

# Modelling Relational Statistics With Bayes Nets Oliver Schulte, Hassan Khosravi, Arthur Kirkpatrick, Tianxiang Gao, Yuke Zhu

School of Computing Science

Simon Fraser University, Vancouver, Canada

Project Website: http://www.cs.sfu.ca/~oschulte/jbn/

### Introduction: Class-Level Queries.

Classic Al research distinguished two types of probabilistic relational queries (Halpern 1990, Bacchus 1990).

#### **Relational Query**

Class-level queries

- · Relational Statistics
- · Concern class proportions
- Type 1 probabilities

Instance-level queries

- Concern individuals, Ground facts
- Type 2 probabilities

Query	Reference	Query			
	Class	Given that Tweety is a bird, what is the probability that Tweety flies?			
What is the percentage	Birds				
of flying birds?		Given that Sam and Hilary are friends,			
What is the percentage of friendship pairs where both are women?	Pairs of Friends	and given the genders of their other friends, what is the probability that Sar and Hilary are both women?			
What is the percentage of A grades awarded to highly intelligence students?	Student-course pairs	Given the grades of Jack in other courses, and that he is highly intelligent, what is the probability that he gets an A in CMPT 310?			

## **Applications**

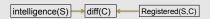
- 1st-order rule or pattern learning (e.g., "intelligent students take difficulty courses").
- Strategic Planning (e.g., "increase SAT requirements to decrease student attrition").
- Query Optimization (Getoor, Taskar, Koller 2001). Choose optimal SQL query evaluation order.
- · Please try our demo!

#### **Related Work**

Class-Level	Instance-Level		
Statistical Relational Model	PRMs, MLNs, LBNs, RDNs,		
Parametrized Bayes Net + new	Parametrized Bayes Net +		
random selection semantics	grounding semantics (Poole 2003)		

## **Random Selection Semantics**

- · Adapted from Halpern 1990.
- · A functor is a function or predicate symbol.
- A population variable X, Y, ... ranges over a population or domain. X randomly select a member of its population.
- A functor node f(X), g(X,Y) is a function of a random variable → also a random variable.



Example: P(int(S)=hi, diff(C) = hi, Reg(S,C) = T) = 20%

Means "if we randomly select a student and a course, there is a 20% probability that the student is highly intelligent, the course is highly difficult, and the student takes the course."

## **Parameter Learning**

Database probability of a formula = 
 # satisfying groundings # possible groundings

- Bayes net parameters = Conditional database probabilities Maximizes the random selection pseudo-likelihood (Schulte 2011).
- How to compute sufficient statistics for negated relations?
   e.g., number of U.S. users who are not friends?
  - For single relation, solved by Getoor et al. (2007).
  - General case: **New application** of the fast Mobius transform (Kennes and Smits 1990).

### The Inverse Fast Mobius Transform

- $\bullet \quad \text{Update equation} \quad P(\sigma,\mathbf{R},R=F) := P(\sigma,\mathbf{R}) P(\sigma,\mathbf{R},R=T)$
- Construct table of joint probabilities. \* means "value unspecified".
- Order relationship variables, change \* to False using update equation.





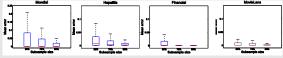
# **Experiments (more in paper)**

- Structure Learning: Learn-and-Join Method (Khosravi et al. 2010, Schulte and Khosravi 2012).
- · Parameter Learning: database probabilities.
- Runtime (seconds): compare Mobius transform (IMT) with constructing complement tables using SQL.

Database	Parameters	#tuples	Complement	IMT	Ratio
Mondial	1618	814	157	7	22
Hepatitis	1987	12,447	18,246	77	237
Financial	10926	17,912	228,114	14,821	15
MovieLens	326	82,623	2,070	50	41

- · Inference Performance on Random gueries.
- Train on whole database as in Getoor et al. 2001.
- Also good performance learning on subsamples, evaluating parameter estimates directly (please see paper).

Figure 4. Query Performance: Absolute difference between estimated vs. true probability. The median observation is the red center line and the box comprises 75% of the observed values. The whisker indicates the maximum acceptable value (1.5 IQR upper). Number of queries/average inference time per query: Mondial, 506/0.08sec; MovieLens, 546/0.05sec; Bepatitis, 489/0.1sec; Financial, 140/0.02sec.



# Conclusion

- Parametrized Bayes nets support class-level inferences with a new random selection semantics.
- $\bullet$  Mobius Transform  $\Rightarrow$  fast and scalable parameter learning even with negated relationships.
- Excellent empirical performance on class-level quries.

#### References

- Getoor, Lise, Friedman, Nir, Koller, Daphne, Pfeffer, Avi, and Taskar, Benjamin. Probabilistic relational models. In Introduction to Statistical Relational Learning
- 2. Poole, David. First-order probabilistic inference. In IJCAI, pp. 985–991, 2003.
- Halpern, Joseph Y. An analysis of first-order logics of probability. Artificial Intelligence, 46(3):311–350, 1990.
- Kennes, Robert and Smets, Philippe. Computational aspects of the Mobius transformation. In UAI, pp. 401–416, 1990.
- H. Khosravi, O. Schulte, T. Man, X. Xu, and B. Bina, Structure learning for Markov logic networks with many descriptive attributes, in AAAI, 2010, pp. 487–493.
   O. Schulte and H. Khosravi. Learning graphical models for relational data via lattice
- search. Machine Learning, 2012. DOI: 10.1007/s10994-012-5289-4.
  7. Schulte, Oliver. A tractable pseudo-likelihood function for Bayes nets applied to relational data. In SIAM SDM, pp. 462–473, 2011.