

Probabilistic Reasoning in the Semantic Web using Markov Logic

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MSc Thesis

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Overview

- **Semantic Web**
- **Markov Logic**
- **Markov Logic + Semantic Web**
 - Formulas
 - Weights
 - Annotated
 - Learned Using Individuals
 - Learning Individuals/Probabilities
- **System**
- **Conclusions**

Semantic Web

■ Semantic Web

- Bring structure to the meaningful content of Web pages
- Knowledge represented by ontologies
 - DAML+OIL, OWL, OWL2
- None of them provide means of dealing with uncertainty
 - Probabilistic reasoning tries to solve this problem through the use of probability theory

Objectives

- **Study mechanisms to perform probabilistic reasoning in the Semantic Web**
 - Markov Logic = First-order Logic + Markov Networks
- **Develop a system that provides a Semantic Web interface to Markov Logic reasoning and learning capabilities**

Markov Logic

■ Markov Logic

- First-order logic and Markov networks in the same representation
- A world that violates a formula is not invalid, but less probable
- Attaching weights to first-order logic formulas
 - The higher the weight, the bigger is the difference between a world that satisfies the formula and one that does not

$$P(X = x) = \frac{1}{Z} \exp \left(\sum_{i=1}^F w_i n_i(x) \right)$$

Markov Logic + Semantic Web

■ Markov Logic = Formulas+Weights

■ Formulas

- Semantic Web ontology languages like OWL2 follow a model-theoretic semantics

OWL2 Axiom	First-order logic formula
<i>SubClassOf</i> (CE_1, CE_2)	$\forall x : CE_1(x) \Rightarrow CE_2(x)$
<i>TransitiveProperty</i> (OPE)	$\forall x, y, z : OPE(x, y) \wedge OPE(y, z) \Rightarrow OPE(x, z)$
<i>ClassAssertion</i> (CE, a)	$CE(a)$

Markov Logic + Semantic Web

■ **Weights**

- Provided
- Learned Using Individuals
- Learning Individuals/Probabilities

Markov Logic + Semantic Web

■ Provided Weights

- Ontology axioms can be annotated with a value that can be used as weight
- Problem: Probabilities \neq Weights
 - Discriminative weight learning

$$\frac{\partial}{\partial w_i} \log P_w(y|x) = n_i(x, y) - E_w[n_i(x, y)]$$

$$n_i(x, y) = \text{count}(i) * p_i$$

Markov Logic + Semantic Web

■ Provided Weights

■ Applications

■ User-created probabilistic ontologies

- E.g., Body Gestures ontology

- $\text{HeadScratch}(A) \rightarrow P(\text{Recalling}(A)) = 0.96$

■ Ontology learning

- E.g., Taxonomies automatically learned from web search engines

- $\text{Acetone}(A) \rightarrow P(\text{Ethanol}(A)) = 0.91$

Markov Logic + Semantic Web

■ Learned weights

- Weights can be learned generatively or discriminatively through example data
- Applications
 - Using a financial ontology, predict the probability of a loan being problematic
 - Semantic Web Social Network analysis
 - Link prediction, link-based classification (64%) and cluster analysis
 - Pure machine learning tasks
 - Classification of mushrooms (94%) and Titanic passengers (75%)

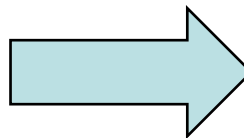
Markov Logic + Semantic Web

■ Learn Individuals

■ Ontology population

- Given a source ontology and a corpus, extract individuals of that ontology from the corpus, with their class and property assertions

Animals such as **dogs** and **cats**
Lions are **animals**
Lions are the **predators** of **zebras**



Animal(Dog)
Animal(Cat)
Animal(Lion)
Predator(Lion,Zebra)

Markov Logic + Semantic Web

■ Learn Individuals

■ Applications

- Automatically populate ontology about diseases and their symptoms and cluster diseases by their symptoms

- 140 diseases (66-70%), 459 symptoms (63%)

- Cluster examples

- Depression (migraines, anxiety, alzheimers, bipolar disorder)
 - Respiratory system (lung cancer, tuberculosis, asthma, pneumonia, diphteria)

Markov Logic + Semantic Web

■ Learn Probabilities

- Use semantic similarity techniques

$$\textit{Pointwise Mutual Information} (P, Q) = \log_2 \left(\frac{H(P, Q)}{H(P)H(Q)} * N \right)$$

- Given (P, R, Q)

- $H(P) = \text{"PR*"}$
- $H(Q) = \text{"*RQ"}$
- $H(P, Q) = \text{"PRQ"}$

	Query	Result Count
H(P)	"dog is a *"	287,000
H(Q)	"* is a pet"	182,000
H(P,Q)	"dog is a pet"	785

Markov Logic + Semantic Web

■ Learn Probabilities

■ Applications

- Infer the uncertainty of automatically learned taxonomies

- E.g.

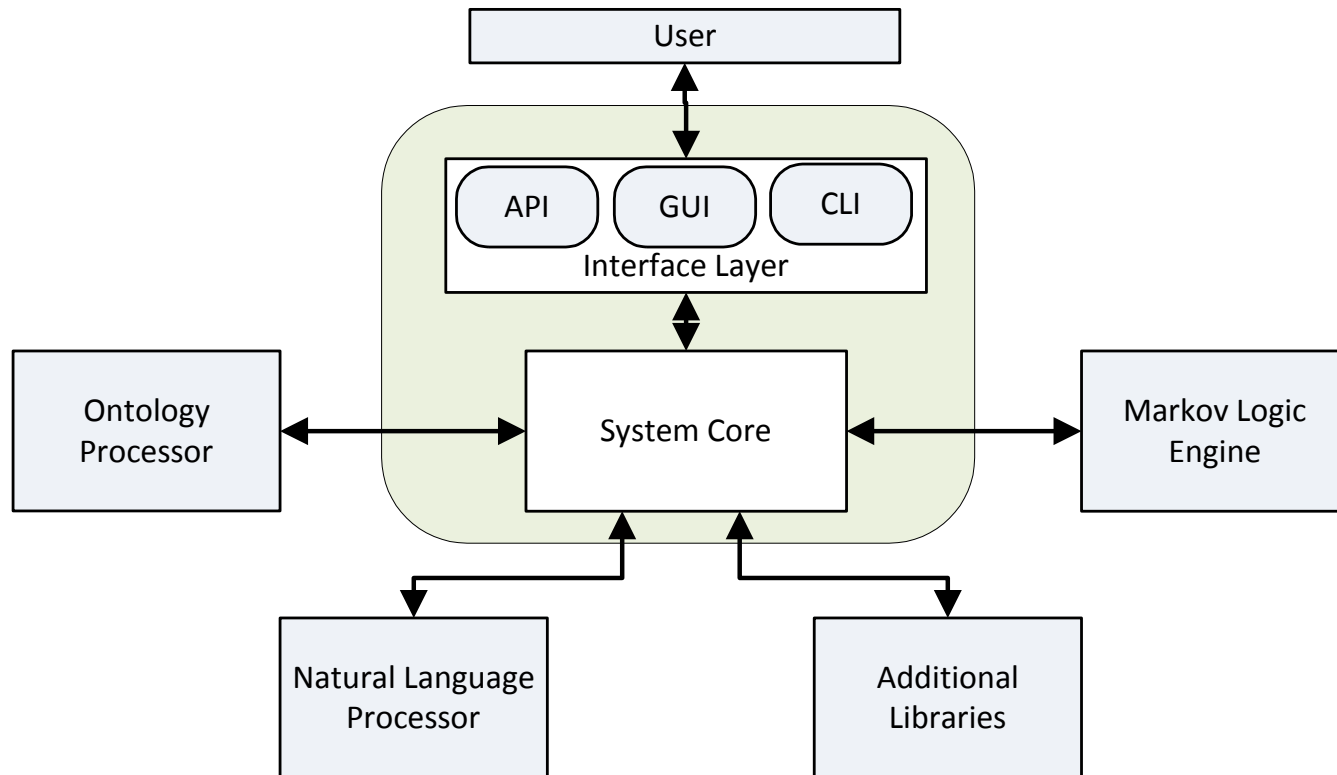
- $P(\text{Animal}(\text{Dog})) = 82\%$

- $P(\text{Dog}(\text{Cat})) = 9\%$

System

■ Incerto

■ <http://code.google.com/p/incerto> (LGPL)



Conclusions

■ Contributions

- Applied Statistical Relational Learning techniques to Semantic Web reasoning
- Studied not only reasoning under uncertainty in the Semantic Web, but also how to learn this uncertainty
- Unlike other approaches, use undirected probabilistic models
- New method to transform probabilities in Markov logic weights

Conclusions

■ Contributions

- New method to learn the probabilities of OWL2 axioms using a web search engine
- Useful for many interesting tasks
 - Ontology learning, reasoning, mapping, refining

Conclusions

■ Publications

- Pedro Oliveira, Paulo Gomes: "Instance-based Probabilistic Reasoning in the Semantic Web", Poster at the ***18th International World Wide Web Conference***, Madrid, Spain, April 2009
 - AR: 31%
- Pedro Oliveira, Paulo Gomes: "Learning and Reasoning about Uncertainty in the Semantic Web", ***14th Portuguese Conference on Artificial Intelligence***, Aveiro, Portugal, October 2009
 - AR: 66%

Conclusions

■ Future Work

- More experimentation
- Other ways to automatically learn the uncertainty of ontology axioms
- Study reasoning/learning with transitivity and cardinality restrictions

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Thank You!