

An unsupervised classification process for large datasets based on web reasoning

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Outline

Context

- Global problem
- The Semantic HMC
- Specific Problem
 - Proposed Solution
- Implementation
 - Setup
 - Results

Conclusion and future work

Global Problem

Value extraction from Big Data sources



Global Problem

Why ontologies

- Ontologies are the most accepted way to represent semantics in the Semantic Web and a good solution for intelligent computer systems that operate close to the human concept level, bridging the gap between human conceptions and computational requirements.
- Semantic HMC
 - Ontology-described predictive model
 - Learned using Big Data technologies
 - Rule-based Web Reasoning to perform classification



Proposition: « Semantic HMC »



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Indexation

- o Extract terms
- Index the items
- Vectorization
 - Calculate term frequency vectors
 - Co-occurrence matrix
- Hierarchization
 - Label selection
 - Hierarchical relations
- Resolution
 - Classification rules creation
- \circ Realization
 - Ontology population
 - Rule-based Web Reasoning to classify items

Proposition : « Semantic HMC »



Unsupervised ontology learning

Rule-based Classification (Web Reasoner)

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Specific Problem

Rule-based reasonning to perform Classification



Specific Problem



Resolution: Learn **classifications rules** from large volumes of unstructured text



Distributed method that exploits the coocurrence matrix

Realization: classify **large volumes** of new data items



Classification using a Web Reasonner

Proposed solution: rule learning (Resolution)

Learning Alpha and Beta sets

<i>P_C</i> (i j)	term ₁	term ₂	term ₃	term ₄	term ₅	term ₆	term ₇
label ₁	0	0	5	0	5	25	25
label ₂	0	75	0	0	0	75	5
label ₃	0	0	75	0	25	0	0
label ₄	5	25	25	0	5	93	25
label ₅	95	0	0	0	60	0	5
label ₆	0	60	0	95	0	0	90
label ₇	5	98	5	60	25	0	79

Coocurrence:
$$P_C(term_i | term_j) = \frac{cfm(term_i, term_j)}{cfm(term_j, term_j)}$$

Alpha set:

$$\omega_{\alpha}^{t_{i}} = \left\{ t_{j} | \forall t_{j} \in Term: P_{C}(t_{i}|t_{j}) > \alpha \right\}$$

Beta set:

$$\omega_{\beta}^{t_{i}} = \left\{ t_{j} | \forall t_{j} \in Term: \beta \leq P_{C}(t_{i}|t_{j}) \leq \alpha \right\}$$

Proposed solution: rule learning (Resolution)

Learning Alpha and Beta sets



Alpha set:

$$\omega_{\alpha}^{t_i} = \{t_j | \forall t_j \in Term: P_C(t_i | t_j) > \alpha\}$$

Beta set:

$$\omega_{\beta}^{t_i} = \{t_j | \forall t_j \in Term: \beta \le P_C(t_i | t_j) \le \alpha\}$$

Proposed solution: rule learning (Resolution)

Example:

%	term ₁	term ₂	term ₃	term ₄	term₅	term ₆	term ₇
label ₁	0	0	5	0	5	25	25
label ₂	0	75	0	0	0	75	5
label ₃	0	0	75	0	25	0	0
label ₄	5	25	25	0	5	93	25
label ₅	95	0	0	0	60	0	5
label ₆	0	60	0	95	0	0	90
label ₇	5	98	5	60	25	0	79

$$\omega_{\alpha}^{t_i} = \{t_j | \forall t_j \in Term: P_C(t_i | t_j) > \alpha\}, \alpha = 91$$

$$\omega_{\beta}^{t_i} = \{t_j | \forall t_j \in Term: \beta \le P_C(t_i | t_j) \le \alpha\}, \beta = 70$$

Proposed solution: classification with web reasoner

Classification at query-time using backward-chaining



Core Ontology

DL concepts	Description
Item $\sqsubseteq \exists has Term. Term$	Items to classify (e.g. doc) has terms
$Term \sqsubseteq T$	Terms (e.g. word) extracted from items
$Label \sqsubseteq Term$	Labels are terms used to classify items
Label ⊑ ∀broader.Label	Broader relation between labels
$Label \sqsubseteq \forall narrower. Label$	Narrower relation between labels
$broader \equiv narrower^-$	Broader and narrower are inverse
$Item \sqcap Term = \emptyset$	Items and Terms are disjoint
Item $\sqsubseteq \forall isClassified.Label$	Relation that links items with labels

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Implementation: rule creation



OWL API used to generate SWRL rules from the output



 $Item(?it), Term(term_i), Label(term_i), has Term(?it, term_j) \rightarrow is Classified(?it, term_i)$

Generated rules Exemple

Alpha rules

 $Item(?it), Term(t_1), Label(term_i), hasTerm(?it, t_1) \rightarrow isClassified(?it, term_i)$

 $Item(?it), Term(t_2), Label(term_i), hasTerm(?it, t_2) \rightarrow isClassified(?it, term_i)$

Beta rules

 $Item(?it), Term(t_1), Term(t_2), Label(term_i), \\hasTerm(?it, t_1), hasTerm(?it, t_2) \rightarrow isClassified(?it, term_i)$

 $Item(?it), Term(t_1), Term(t_3), Label(term_i), hasTerm(?it, t_1), hasTerm(?it, t_3) \rightarrow isClassified(?it, term_i)$

 $Item(?it), Term(t_2), Term(t_3), Label(term_i), \\ hasTerm(?it, t_2), hasTerm(?it, t_3) \rightarrow isClassified(?it, term_i)$

Implementation: Classification at query-time

Stardog used as a scalable triple-store (compatible with **backwardchaining** inference as well as **SWRL** rules inference)

Rule selection process developped in Java interacting with Stardog to optimize query performance



Implementation: test environment

Dataset
To Jo STA ST
A Q S S CA
नी से दिन
A BG
WIKIPEDIA
The Free Encyclopedia

Sub-Dataset	Number of articles		
Wikipedia 1	174900		
Wikipedia 2	407000		
Wikipedia 3	994000		

Cluster •

Google Cloud Platform

Resource type	Description
Number of nodes	4
CPU (per node)	Intel Xeon E5 v2
RAM (per node)	7.5GB
Disk (per node)	500GB

Implementation: parameter setup

Parameter	Step	Value
Alpha Threshold		90
Beta Threshold	Resolution	80
Term ranking (n)		5
р		0.25
Term Threshold ($oldsymbol{\gamma}$)	Realization	2

Results

Number of **classifications**: *Item* $\sqsubseteq \forall isClassified.Label$



Results

Number of learned rules (Alpha + Beta)



Results

Number of **learned rules** (Alpha + Beta) $\alpha = \frac{90}{\beta} = \frac{\beta}{80}$



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Conclusion

- A new unsupervised process to automatically classify items
 - A highly scalable rule learning method based on statistical and lexical approaches
 - A novel method to classify items using a web reasoner
- The process prototype was successfully implemented in a scalable and distributed platform to process Big Data
- Preliminary results show that the items are classified automatically by the reasonner

Ongoing and Future Work

- Quality Evaluation of the process: comparison with state-ofthe art in classification
- Predictive performance evaluation based on cross-validation with large dataset
- Optimization of the process by exhaustive analysis of parameters' impact
- Application to classification of news articles on the web



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Thank you !

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