## Assigning lexical types using tree kernels

João Ricardo Martins Ferreira da Silva Supervisor: Prof. Dr. António Branco

Faculty of Sciences, University of Lisbon NLX — Natural Language and Speech Group

DELPH-IN Summit Suquamish, WA June 2011

- Introduction
- 2 Dataset
- Classifiers
- 4 Conclusion

- Introduction
- 2 Dataset
- Classifiers
- 4 Conclusion

## Task and approach

Assigning lexical types to (unknown) words

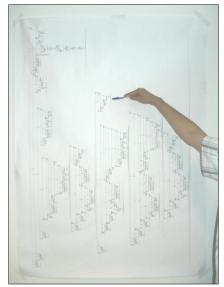
- On-line/on-the-fly
- Machine learning
- Use structured information (viz. constituency and/or dependency)

- Introduction
- 2 Dataset
- Classifiers
- 4 Conclusion

# DeepGramBank

#### Overview

- Produced with LX-Gram (two annotators + adjudicator)
- 5,422 sentences in Portuguese (mostly newspaper excerpts)
- Breakdown of some types:
   129 types of verb
   146 types of noun
   75 types of adjective
   (each is highly skewed)



Representation of "Todos os computadores têm um disco" (arm provided for scale)  $% \begin{center} \end{center} \b$ 

## Extracting vistas

### DeepGramBank to PropBank

#### Ikb2standard

- Runs over data exported by tsdb
- Normalization: X-bar, punctuation, empty nodes, slashes, . . .
- Add information to leafs: Lemma, inflection, lexical type, . . .
- Other fixes

NP-SJ-ARG1 VP

ART-SP N V NP-DO-ARG2

O sol aqueceu ART-SP N

V:AQUECER:ppi-3s:0 o pelotão
verb-external-anticausative-lex

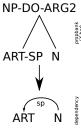
To see more, check the Treebank Searcher at: http://lxcenter.di.fc.ul.pt

## Extracting vistas

#### PropBank to DepBank

### propbank2dependency

- Runs over the PropBank
- Output:
  - Dependency triples and/or CoNLL format
- NB: not implemented by me



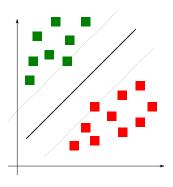
Dependency extraction (general rule)

- Introduction
- 2 Dataset
- Classifiers
- 4 Conclusion

# Support vector machine (SVM)

Overview

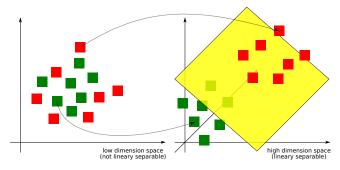
- Machine-learning algorithm
- Linear binary classifier
- Instances as vectors in  $\mathbb{R}^n$
- Learns separating hyperplane (with maximal margin)
- Uses the dot product (to measure vector similarity)



# Support vector machine (SVM)

#### Kernel trick

- Kernel function replaces dot product (if certain conditions are met)
- Feature vectors are not explicitly generated



# SVM with tree kernels (SVM-TK)

### Representing parse trees as feature vectors

Kernel function:
 Number of subtrees in common between two trees

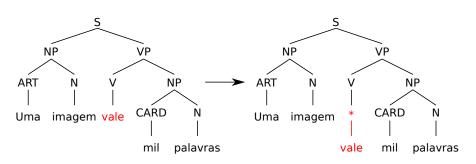
#### Software

- Tree kernel by Alessandro Moschitti (SVM-TK)
   http://disi.unitn.it/moschitti/Tree-Kernel.htm
- SVM by Thorsten Joachims (SVM-Light) http://svmlight.joachims.org

### Features for tree kernel

TreeBank/PropBank

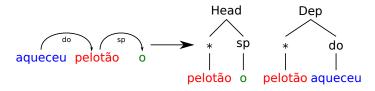
Take whole parse tree, mark pre-terminal node of target



## Features for tree kernel

DepBank

Take immediate dependents and head of target

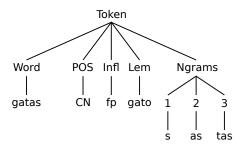


NB: In SVM-TK, an instance can have multiple vectors and tress

### Features for tree kernel

Token

Word form, POS, lemma, n-grams, etc.



### OvA and OvO

## Voting strategy?

One-vs-all (OvA)

- One per lexical type i.e. *n* classifiers
- Choose best vote

One-vs-one (OvO)

- One per each pair of types i.e.  $n \cdot (n-1)/2$  classifiers
- Choose most voted

### **Evaluation**

10-fold cross-evaluation for top-10 verbal types (3188 instances: 1107, 434, 333, . . . , 140)

Sequential classifiers

TnT 92.16%

Pointwise classifiers

(SVM-TK, OvO voting, over gold data)

treebank 86.98% propbank 89.05% depbank 92.28%

- Introduction
- 2 Dataset
- Classifiers
- 4 Conclusion

# Closing remarks

- Other experiments that did not fare well:
   C&C, TiMBL, SMOTE, ...
- Trees for SVM-TK are a very flexible approach (one can encode a great variety of features)
- SVM-TK vs. TnT (results shown for SVM-TK are over gold data)
- Unbalanced classes
- Data sparseness issues

