META
MultilanguagE Text Analyzer

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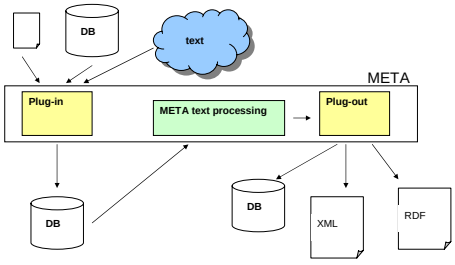
Overview

- META is a tool for text analysis which implements some NLP functionalities
- META provides the tools for semantic indexing and exploits WordNet as knowledge source in Word Sense Disambiguation processing

Architecture



Plug-In

- The Plug-In is a component that is able to import data from different sources and inserts them in a database. Then, data are processed by META.
- In order to integrate this component into META it is necessary to:
  - develop a class that implements the interface `plugs.plugIn.PlugIn` and inserts it into package `plugs.plugIn.plugInImpl.<new_package>`
- The developed Plug-In is able to import text from: PDF, DOC, HTML, OpenOffice, XLS, RTF, TXT, XML

META Text-processing

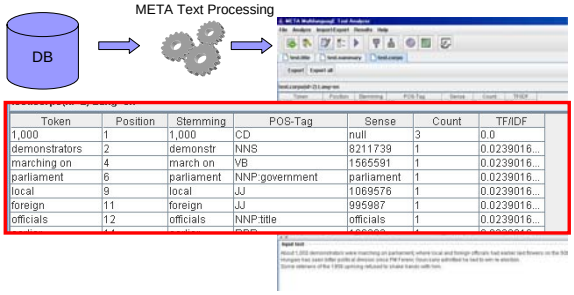
- Automatic language recognition
- Text normalization
- Tokenization
- Stop word elimination
- Stemming
- Text summarization (TF/IDF based)
- POS-tagging
  - Based on ACOPOST T3 (HMM - Hidden Markov Model)
- Entity recognize
- WSD (Word Sense Disambiguation)
  - The WSD algorithm was evaluated by SENSEVAL framework
- TF/IDF parametric on features

Plug-Out

- The Plug-Out is a component that is able to export META output in a different format.
- In order to integrate this component into META it is necessary to:
  - develop a class that implements the interface `plugs.plugOut.PlugOut` and inserts it into package `plugs.plugOut.plugOutImpl.<new_package>`
- The developed Plug-Out is able to export META output in:
  - Database, RDF, XML, TXT
  - different indexing models: Vector Space Model, LSI (Latent Semantic Indexing), …

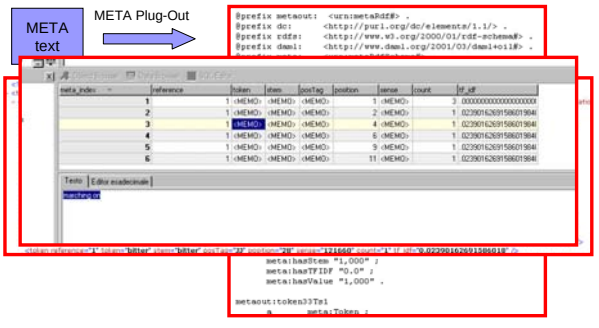
Demonstration – PlugIn

Demonstration – Text Processing



Token	Position	Stemming	POS-Tag	Sense	Count	TF/IDF
1,000	1	1,000	CD	null	3	0.0
demonstrators	2	demonstr	NNS	8211739	1	0.0239016...
marching on	4	march on	VB	1565591	1	0.0239016...
parliament	6	parliament	NNP:government	parliament	1	0.0239016...
local	9	local	JJ	1069576	1	0.0239016...
foreign	11	foreign	JJ	995987	1	0.0239016...
officials	12	officials	NNP:title	officials	1	0.0239016...

Demonstration - PlugOut



Future work

- Improve entity recognition through Machine Learning techniques
  - Currently, META includes an annotation tool for the development of tagged-corpus
- Exploit domain ontologies in the indexing process, in order to map entities to instances available in the ontologies

JIGSAW – WSD algorithm

- JIGSAW is a Word Sense Disambiguation algorithm that uses three different kinds of techniques to disambiguate nouns, verbs, adjectives and adverbs.
- Input:
  - W = {w_1, w_2, …. , w_n} is the set of all words in text which will be disambiguated
  - synVerb is the algorithm for disambiguating verbs
  - synNoun is the algorithm for disambiguating nouns
  - synAdjAdv is a Lesk-based algorithm for disambiguating adjectives and adverbs

JIGSAW – WSD algorithm

```
for each wi ∈ W
      if (wi is a verb) execute synVerb on wi
for each wi ∈ W
      if (wi is a noun) execute synNoun on wi
      else if (wi is a adjective or wi is a adverb)
            execute synAdjAdv su wi
```

- Input:
  - W = {w_1, w_2, …. , w_n} is the set of all words in text which will be disambiguated
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LB (*Lesk-based*) algorithm

- LB algorithm uses WordNet glosses to create a relation between grammatical categories and the context.
- This allows to create semantic relations with words in the context of the word to be disambiguated (*target word*)
- The algorithm measures the similarity between glosses of target words and glosses of context words. This operation is performed in 4 steps:
  - keep *target word* context
  - create the string *(glossContext)* which contains the glosses of words in the context
  - for each meaning of the *target word*, create a string *(glossTarget)* which contains the gloss of the meaning and all words related with *target word* and compute the similarity between *glossContext* and *glossTarget*
  - select the meaning for *target word* which has the max similarity wrt the *glossContext*

LB (*Lesk-based*) algorithm

I play basketball.

contextGloss: partecipate in games or sports We played hockey all afternoon Play cards Pele plays for Brasilian teams in many important matchs act or have an effect in specified way...

targetGloss #1: basketball game a game played on a court by two opposing teams of five players points are scored by throwing the basketball through an elevated horizontal hoop *court game athletic game sports athletic diversion ricreation activity game basketball shot rebound fastbreak dribbling tip-off tap-off basketball play half*

targetGloss #2: an inflated ball used in playing basketball ball game *equipment instrumentality object whole*

Algorithm for disambiguating nouns

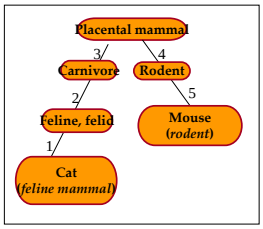
- The algorithm is based on observation that when 2 words have more than one meaning, the common minimal meaning (*Most Specific Subsumer - MSS* - in the WordNet hierarchy) supplies information on the most appropriate meaning for each word.
- Let *W* be the set of nouns in a sentence and *S* the set of all possible meanings, the goal is to define a function φ (between 0 and 1) that computes the probability of the meaning $s_{ij} \in S$ for the word $w_i \in W$.
- For each word w_i in *W*, the algorithm selects the most appropriate meaning $s_{i\,max}$

$$S_{i\max} = \arg\max_{j} \varphi(s_{ij})$$

Algorithm for disambiguating nouns

- In order to compute φ, the MSS, the distance between words and the similarity are exploited.

$$sim_{ab} = \max\left(-\log\left(\frac{N_p}{2D}\right)\right)$$ Leacock-Chodorow



N_p = 5 and
D = 16 (in WordNet 1.7.1)
sim(cat,mouse) =
-*log*(5/32) = 0.806

Most Specific Subsumer
PLACENTAL MAMMAL

Algorithm for disambiguating nouns

Let *d* be the noun to be disambiguated:

```
for j=1,..,|CONTEXT|
        v[j] ← sim(d, w_j) * G(position(d) - position(w_j))
        c[j] ← most_specific_subsumer(d,w_j)
        for k=1,..,|S|
                if (c[j] is hypernym of k-th meaning of d)
                        support[k] ← support[k] + v[j]
        normalization ← normalization + v[j]
end for
posmax ← 1
maxφ ← - MAX_DOUBLE
for k=1,..,|S|
        if (normalization!=0)
                φ[k] ← α * support[k] / normalization + β * R(k)
        else
                φ[k] ← α / |S| + β * R(k)
        if (φ[k] > maxφ)
                maxφ ← φ[k]
                posmax ← k
        end if
end for
best meaning of d is equal to s_posmax ∈ S
```

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        for k=1,..,|S|
```

v[j] ← **sim**(*d*, w_j) * G((position(d) – position(w_j))
•It computes the similarity between j-th noun in W and *d*.
•G is the Gaussian function which takes into account the difference between the noun's positions in the text

```
        if (normalization!=0)
                φ[k] ← α * support[k] / normalization + β * R(k)
        else
                φ[k] ← α / |S| + β * R(k)
        if (φ[k] > maxφ)
                maxφ ← φ[k]
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                        support[k] ← support[k] + v[j]
        normalization ← normalization + v[j]
end for
```

c[j] ← most_specific_subsumer(*d*,w_j)
for k=1,..,|S|
if (c[j] is the hypernym of k-th meaning of *d*)
support[k] ← support[k] + v[j]

In this way we give most importance to the meanings that are hyponym of *Most Specific Subsumer*

```
        end if
end for
best meaning of d is equal to s_posmax ∈ S
```

Algorithm for disambiguating nouns

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                φ[k] ← α * support[k] / normalization + β * R(k)
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                φ[k] ← α / |S| + β * R(k)
        if (φ[k] > maxφ)
end for
best mea
```

R(k)=1-0,8*k/(n-1), where *k* is the rank of the meaning (meanings are ordered according to their frequency of use) and |*S*| is the total number of meanings

Verbs' algorithm

- In order to disambiguate a verb *w*, the algorithm uses the nouns in the context of *w* and the nouns into the glosses and example phrases for *w* that WordNet utilizes to explain the use of the verb *w*
- The algorithm extracts the nouns in the gloss and in the examples for each meaning of *w*. *nouns* (*w*,*k*) is the set of nouns into the description of meaning *k* for *w*. *N* is the set of nouns in the context in which *w* appears

Verbs' algorithm

- Each noun w_i in *N* is compared with each noun w_j in *nouns(w,k)* by computing a similarity value between w_i and w_j

$$sim(w_i, w_j) = \frac{-\ln\left(\frac{N_p}{2D}\right)}{-\ln\left(\frac{1}{2D}\right)}$$

Verbs' algorithm

- The algorithm computes the similarity for each pair of nouns and then, for the *i*-th noun w_i in *N*, computes the following value: $max_i = max\ \{sim(w_i,w_j) \mid j = 1, 2, ..., m\}$, where *m* is |*nouns(w,k)*|.
- The function φ is computed by the following equation:

$$\varphi(v,k) = R(k) * \sum_i \frac{G(d_i) * \max_i}{\sum_i G(d_i)}$$

- *R(k)* is the same function in the nouns' algorithm but has a different coefficient (0.9)

Evaluation

- All algorithms has been evaluated with SENSEVAL framework

Algorithm	Precision
LB (nouns)	0,246
LB (verbs)	0,295
LB (adjectives)	0,403
Verbs	0,405
Nouns	0,319

Evaluation

- All algorithms has been evaluated with SENSEVAL

Algorithm	Precision
LB (nouns)	0,246

JIGSAW precision
sample task = 0,376
all word task = 0.52