Probabilistic Reasoning in the Semantic Web using Markov Logic

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MSc Thesis
Overview

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

- System
- Conclusions
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

<table>
<thead>
<tr>
<th>OWL2 Axiom</th>
<th>First-order logic formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>SubClassOf($CE_1$, $CE_2$)</td>
<td>$\forall x : CE_1(x) \Rightarrow CE_2(x)$</td>
</tr>
<tr>
<td>TransitiveProperty($OPE$)</td>
<td>$\forall x, y, z : OPE(x, y) \land OPE(y, z) \Rightarrow OPE(x, z)$</td>
</tr>
<tr>
<td>ClassAssertion($CE$, $a$)</td>
<td>$CE(a)$</td>
</tr>
</tbody>
</table>
Markov Logic + Semantic Web

- **Weights**
  - Provided
  - Learned Using Individuals
  - Learning Individuals/Probabilities
Provided Weights

Ontology axioms can be annotated with a value that can be used as weight

Problem: Probabilities ≠ Weights

Discriminative weight learning

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

\[
n_i(x, y) = \text{count}(i) \times p_i
\]
Markov Logic + Semantic Web

Provided Weights

Applications
- User-created probabilistic ontologies
  - E.g., Body Gestures ontology
    - HeadScratch(A) → P(Recalling(A)) = 0.96
- Ontology learning
  - E.g., Taxonomies automatically learned from web search engines
    - Acetone(A) → P(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%)
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)
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

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

Given \((P, R, Q)\)

- \(H(P) = “PR*”\)
- \(H(Q) = “*RQ”\)
- \(H(P, Q) = “PRQ”\)

<table>
<thead>
<tr>
<th>Query</th>
<th>Result Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>H(P)</td>
<td>“dog is a *”</td>
</tr>
<tr>
<td>H(Q)</td>
<td>“* is a pet”</td>
</tr>
<tr>
<td>H(P, Q)</td>
<td>“dog is a pet”</td>
</tr>
</tbody>
</table>
Learn Probabilities

- Applications
  - Infer the uncertainty of automatically learned taxonomies
    - E.g.
      - $P(\text{Animal(Dog)}) = 82\%$
      - $P(\text{Dog(Cat)}) = 9\%$
System

- Incerto
  - http://code.google.com/p/incerto (LGPL)

![Diagram of system architecture]

- User
  - Interface Layer
    - API
    - GUI
    - CLI
  - System Core
  - Ontology Processor
  - Natural Language Processor
  - Markov Logic Engine
  - Additional Libraries

- 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
    - 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!