TaxoLearn: a Semantic Approach to Domain Taxonomy Learning

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Introduction

- Taxonomies important in information science
- Manually construction is time consuming
 - requires expert knowledge
- Solution = taxonomy learning
 - automatically construct taxonomy given a corpus of data

Introduction

Aspects in taxonomy learning

- data sparseness
- syntactical structure vs semantics
- relevance of concepts
- relations between concepts

- Requires:
 - corpus of documents of interest
 - corpora of documents unrelated to the domain of interest
- Outputs:
 - taxonomy of concepts, deduced from the provided documents of interest

- I. Find (disambiguated) candidate concepts
- 2. Select relevant concepts
- 3. Determine concept similarities
- 4. Construct and label taxonomy

I. Find candidate concepts

The stock market was heavily shaken after the European Bank lowered the interest rates.

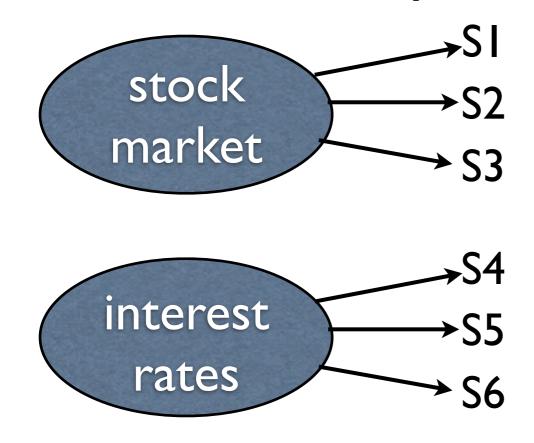
I. Find candidate concepts

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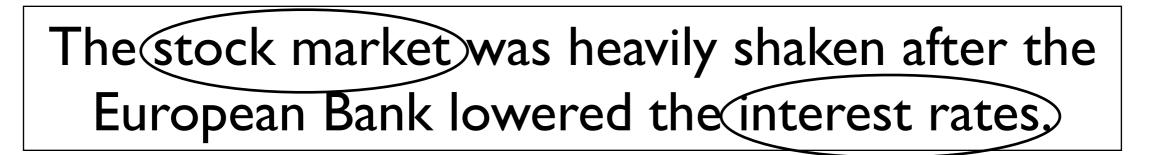
I. Find candidate concepts

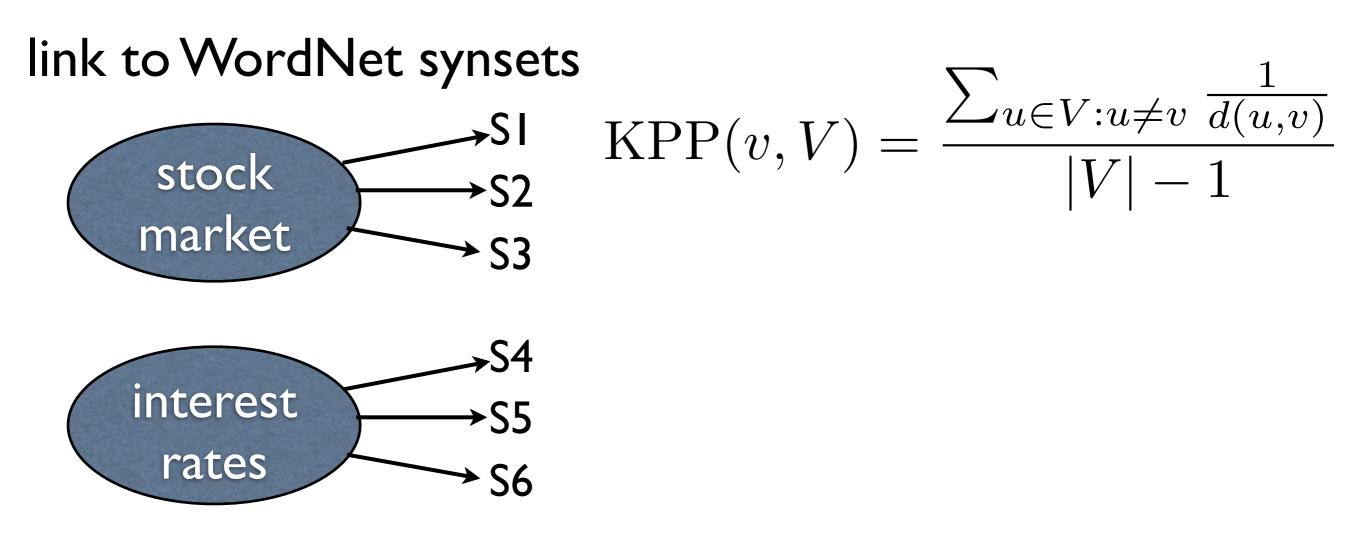
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link to WordNet synsets

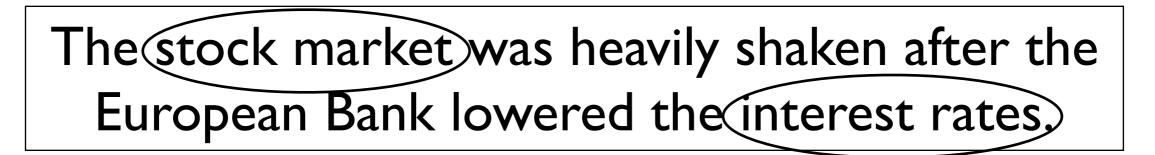


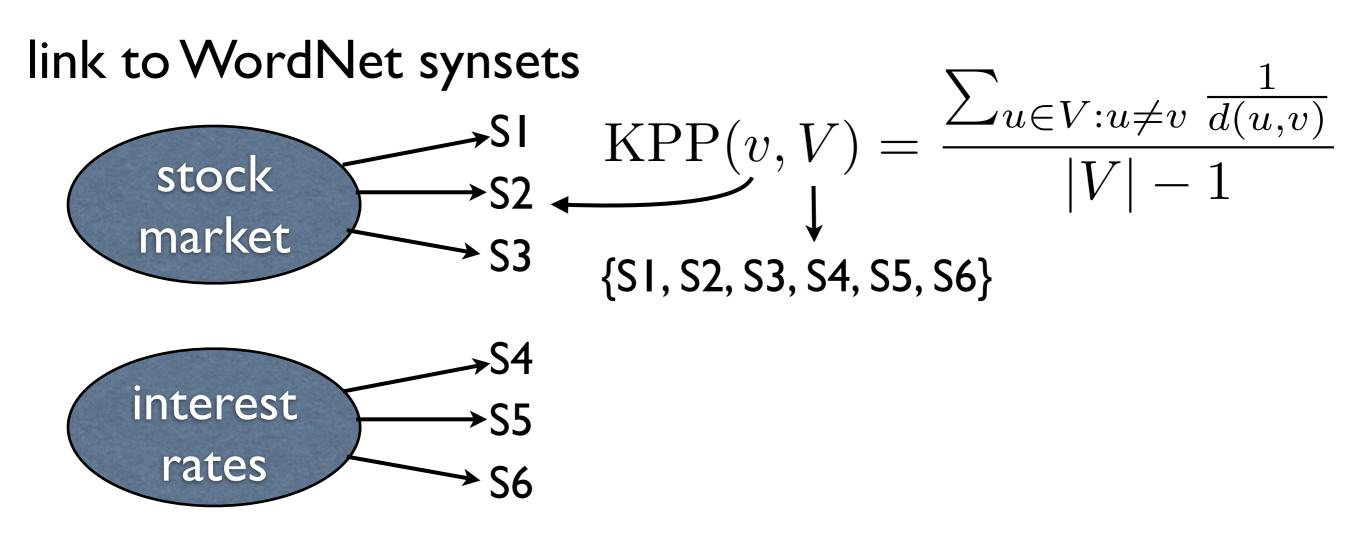
I. Find candidate concepts





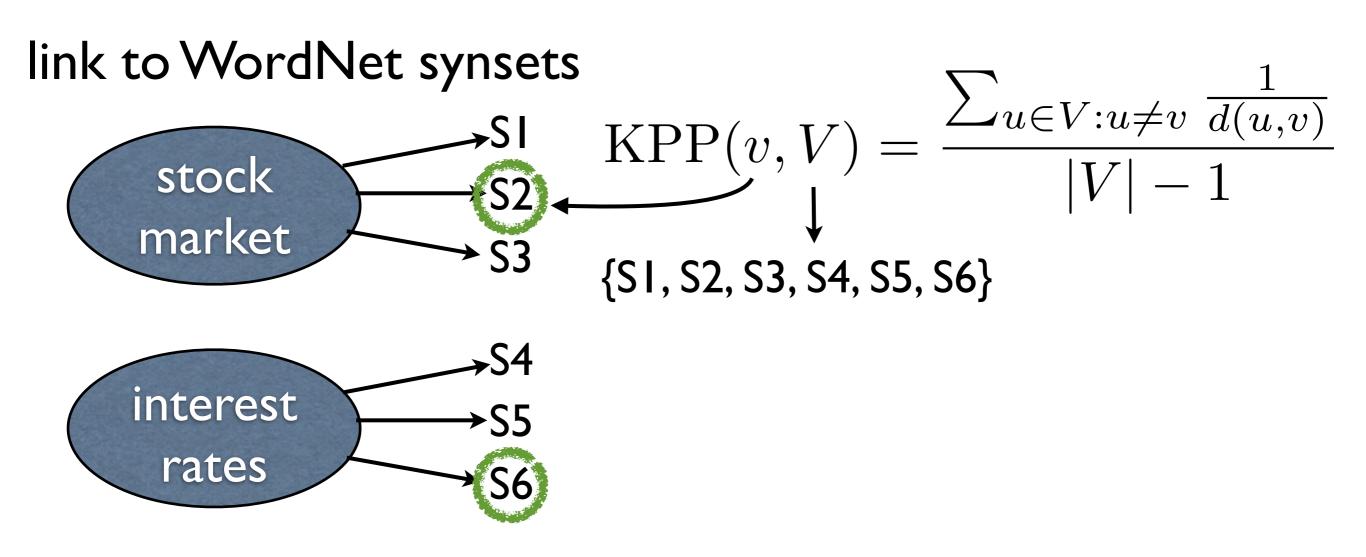
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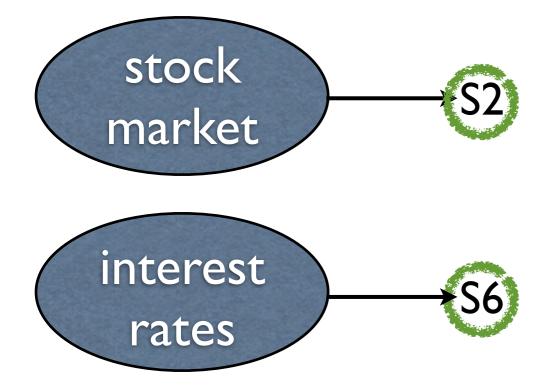
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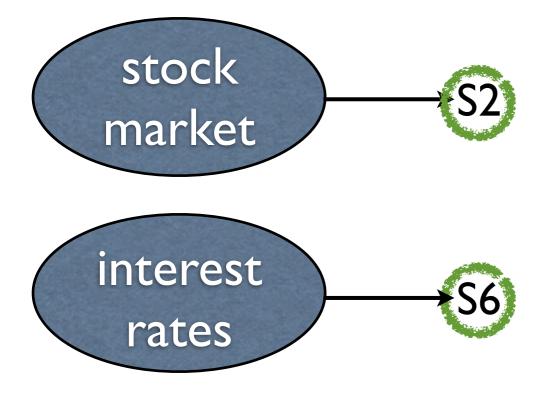


2. Select relevant concepts

TaxoLearn 2. Select relevant concepts

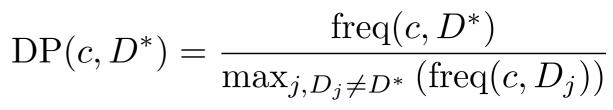


TaxoLearn 2. Select relevant concepts

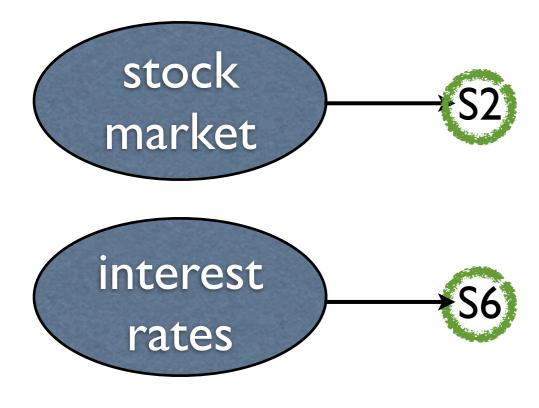


Use two filters:

• Domain Pertinence



TaxoLearn 2. Select relevant concepts



Use two filters:

• Domain Pertinence

$$DP(c, D^*) = \frac{\operatorname{freq}(c, D^*)}{\max_{j, D_j \neq D^*} (\operatorname{freq}(c, D_j))}$$

• Domain Consensus

$$DC(c, D^*) = -\sum_{d_k \in D^*} \operatorname{norm_freq}(c, d_k) \times$$

 $\log(\operatorname{norm_freq}(c, d_k))$

with

norm_freq
$$(c, d_k) = \frac{\operatorname{freq}(c, d_k)}{\max(\operatorname{freq}(c, D))}$$



3. Determine concept similarities

Three methods for computing similarity:

- The WordNet method
- The PMI method (Pointwise Mutual Information)
- The Web method



3. Determine concept similarities

The WordNet method

$$\operatorname{sim}_{WN}(c_i, c_j) = \frac{1}{d(c_i, c_j)}$$



3. Determine concept similarities

The PMI method

$$\operatorname{sim}_{PMI}(c_i, c_j) = \log \frac{F_{c_i \cap c_j} / F_{all}}{(F_{c_i} / F_{all}) \times (F_{c_j} / F_{all})}$$



3. Determine concept sim

The Web method

$$\operatorname{sim}_{WEB}(c_i, c_j) = \log \frac{H_{c_i \cap}}{(H_{c_i}/H_{all})}$$

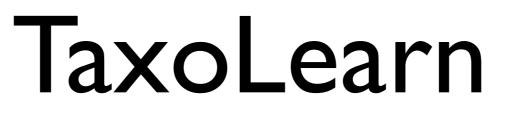
4. Construct and label taxonomy

Constructing the taxonomy

- Hierarchical clustering is used for the WordNet, PMI, and Web method
- Advantages:
 - Able to inspect dendogram
 - Average linkage is used



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Labeling the taxonomy

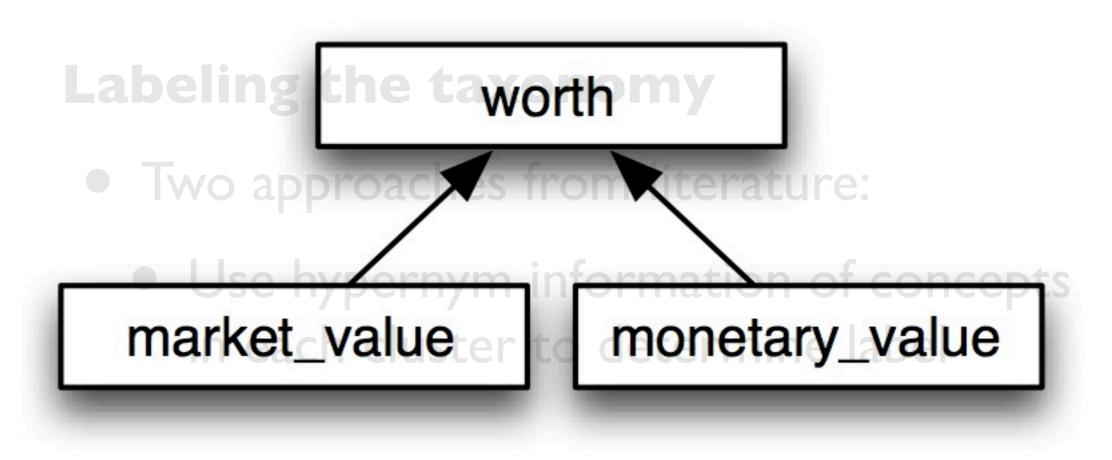
• Two approaches from literature:

4. Construct and label taxonomy

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 - Use hypernym information of concepts in each cluster to determine label



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 - Use centroid of each cluster as label

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- Two approaches from literature:
 - Use hypernym information of concepts in each cluster to determine label
 - Use centroid of each cluster as label
- We employ a hybrid approach

4. Construct and label taxonomy

Labeling the taxonomy (hybrid)

- Our hybrid approach:
 - first checks whether there is a concept that is a hypernym of x other concepts
 - for clusters of size 2, we use the common hypernym
 - otherwise: we use a modified version of the centroid approach

Several measures used to obtain the precision, recall, and FI-measure

• Lexical recall

• Taxonomy Overlap

Several measures used to obtain the precision, recall, and FI-measure

• Lexical recall

$$LR(O_1, O_2) := \frac{|O_1 \cap O_2|}{|O_2|}$$

• Taxonomy Overlap

Taxonomy Overlap $\overline{TO}(O_1, O_2) := \frac{1}{|O_1|} \times \sum_{c \in O_1} TO(c, O_1, O_2)$ $TO(c, O_1, O_2) := \begin{cases} TO'(c, O_1, O_2), & c \in O_2 \\ TO''(c, O_1, O_2), & c \notin O_2 \end{cases}$ $TO'(c, O_1, O_2) := \frac{|SC(c, O_1) \cap SC(c, O_2)|}{|SC(c, O_1) \cup SC(c, O_2)|}$ $TO''(c, O_1, O_2) := max_{c' \in O_2} \frac{|SC(c, O_1) \cap SC(c', O_2)|}{|SC(c, O_1) \cup SC(c', O_2)|}$

$$Precision: P(O_1, O_2) := \overline{TO}(O_1, O_2)$$
$$Recall: R(O_1, O_2) := \overline{TO}(O_2, O_1)$$

 $\begin{aligned} F-Measure: \\ F(O_1, O_2) &:= \frac{2 \times P(O_1, O_2) \times R(O_1, O_2)}{P(O_1, O_2) + R(O_1, O_2)} \\ F'(O_1, O_2) &:= \frac{2 \times LR(O_1, O_2) \times F(O_1, O_2)}{LR(O_1, O_2) + F(O_1, O_2)} \end{aligned}$

- Data set from Erasmus RePub repository
 - consists of 236 papers in the domain of Financial Economics
 - abstracts of papers in medicine & health, law, and culture & society were also used
- Manually constructed golden taxonomy
 - using WordNet synsets
 - only utilizing knowledge from the data set

Measure	WordNet	Web	ΡΜΙ
Lexical recall	0.42	0.43	0.44
Precision	0.50	0.99	0.69
Recall	0.27	0.19	0.21
F-measure	0.35	0.32	0.32
F'-measure	0.38	0.37	0.37

Questions?