models**
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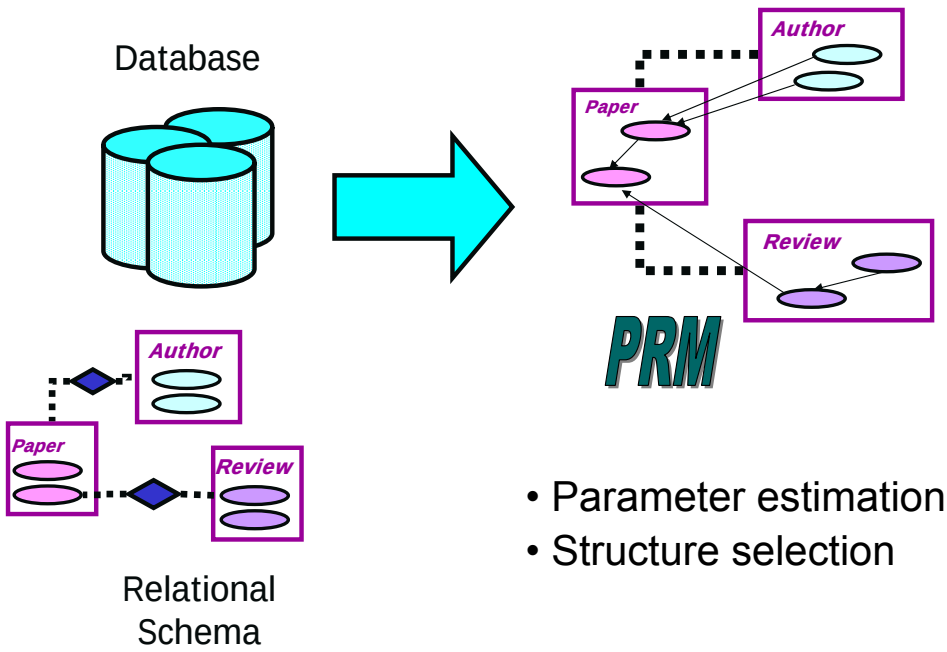
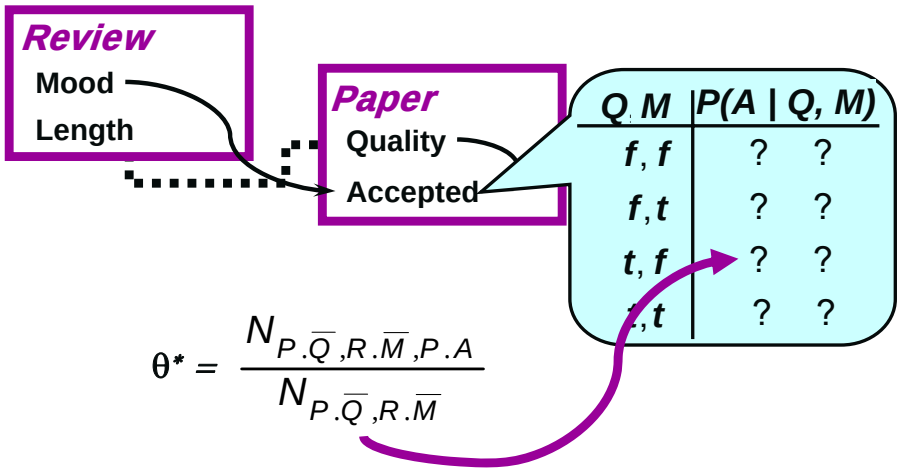
    - Inference in PRMs
    - Learning in PRMs
    - PRMs w/ Structural Uncertainty
    - PRMs w/ Class Hierarchies
- Undirected Approaches
  - Markov Network Tutorial
  - Frame-based Undirected Models
  - Rule-based Undirected Models

# Learning PRMs w/ AU




- Parameter estimation
- Structure selection

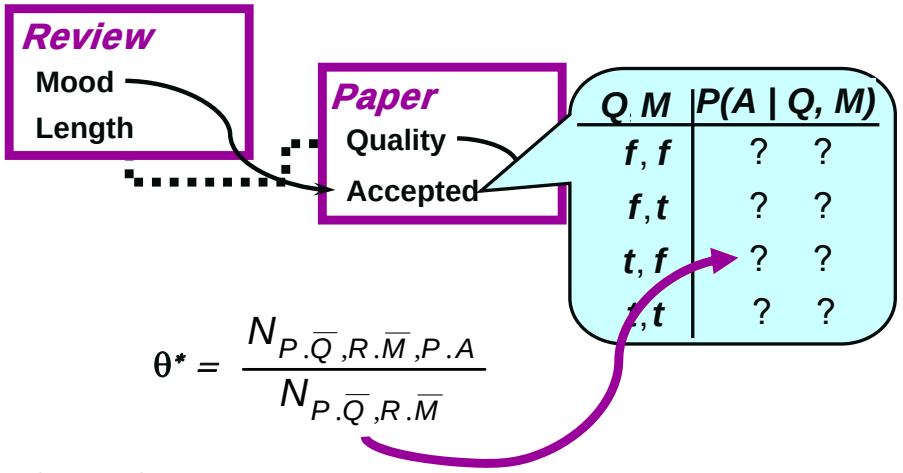
## ML Parameter Estimation




$$\theta^* = \frac{N_{P.\bar{Q},R.\bar{M},P.A}}{N_{P.\bar{Q},R.\bar{M}}}$$

where $N_{P.\bar{Q},R.\bar{M},P.A}$ is the number of accepted, low quality papers whose reviewer was in a poor mood

## ML Parameter Estimation




$$\theta^* = \frac{N_{P.\bar{Q},R.\bar{M},P.A}}{N_{P.\bar{Q},R.\bar{M}}}$$

Query for counts:

$$Count\left(\pi_{\substack{P.Quality \\ R.Mood \\ P.Accepted}}\left(\text{Review table} \bowtie \text{Paper table}\right)\right)$$

## Structure Selection

- Idea:
  - define scoring function
  - do local search over legal structures
- Key Components:
  - legal models
  - scoring models
  - searching model space

## Structure Selection

- Idea:
  - define scoring function
  - do local search over legal structures
- Key Components:
  - » legal models
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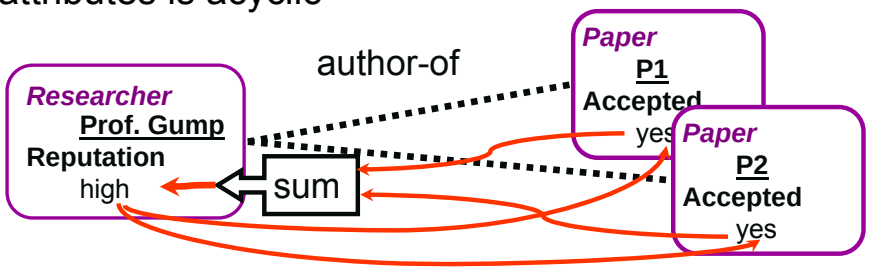
## Legal Models

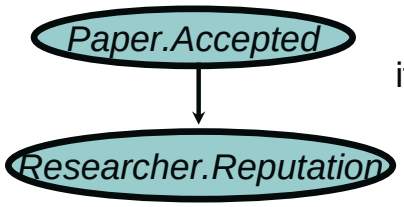
- PRM defines a coherent probability model over a skeleton $\sigma$ if the dependencies between object attributes is acyclic




How do we guarantee that a PRM is acyclic for ***every*** skeleton?

## Attribute Stratification

PRM dependency structure *S* ⇒ dependency graph




if *Researcher.Reputation* depends directly on *Paper.Accepted*

Attribute stratification:

dependency graph acyclic ⇒ acyclic for any $\sigma$

*cycles along guaranteed acyclic relations*

## Structure Selection

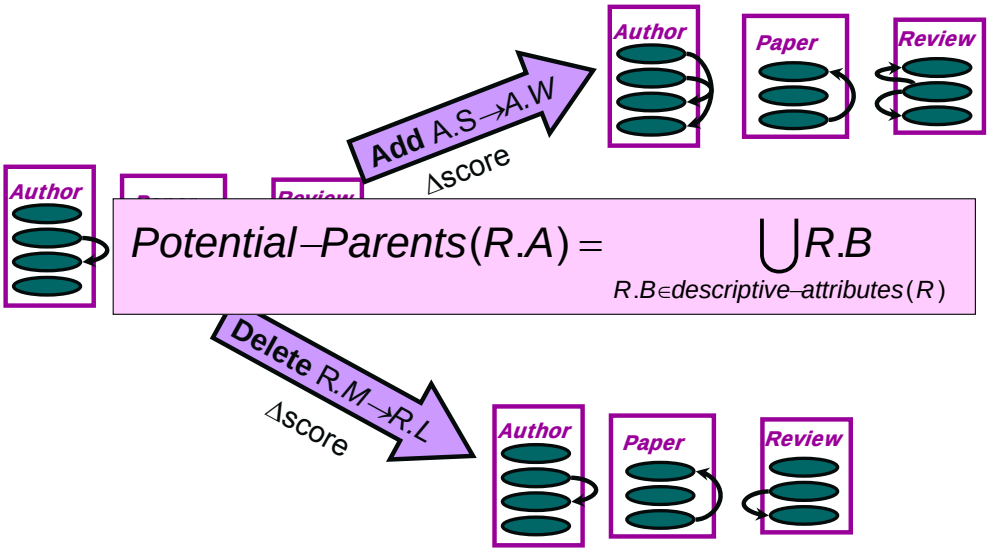
- Idea:
  - define scoring function
  - do local search over legal structures
- Key Components:
  - legal models
  - » scoring models – same as BN
  - searching model space

## Structure Selection

- Idea:
  - define scoring function
  - do local search over legal structures
- Key Components:
  - legal models
  - scoring models
  - » searching model space

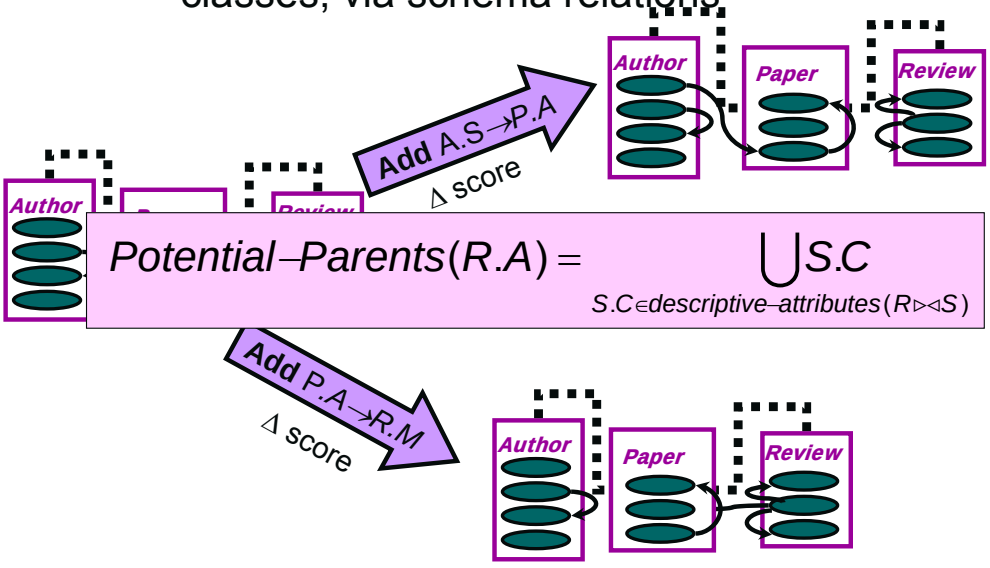
## Searching Model Space

Phase 0: consider only dependencies within a class



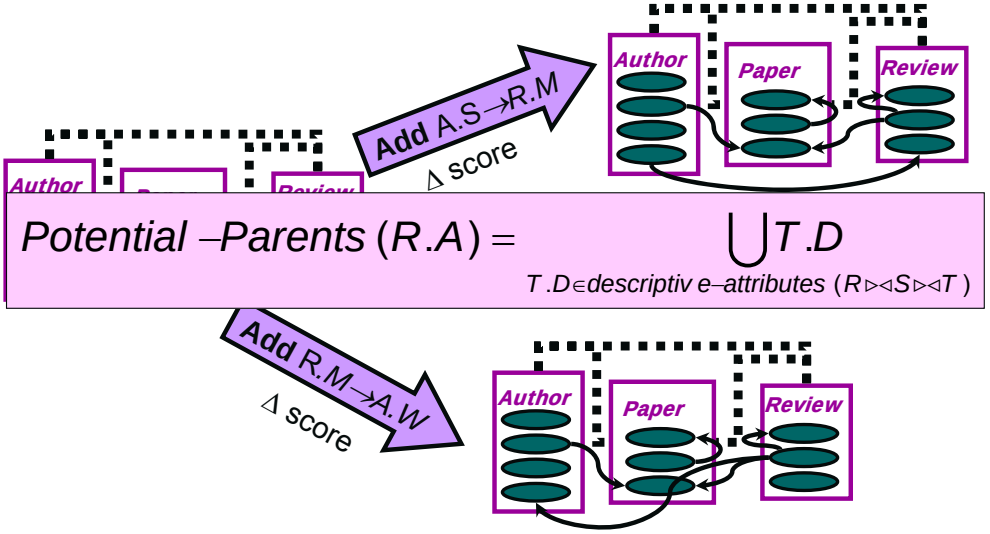

## Phased Structure Search

Phase 1: consider dependencies from "neighboring" classes, via schema relations



# Phased Structure Search

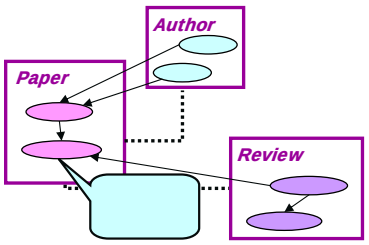
Phase 2: consider dependencies from "further" classes, via relation chains

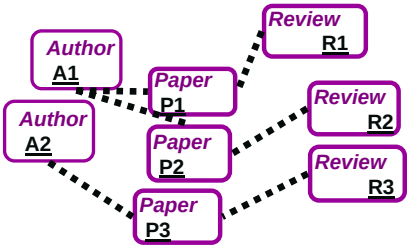



# Four SRL Approaches

- Directed Approaches
  - BN Tutorial
  - Rule-based Directed Models
  - **Frame-based Directed Models**
    - PRMs w/ Attribute Uncertainty
    - Inference in PRMs
    - Learning in PRMs
    - PRMs w/ Structural Uncertainty
    - PRMs w/ Class Hierarchies
- Undirected Approaches
  - Markov Network Tutorial
  - Frame-based Undirected Models
  - Rule-based Undirected Models

## Reminder: PRM w/ AU Semantics




PRM + relational skeleton $\sigma$ =

probability distribution over completions I:

$$P(I \mid \sigma, S, \Theta) = \prod_{x \in \sigma} \prod_{x.A} P(x.A \mid parents_{S,\sigma}(x.A))$$

Objects Attributes

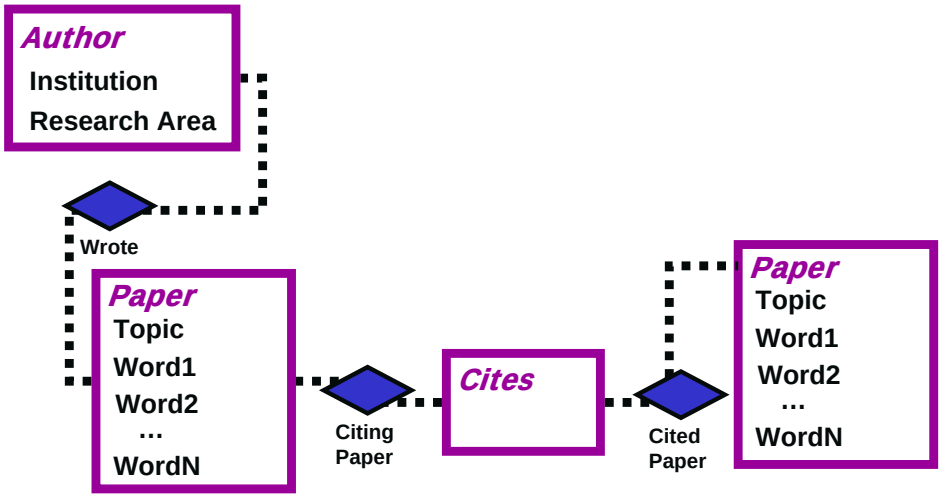
## Kinds of structural uncertainty

- How many objects does an object relate to?
  - how many Authors does *Paper1* have?
- Which object is an object related to?
  - does *Paper1* cite *Paper2* or *Paper3*?
- Which class does an object belong to?
  - is *Paper1* a *JournalArticle* or a *ConferencePaper*?
- Does an object actually exist?
- Are two objects identical?

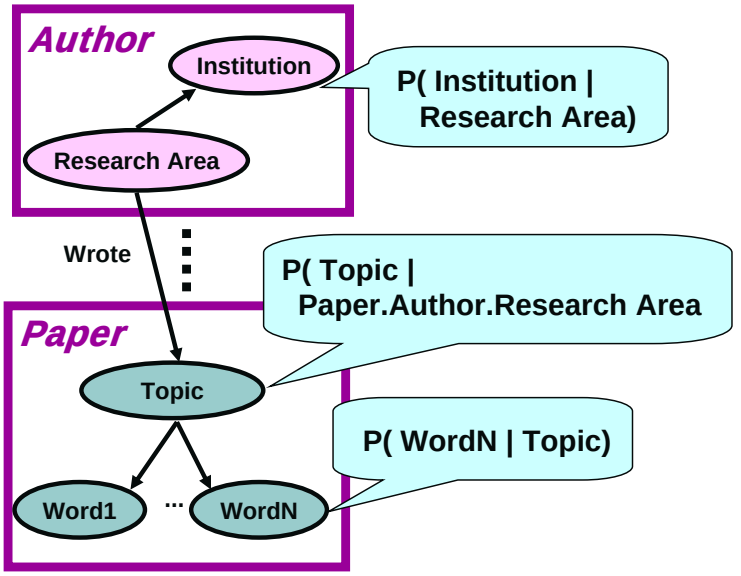
## Structural Uncertainty

- Motivation: PRM with AU only well-defined when the skeleton structure is known
- May be uncertain about relational structure itself
- Construct probabilistic models of relational structure that capture structural uncertainty
- Mechanisms:
  - Reference uncertainty
  - Existence uncertainty
  - Number uncertainty
  - Type uncertainty
  - Identity uncertainty

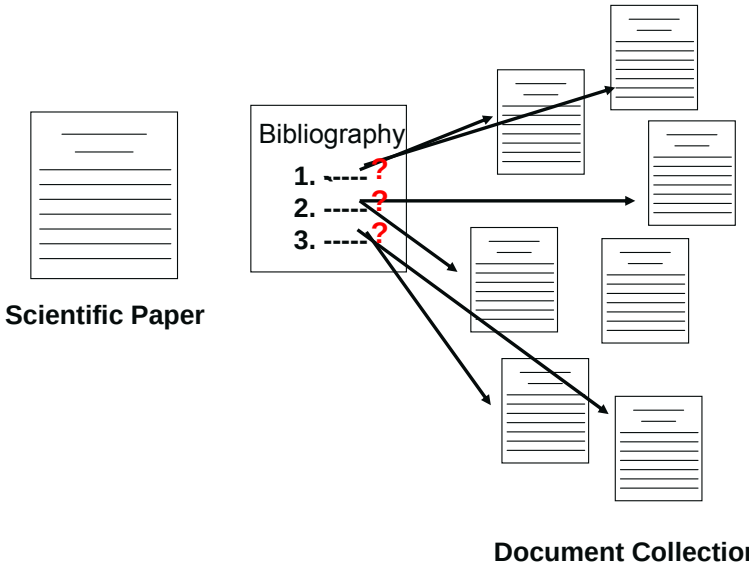
## Citation Relational Schema



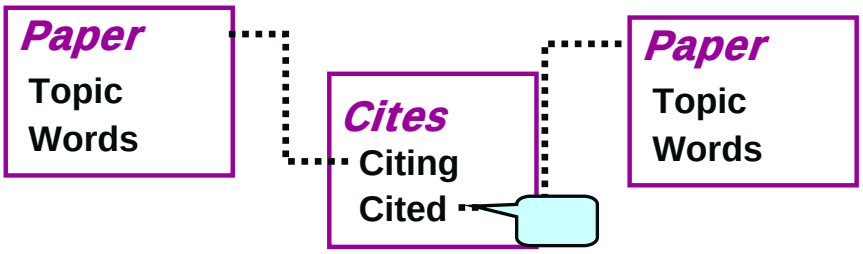
## Attribute Uncertainty




## Reference Uncertainty



## PRM w/ Reference Uncertainty

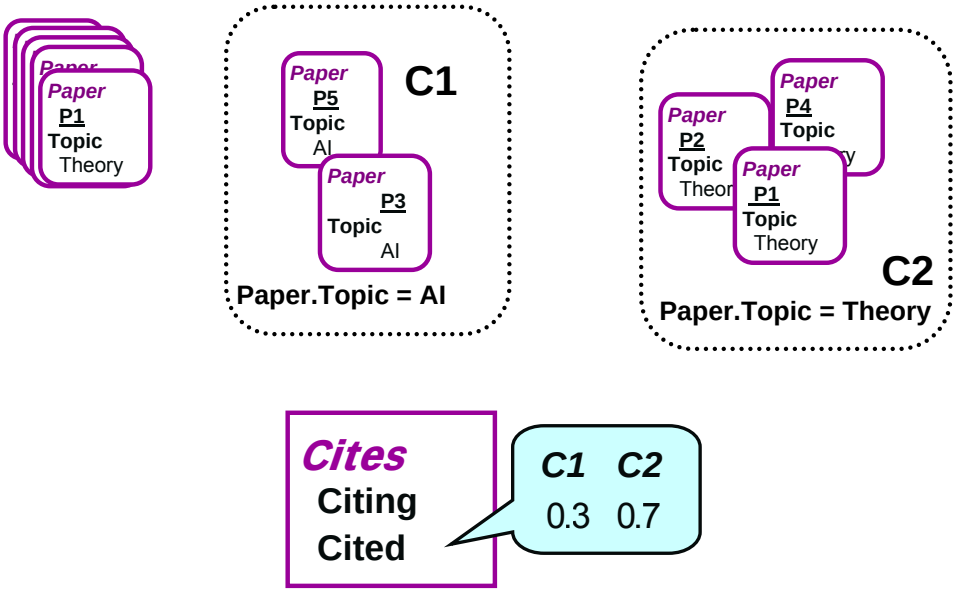



*Dependency model for foreign keys*

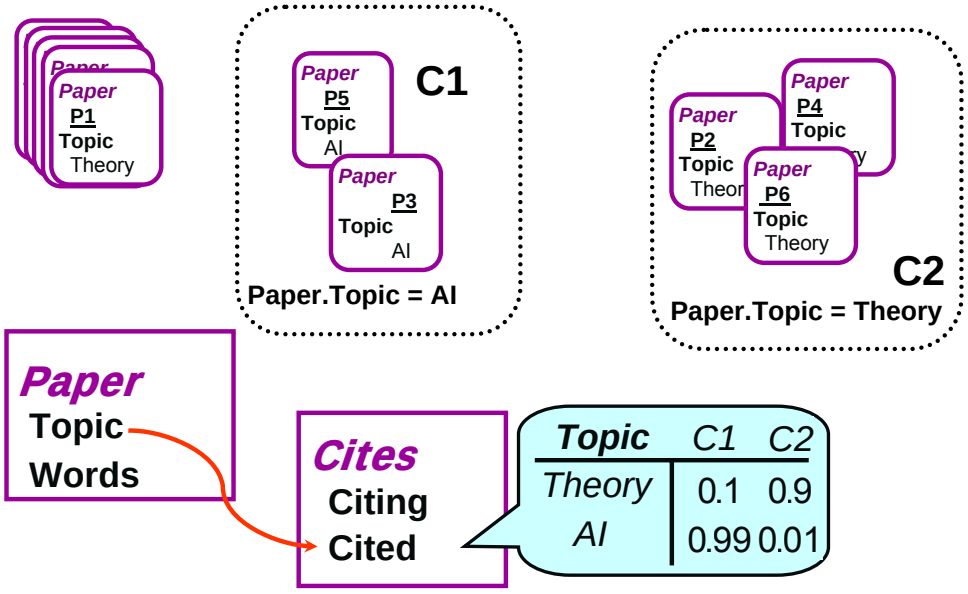
Naïve Approach: multinomial over primary key

- noncompact
- limits ability to generalize

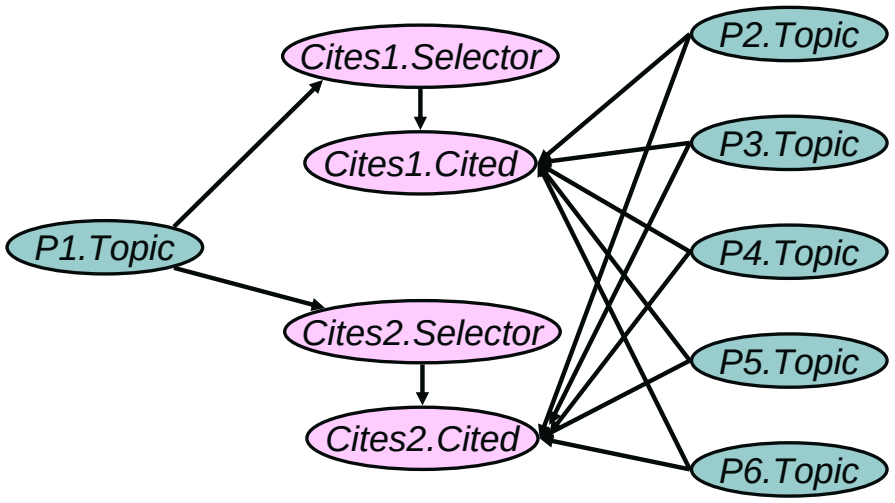
## Reference Uncertainty Example



## Reference Uncertainty Example

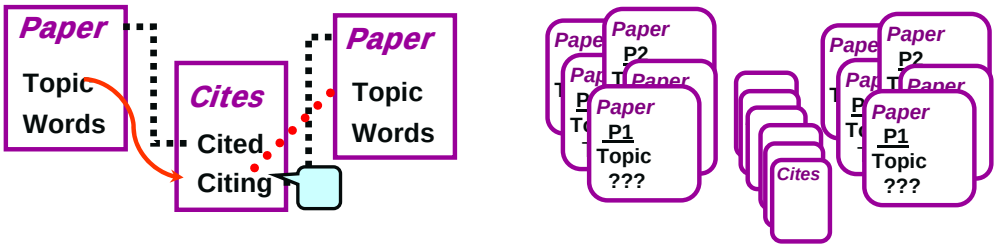



## Introduce Selector RVs




Introduce Selector RV, whose domain is {C1,C2}
The distribution over Cited depends on all of the topics, and the selector

## PRMs w/ RU Semantics




PRM RU

entity skeleton σ

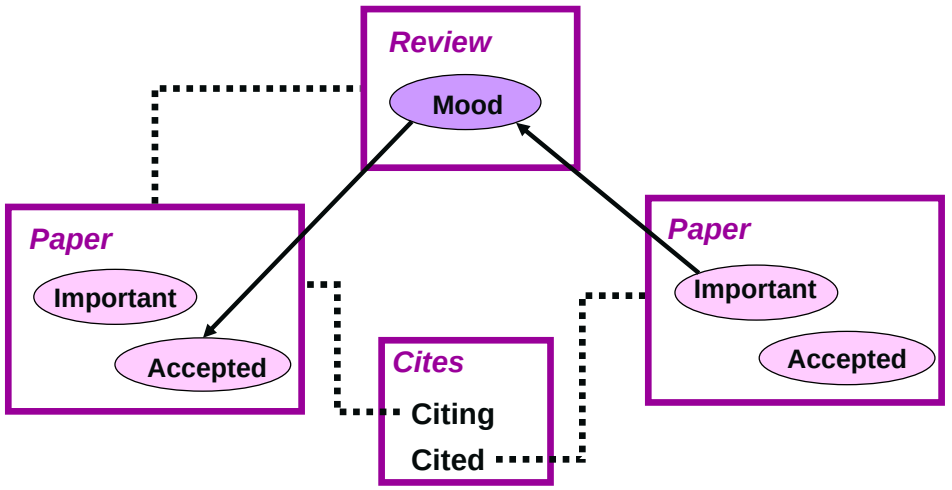
*PRM-RU* + *entity skeleton* σ

⇒ probability distribution over full instantiations I

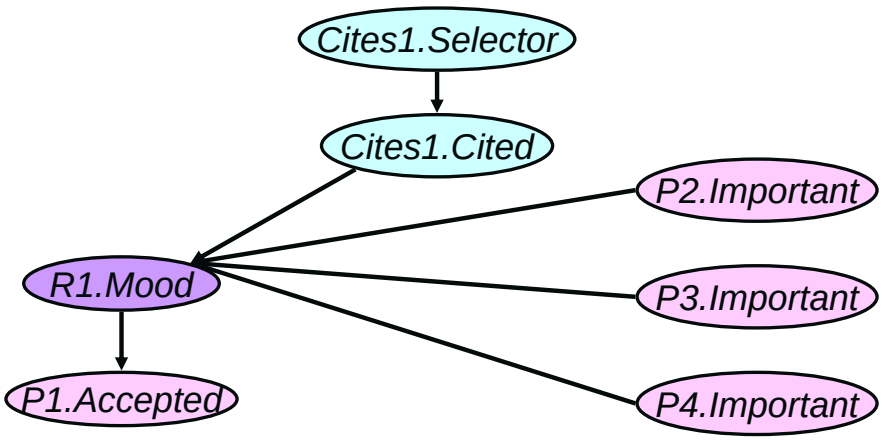
## Learning ***PRMs w/ RU***

- **Idea:**
  - **define scoring function**
  - **do phased local search over legal structures**
- **Key Components:**
  - **legal models**
    ***model new dependencies***
  - **scoring models**
    ***unchanged***
  - **searching model space**
    ***new operators***

## Legal Models

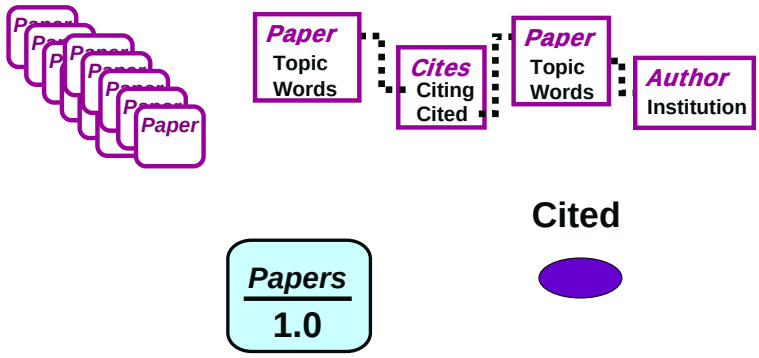



## Legal Models

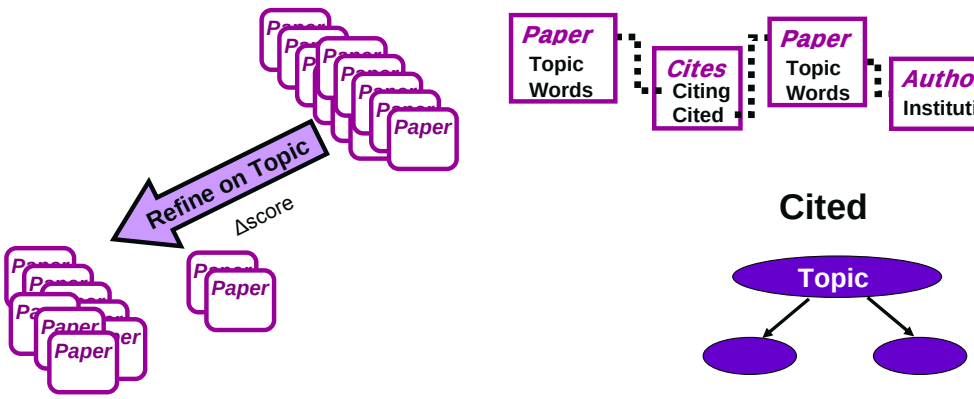



When a node's parent is defined using an uncertain relation, the reference RV must be a parent of the node as well.

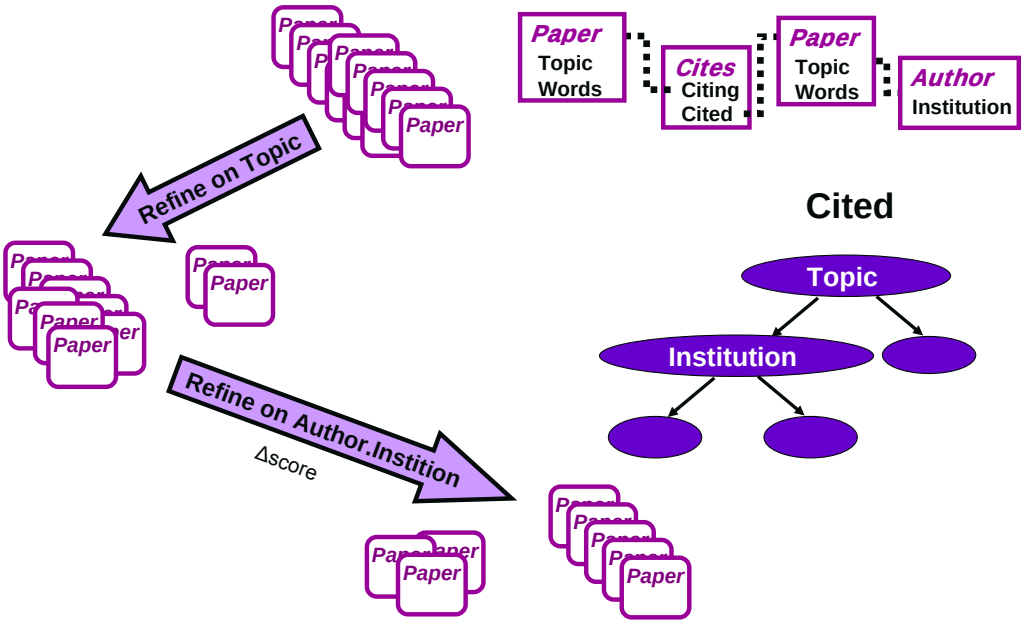
## Structure Search




## Structure Search: New Operators



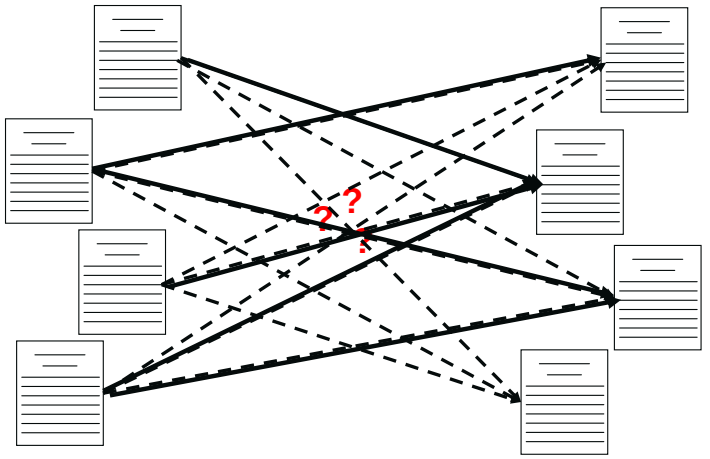
## Structure Search: New Operators




## PRMs w/ RU Summary

- Define semantics for uncertainty over which entities are related to each other
- Search now includes operators **Refine** and **Abstract** for constructing foreign-key dependency model
- Provides one simple mechanism for link uncertainty

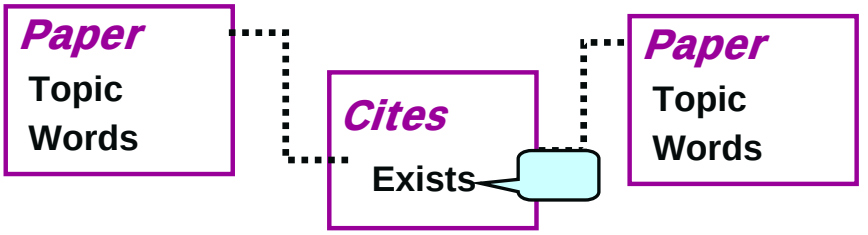
## Existence Uncertainty




Document Collection

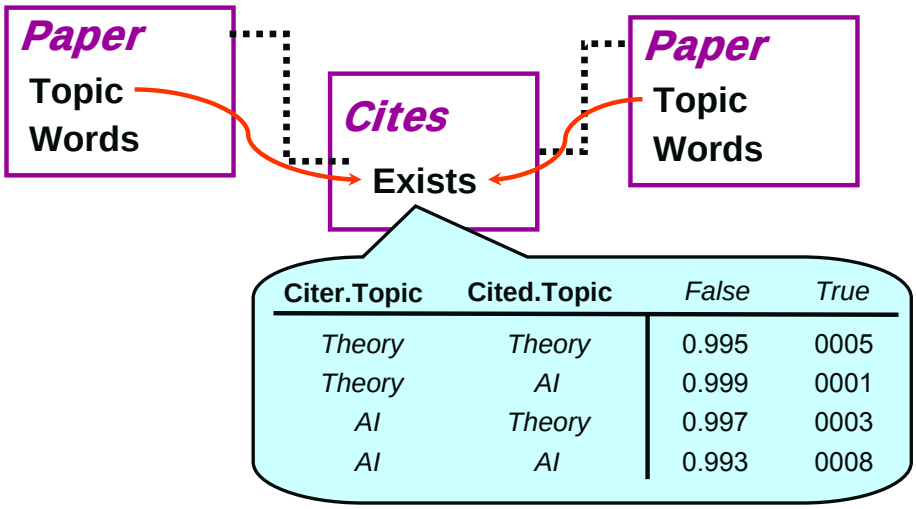
Document Collection

## PRM w/ Exists Uncertainty



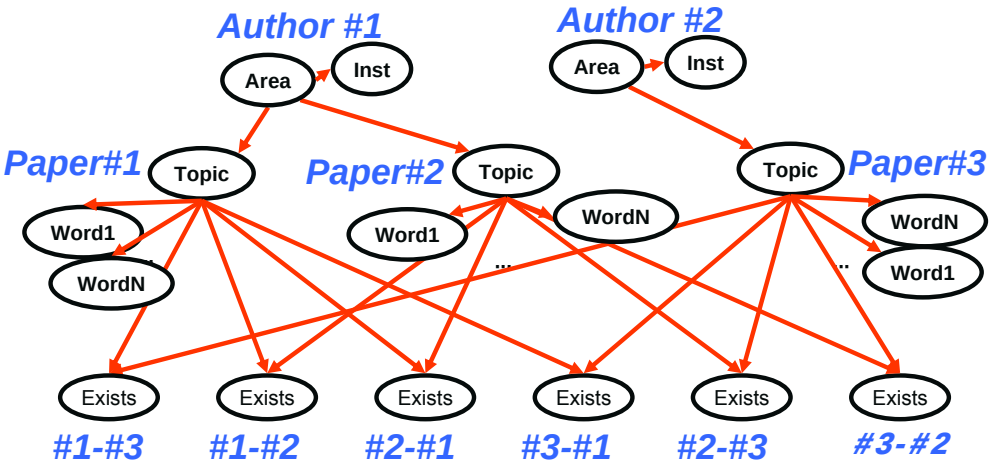

*Dependency model for existence of relationship*

## Exists Uncertainty Example

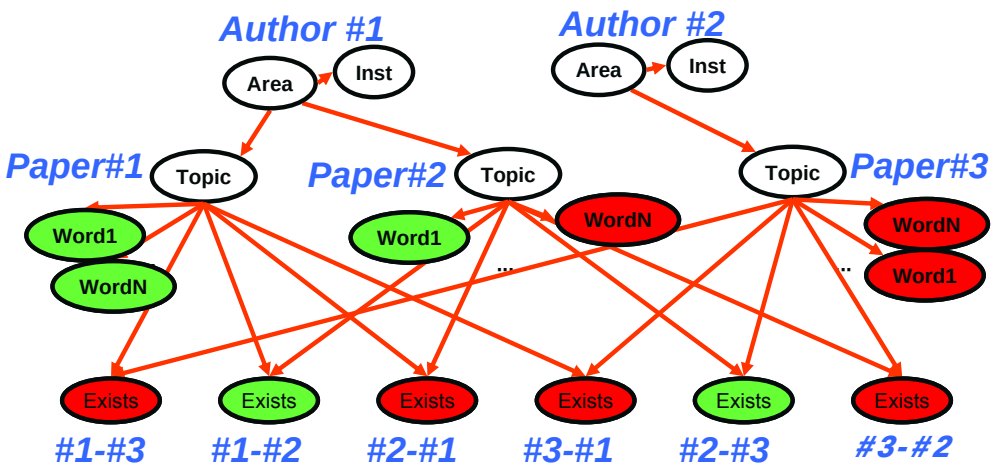



| Citer.Topic | Cited.Topic | False | True |
|---|---|---|---|
| *Theory* | *Theory* | 0.995 | 0005 |
| *Theory* | *AI* | 0.999 | 0001 |
| *AI* | *Theory* | 0.997 | 0003 |
| *AI* | *AI* | 0.993 | 0008 |

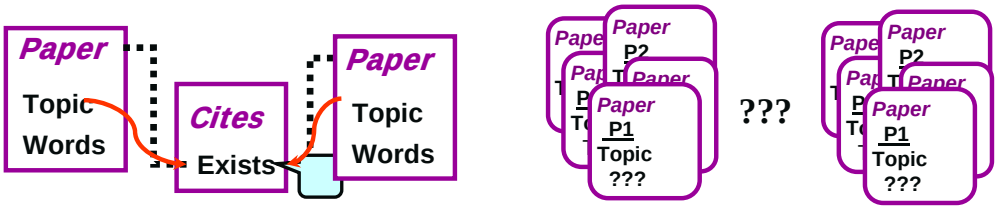
## Introduce Exists RVs



## Introduce Exists RVs




## PRMs w/ EU Semantics




PRM EU

object skeleton σ

*PRM-EU* + *object skeleton* σ

⇒ probability distribution over full instantiations $I$

## Learning *PRMs w/ EU*

- **Idea:**
  - **define scoring function**
  - **do phased local search over legal structures**
- **Key Components:**
  - **legal models**

    ***model new dependencies***
  - **scoring models**

    ***unchanged***
  - **searching model space**

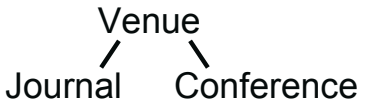
    ***unchanged***

## Four SRL Approaches

- Directed Approaches
  - BN Tutorial
  - Rule-based Directed Models
  - **Frame-based Directed Models**
    - PRMs w/ Attribute Uncertainty
    - Inference in PRMs
    - Learning in PRMs
    - PRMs w/ Structural Uncertainty
    - PRMs w/ Class Hierarchies
- Undirected Approaches
  - Markov Network Tutorial
  - Frame-based Undirected Models
  - Rule-based Undirected Models

## PRMs with classes

- Relations organized in a class hierarchy

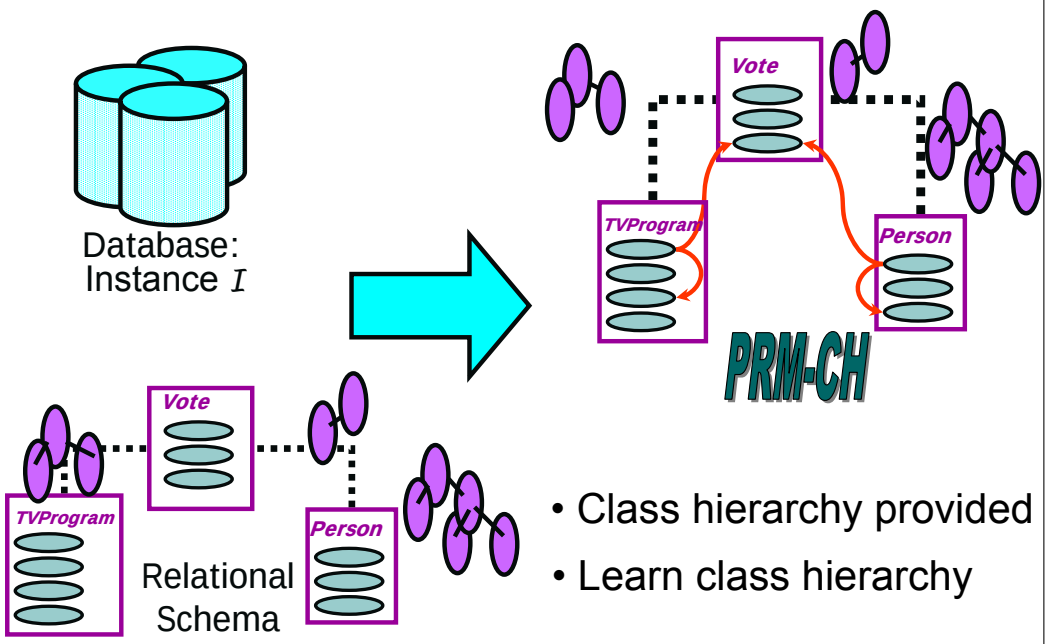



- Subclasses inherit their probability model from superclasses
- Instances are a special case of subclasses of size 1
- As you descend through the class hierarchy, you can have richer dependency models
  - e.g. cannot say **Accepted(P1) <- Accepted(P2)** (cyclic)
  - but can say **Accepted(JournalP1) <- Accepted(ConfP2)**

## Type Uncertainty

- Is *1st-Venue* a *Journal* or *Conference* ?
- Create *1st-Journal* and *1st-Conference* objects
- Introduce *Type(1st-Venue)* variable with possible values *Journal* and *Conference*
- Make *1st-Venue* equal to *1st-Journal* or *1st-Conference* according to value of *Type(1st-Venue)*

## Learning PRM-CHs

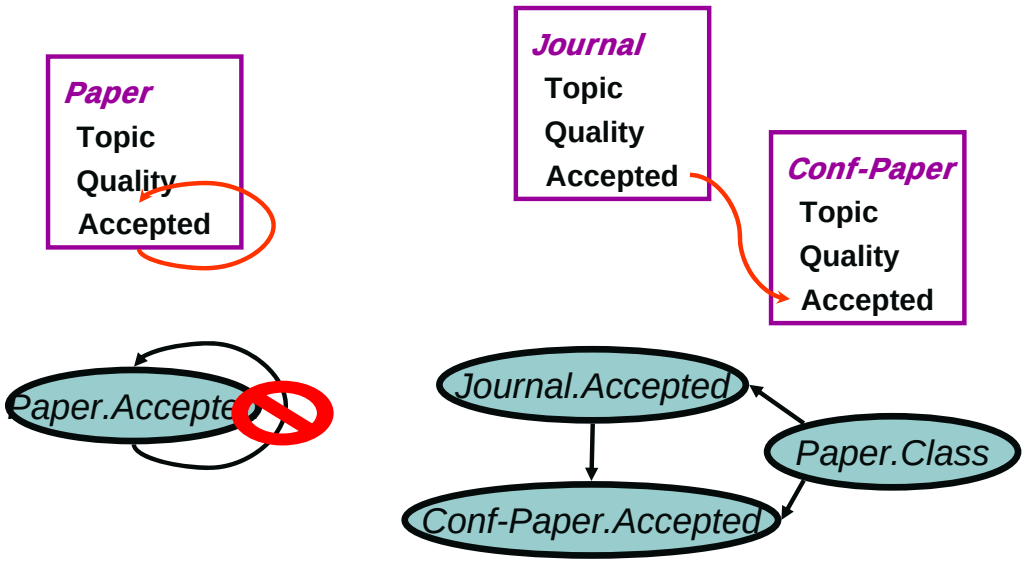



- Class hierarchy provided
- Learn class hierarchy

## Learning *PRMs w/ CH*

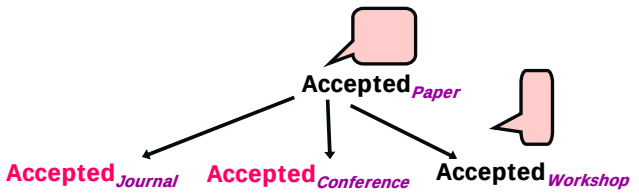
- **Idea:**
  - **define scoring function**
  - **do phased local search over legal structures**
- **Key Components:**
  - **legal models**
    ***model new dependencies***
  - **scoring models**
    ***unchanged***
  - **searching model space**
    ***new operators***

## Guaranteeing Acyclicity w/ Subclasses



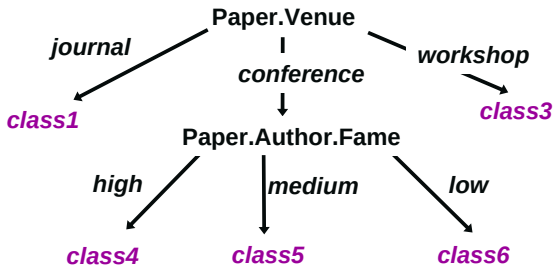

## Learning PRM-CH

- Scenario 1: Class hierarchy is provided
- New Operators
  - Specialize/Inherit



## Learning Class Hierarchy

- Issue: partially observable data set
- Construct decision tree for class defined over attributes *observed in training set*
- New operator
  - Split on class attribute
  - Related class attribute




## PRMs w/ Class Hierarchies

Allow us to:

- Refine a "heterogenous" class into more coherent subclasses
- Refine probabilistic model along class hierarchy
  - Can specialize/inherit CPDs
  - Construct new dependencies that were originally "acyclic"

*Provides bridge from class-based model to instance-based model*

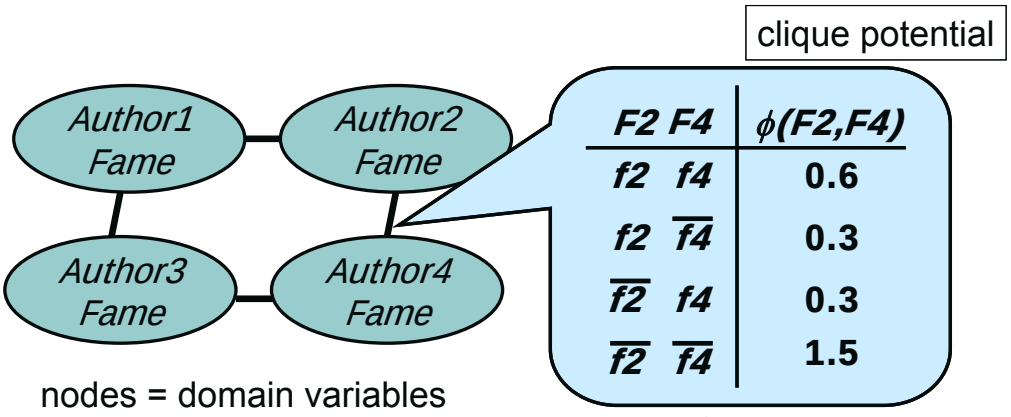
## Summary: Directed Frame-based Approaches

- Focus on objects and relationships
  - what types of objects are there, and how are they related to each other?
  - how does a property of an object depend on other properties (of the same or other objects)?
- Representation support
  - Attribute uncertainty
  - Structural uncertainty
  - Class Hierarchies
- Efficient Inference and Learning Algorithms

## Four SRL Approaches

- Directed Approaches
  - BN Tutorial
  - Rule-based Directed Models
  - Frame-based Directed Models
- **Undirected Approaches**
  - **Markov Network Tutorial**
  - Frame-based Undirected Models
  - Rule-based Undirected Models

## Markov Networks

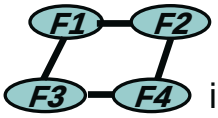



nodes = domain variables
edges = mutual influence

parameters measure compatibility of values

Network structure encodes conditional independencies:
*I(A1 Fame, A4 Fame | A2 Fame, A3 Fame)*

## Markov Network Semantics




conditional independencies in MN structure + local clique potentials = full joint distribution over domain

$$P(f1,\bar{f}2,f3,\bar{f}4) = \frac{1}{Z}\phi_{12}(f1,\bar{f}2)\phi_{13}(f1,f3)\phi_{24}(\bar{f}2,\bar{f}4)\phi_{34}(f3,\bar{f}4)$$

where Z is a normalizing factor that ensures that the probabilities sum to 1

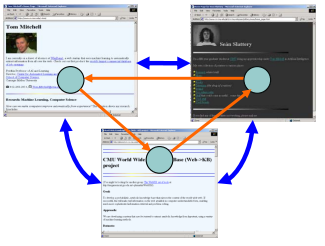
Good news: no acyclicity constraints
Bad news: global normalization (1/Z)

# Four SRL Approaches

- Directed Approaches
  - BN Tutorial
  - Rule-based Directed Models
  - Frame-based Directed Models
- **Undirected Approaches**
  - Markov Network Tutorial
  - **Frame-based Undirected Models**
  - Rule-based Undirected Models

# Advantages of Undirected Models

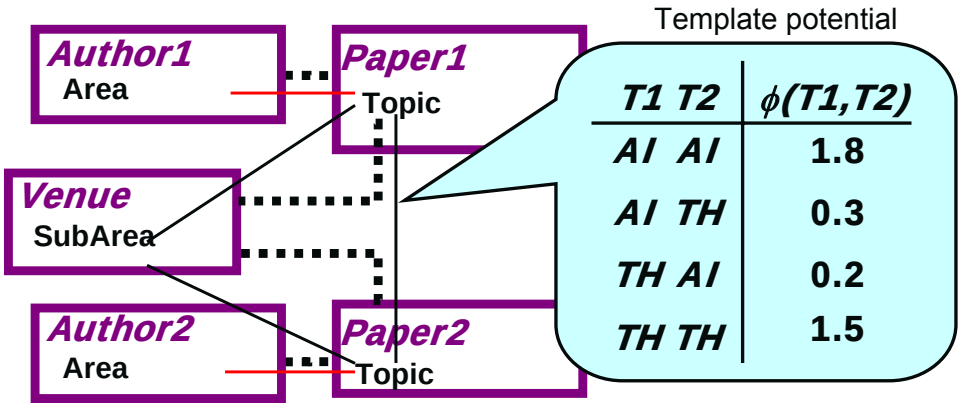
- Symmetric, non-causal interactions
  - Web: categories of linked pages are correlated
  - Social nets: individual correlated with peers
  - Cannot introduce direct edges because of cycles



- Patterns involving multiple entities
  - Web: “triangle” patterns
  - Social nets: transitive relations

# Relational Markov Networks

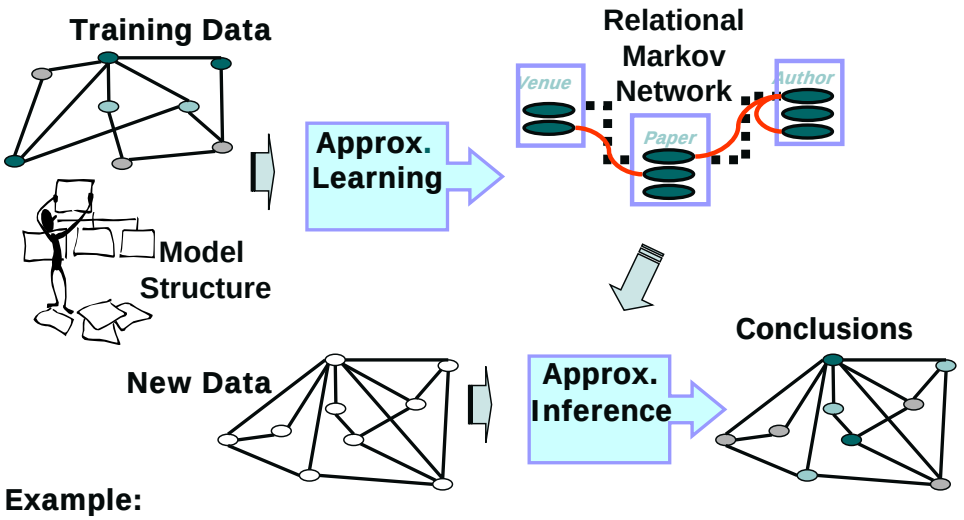
- Locality:
  - Local probabilistic dependencies given by relational links
- Universals:
  - Same dependencies hold for all objects linked in a particular pattern




# RMNs

- Semantics
  - Instantiated RMN → MN
  - variables: attributes of all objects
  - dependencies: determined by links & RMN
- Learning
  - Discriminative training
  - Max-margin Markov networks
  - Associative Markov networks
- Collective classification:
  - Classifies multiple entities and links simultaneously
  - Exploits links & correlations between related entities

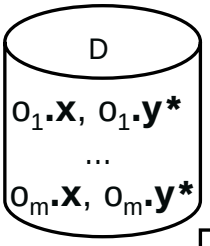
# Collective Classification Overview

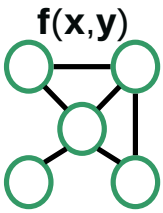



**Example:**

- Train on one labeled conference/venue
- Predict labels on a new conference given papers and links

# Maximum Likelihood




Estimation

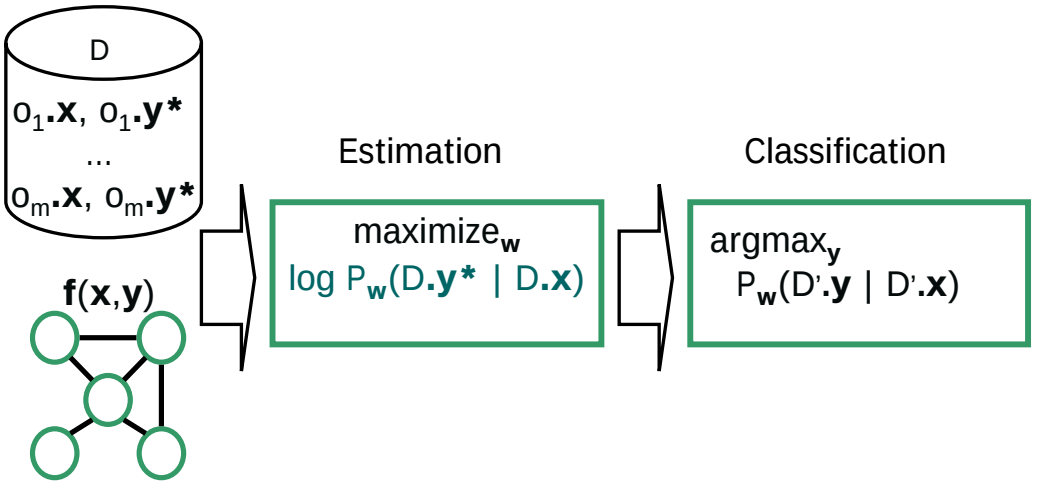
$\text{maximize}_{\mathbf{w}}$ $\log P_{\mathbf{w}}(D.\mathbf{y}^*, D.\mathbf{x})$

Classification

$\text{argmax}_{\mathbf{y}}$ $P_{\mathbf{w}}(D'.\mathbf{y} \mid D'.\mathbf{x})$

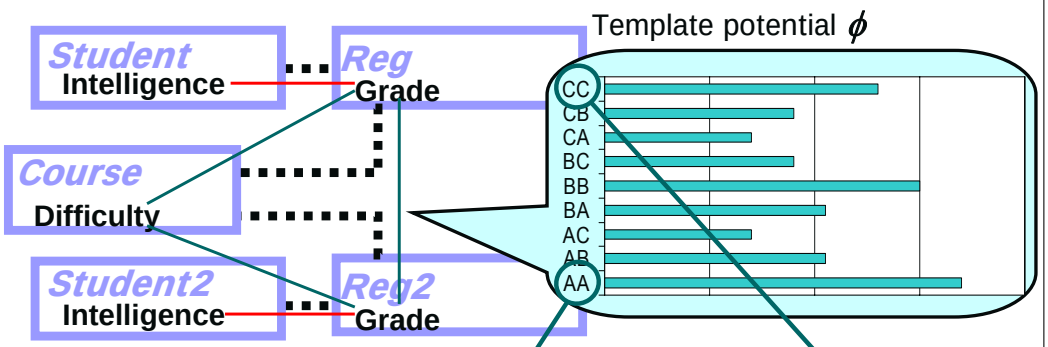
**We don't care about the *joint* distribution P(D.X=x, D.Y=y*)**

## Maximum Conditional Likelihood




[**Lafferty et al '01**]

## Learning RMNs



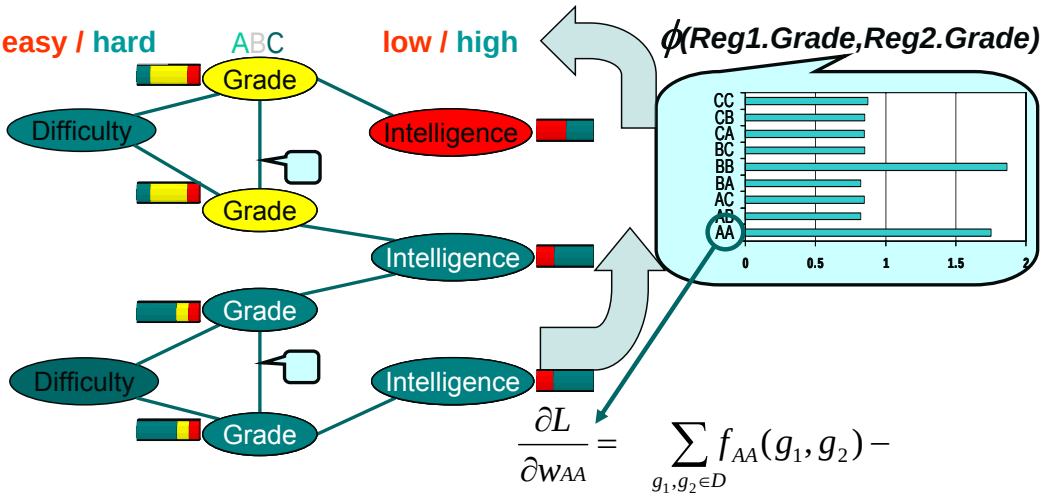

$$\phi(y_1, y_2) = \exp\{w_{AA} \cdot f_{AA}(y_1, y_2) + \ldots + w_{CC} \cdot f_{CC}(y_1, y_2)\}$$

$$\log P_{\mathbf{w}}(D.Y \mid D.X) = \mathbf{w} \cdot \mathbf{f}(D.Y, D.X) - \log Z(D.X)$$

$$\nabla_{\mathbf{w}} \log P_{\mathbf{w}}(D.Y \mid D.X) = \mathbf{f}(D.Y, D.X) - E_{P_{\mathbf{w}}(D.Y \mid D.X)} \mathbf{f}(D.Y, D.X)$$

# Learning RMNs

*Maximize L = log P(D.Grade,D.Intelligence|D.Difficulty)*




$$\frac{\partial L}{\partial w_{AA}} = \sum_{g_1,g_2 \in D} f_{AA}(g_1,g_2) - \sum_{g_1,g_2 \in D} f_{AA}(g_1,g_2) P(g_1,g_2 \mid D.Difficulty)$$

# Four SRL Approaches

- Directed Approaches
  - BN Tutorial
  - Rule-based Directed Models
  - Frame-based Directed Models
- **Undirected Approaches**
  - Markov Network Tutorial
  - Frame-based Undirected Models
  - **Rule-based Undirected Models**

# Markov Logic Networks

- [Richardson and Domingos 03,Singla & Domingos 05, Kok & Domingos 05]
- A Markov Logic Network (MLN) is a set of pairs (F, w) where
  - F is a formula in first-order logic
  - w is a real number
- Together with a finite set of constants, it defines a Markov network with
  - One node for each grounding of each predicate in the MLN
  - One feature for each grounding of each formula F in the MLN, with the corresponding weight w

# Example of an MLN

| | |
|---|---|
| 1.5 | $\forall x\ author(x, p) \wedge smart(x) \Rightarrow high\_quality(p)$ |
| 1.1 | $\forall x\ high\_quality(p) \Rightarrow accepted(p)$ |
| 1.2 | $\forall x, y\ co\_author(x, y) \Rightarrow (smart(x) \Leftrightarrow smart(y))$ |
| ∞ | $\forall x, y\ \exists p\ author(x, p) \wedge author(y, p) \Rightarrow co\_author(x, y)$ |

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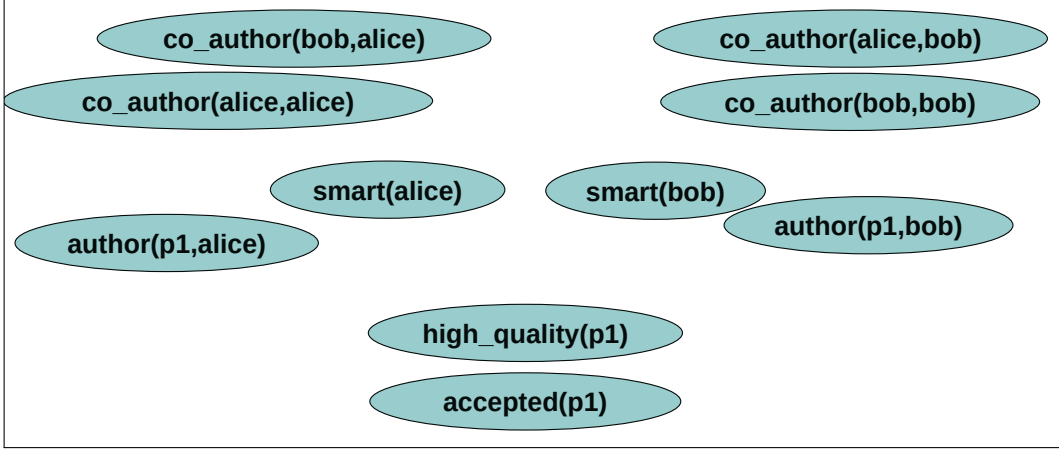

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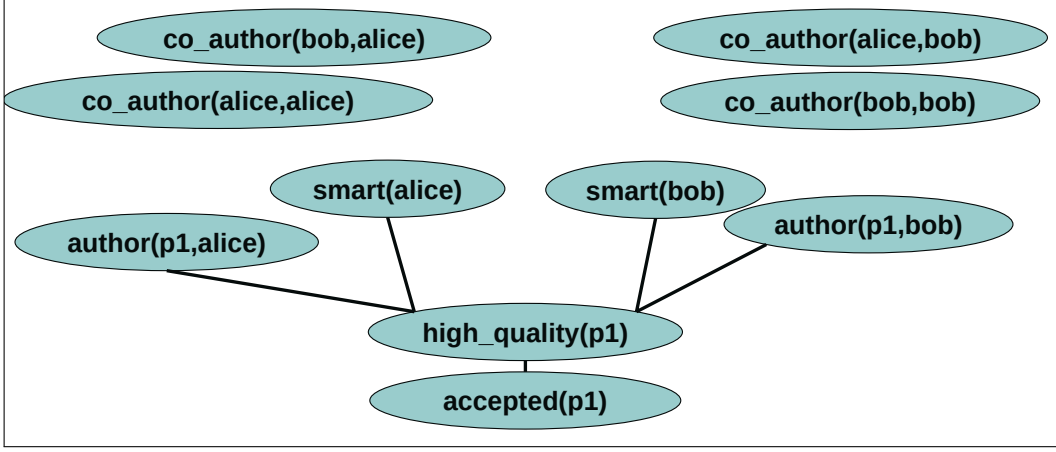



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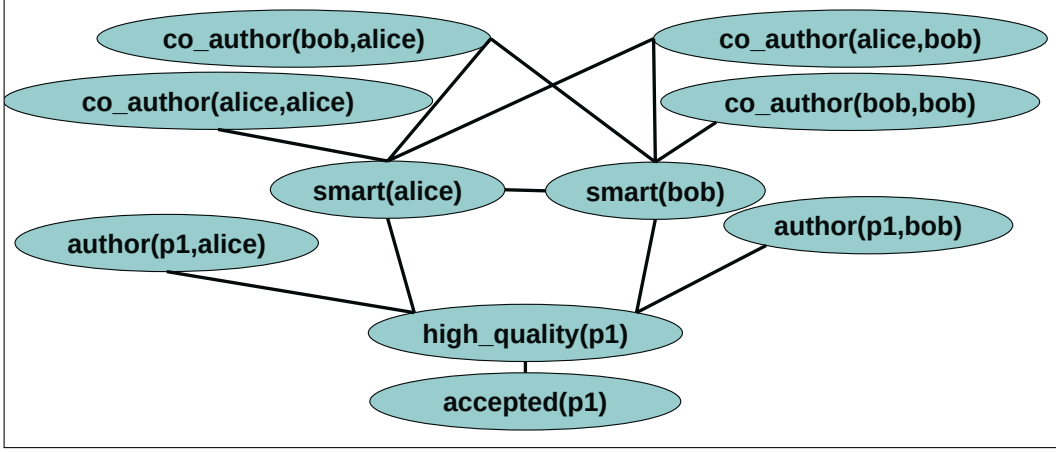

## Markov Logic Networks

- Combine first-order logic and Markov networks
  - **Syntax:** First-order logic + Weights
  - **Semantics:** Templates for Markov networks
- **Inference:** KBMC + MaxWalkSat + MCMC
- **Learning:** ILP + Pseudo-likelihood / discriminitive training

## Summary: Undirected Approaches

- Focus on symmetric, non-causal relationships
  - Like directed approaches, support collective classification

## Four SRL Approaches

- Directed Approaches
  - Rule-based Directed Models
  - Frame-based Directed Models
- **Undirected Approaches**
  - Frame-based Undirected Models
  - Rule-based Undirected Models

## Themes: Representation

- Basic representational elements and focus
  - rules: facts
  - frames: objects
  - programs: processes
- Representing domain structure
  - context
  - relational skeleton
  - non-probabilistic language constructs
- Representing local probabilities
  - noise factors
  - conditional probability tables
  - clique potentials

## Themes: Representational Issues

- Structural uncertainty
  - reference, exists, type, number, identity
- Combining probabilities from multiple sources
  - combining rules
  - aggregation
- Cyclicity
  - ruling out (stratification)
  - introducing time
  - guaranteed acyclic relations
  - undirected models
- Functions and infinite chains
  - iterative approximation

## Themes: Inference

- Inference on ground random variables
  - knowledge based model construction
- Inference at the first-order object level
  - first-order variable elimination
    - unification
    - quantification over populations
  - structured variable elimination
  - memoization
- Utilizing entity-relations structure
- Query-directed inference
  - backward chaining on query and evidence
  - lazy evaluation

## Themes: Learning

- Learning parameters
  - Parameter sharing
    - rules apply many times
    - same type of object appears many times
    - same function is called many times
  - Expectation-Maximization
- Learning structure
  - structure search
  - legal models
  - scoring function
  - search operators

## Goals

- By the end of this tutorial, hopefully, you will be:
  1. able to distinguish among different SRL tasks
  2. able to represent a problem in one of several SRL representations
  3. excited about SRL research problems and practical applications

- Many other interesting topics that I didn't have time to cover…

# Conclusion

- Statistical Relational Learning
  - Supports multi-relational, heterogeneous domains
  - Supports noisy, uncertain, non-IID data
  - aka, real-world data!
- Differences in approaches:
  - rule-based vs. frame-based
  - directed vs. undirected
- Many common issues:
  - Need for collective classification and consolidation
  - Need for aggregation and combining rules
  - Need to handle labeled and unlabeled data
  - Need to handle structural uncertainty
  - etc.
- Great opportunity for combining rich logical representation and inference and learning with hierarchical statistical models!!