



# POS Tagging <sup>1</sup>

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- POS Tagging
- Rule-based taggers
- Statistical taggers
- Hybrid approaches

# POS Tagging <sub>2</sub>

Words taken isolatedly are ambiguous regarding its POS

|    |      |     |    |        |      |    |
|----|------|-----|----|--------|------|----|
| Yo | bajo | con | el | hombre | bajo | a  |
| PP | VM   | SP  | TD | NC     | VM   | NC |
|    | VM   |     |    |        | VM   | SP |
|    | AQ   |     |    |        | AQ   |    |
|    | NC   |     |    |        | NC   |    |
|    | SP   |     |    |        | SP   |    |

|       |    |      |      |    |          |    |
|-------|----|------|------|----|----------|----|
| tocar | el | bajo | bajo | la | escalera | .  |
| VM    | TD | VM   | VM   | TD | NC       | FP |
| VM    |    | VM   | VM   | NC |          |    |
|       |    | AQ   | AQ   | PP |          |    |
|       |    | NC   | NC   |    |          |    |
|       |    | SP   | SP   |    |          |    |

# POS Tagging <sub>3</sub>

Most of words have a unique POS within a context

Yo bajo con el hombre bajo a

|    |           |    |    |    |           |           |
|----|-----------|----|----|----|-----------|-----------|
| PP | <b>VM</b> | SP | TD | NC | <b>VM</b> | <b>NC</b> |
|    | VM        |    |    |    | VM        | SP        |
|    | AQ        |    |    |    | <b>AQ</b> |           |
|    | NC        |    |    |    | NC        |           |
|    | SP        |    |    |    | SP        |           |

tocar el bajo bajo la escalera .

|    |    |           |           |           |    |    |
|----|----|-----------|-----------|-----------|----|----|
| VM | TD | VM        | VM        | <b>TD</b> | NC | FP |
| VM |    | VM        | VM        | NC        |    |    |
|    |    | AQ        | AQ        | PP        |    |    |
|    |    | <b>NC</b> | NC        |           |    |    |
|    |    | SP        | <b>SP</b> |           |    |    |

## Pos taggers

The goal of a POS tagger is to assign each word the most likely within a context

- Rule-based
- Statistical
- Hybrid

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$W$  =  $w_1 w_2 \dots w_n$  sequence of words

$T$  =  $t_1 t_2 \dots t_n$  sequence of POS tags

For each word  $w_i$  only some of the tags can be assigned (except the unknown words). We can get them from a lexicon or a morphological analyzer.

Tagset.

Open vs closed categories

$$f : W \rightarrow T = f(W)$$

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## Rule-based taggers

- Knowledge-driven taggers
- Usually rules built manually
- Limited amount of rules ( $\approx 1000$ )
- LM and smoothing explicitly defined.

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## Rule-based taggers

- + Linguistically motivated rules
- + High precision
  - + ej. EngCG 99.5%
- High development cost
- Not transportable
- Time cost of tagging

- TAGGIT, Green, Rubin, 1971
- TOSCA, Oosdijk, 1991
- Constraint Grammars, EngCG, Voutilainen, 1994, Karlsson et al, 1995
- AMBILIC, de Yzaguirre et al, 2000

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## Constraint Grammars CG

- A CG consists of a sequence of subgrammars each one consisting of a set of restrictions (constraints) which set context conditions
  - ej. (@w =0 VFIN (-1 TO))
    - Discards POS VFIN when the previous word is “to”
- ENGCG
  - ENGTWOL
  - Reductionist POS tagging
    - 1,100 constraints
    - 93-97% of the words are correctly disambiguated
    - 99.7% accuracy
    - Heuristic rules can be applied over the rest
      - 2-3% residual ambiguity with 99.6% precision
  - CG syntactic



## Statistical POS taggers

- LM and smoothing automatically learned from tagged corpora (supervised learning).
- Data-driven taggers
- Statistical inference
- Techniques coming from speech processing

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## Statistical POS taggers

- + Well founded theoretical framework
- + Simple models.
- + Acceptable precision
  - + > 97%
- + Language independent
- Learning the model
  - Sparseness
- less precision

- CLAWS, Garside et al, 1987
- De Rose, 1988
- Church, 1988
- Cutting et al, 1992
- Merialdo, 1994

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## Statistical POS taggers

- N-gram
  - smoothing
  - interpolation
- HMM
- ML
  - Supervised learning
    - MLE
  - Semi-supervised
    - Forward-Backward, Baum-Welch (EM Expectation Maximization)

Charniak, 1993  
Jelinek, 1998  
Manning, Schütze, 1999

3-gram tagger

$$\arg \max_{t_1 \cdots t_n} P(t_1, \dots, t_n \mid w_1, \dots, w_n) \approx$$

$$\prod_{k=1}^n P(t_k \mid t_{k-2}, t_{k-1}) \cdot P(w_k \mid t_k)$$

Contextual  
probability  
(trigrams)

Lexical  
Probability

## HMM tagger

- Hidden States associated to n-grams
- Transition probabilities restricted to valid transitions:
  - \*BC -> BC\*
- Emission probabilities restricted by lexicons

## Hybrid systems

- Transformation-based, error-driven
  - Based on rules automatically acquired

→ Brill, 1995  
Roche, Schabes, 1995

- Maximum Entropy
  - Combination of several knowledge sources
  - No independence is assumed
  - A high number of parameters is allowed (e.g. lexical features)

→ Ratnaparkhi, 1998,  
Rosenfeld, 1994  
Ristad, 1997


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## Brill's system

- Based on transformation rules that correct errors produced by an initial HMM tagger
- rule
  - change label A into label B when ...
  - Each rule corresponds to the instantiation of a template
- templates
  - The previous (following) word is tagged with Z
  - One of the two previous (following) words is tagged with Z
  - The previous word is tagged with Z and the following with W
  - ...
- Learning of the variables A,B,Z,W through an iterative process That choose at each iteration the rule (the instantiation) correcting more errors.

## Other complex systems

- Decision trees
  - Supervised learning
  - ej. TreeTagger

Black, Magerman, 1992  
Magerman 1996  
Màrquez, 1999  
Màrquez, Rodríguez, 1997
- Case-based, Memory-based Learning
  - IGTre

TiMBL  
Daelemans et al, 1996
- Relaxation labelling
  - Statistical and linguistic constraints
    - ej. RELAX

Padrò, 1997



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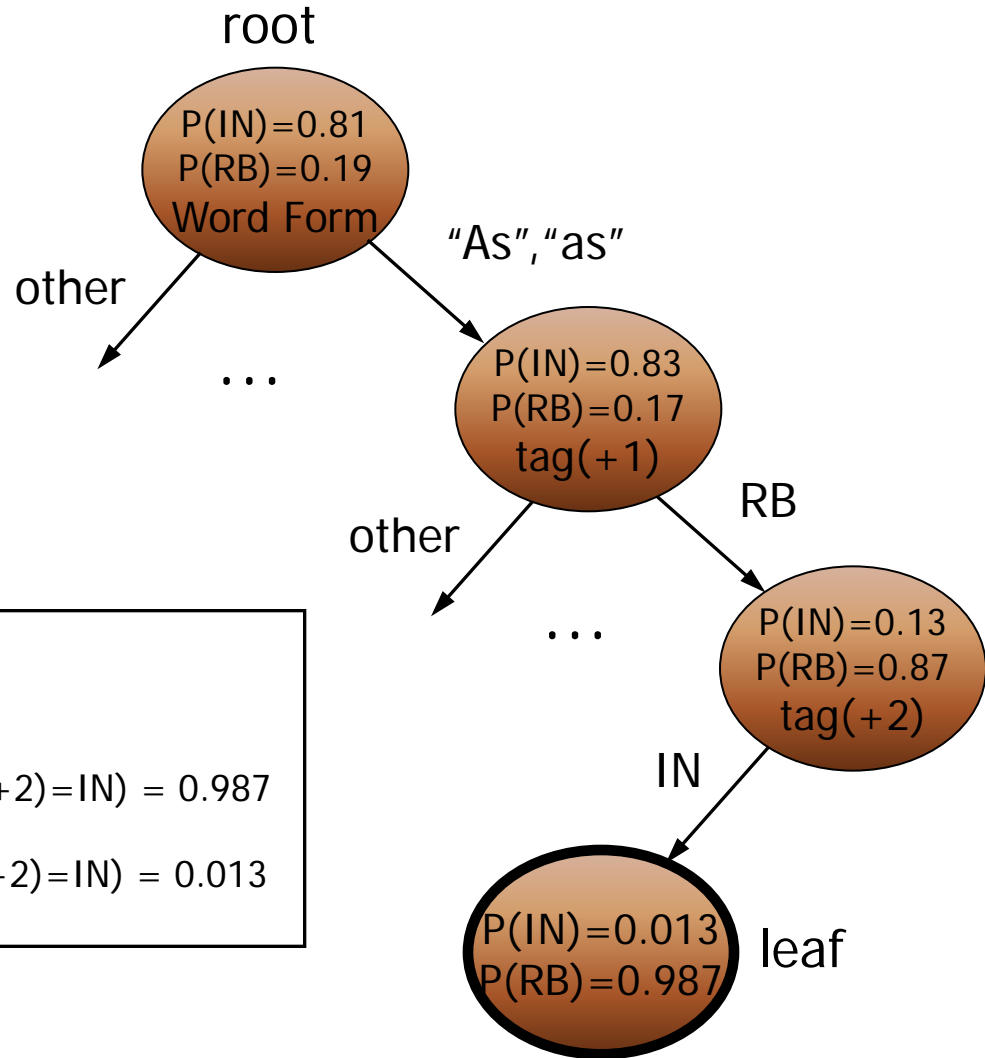
## Màrquez's Tree-tagger

IN/RB ambiguity  
IN (preposition)  
RB (adverb)

statistical interpretation :

$$\hat{P}(RB \mid \text{word}="A/as" \ \& \ \text{tag}(+1)=RB \ \& \ \text{tag}(+2)=IN) = 0.987$$

$$\hat{P}(IN \mid \text{word}="A/as" \ \& \ \text{tag}(+1)=RB \ \& \ \text{tag}(+2)=IN) = 0.013$$



# POS Tagging <sup>17</sup>

## Combining taggers

- Combination of LM in a tagger

- STT+
- RELAX

Màrquez, Rodríguez, 1998  
Màrquez, 1999  
Padrò, 1997

- Combination of taggers through  
votation

- bootstrapping

Màrquez et al, 1998

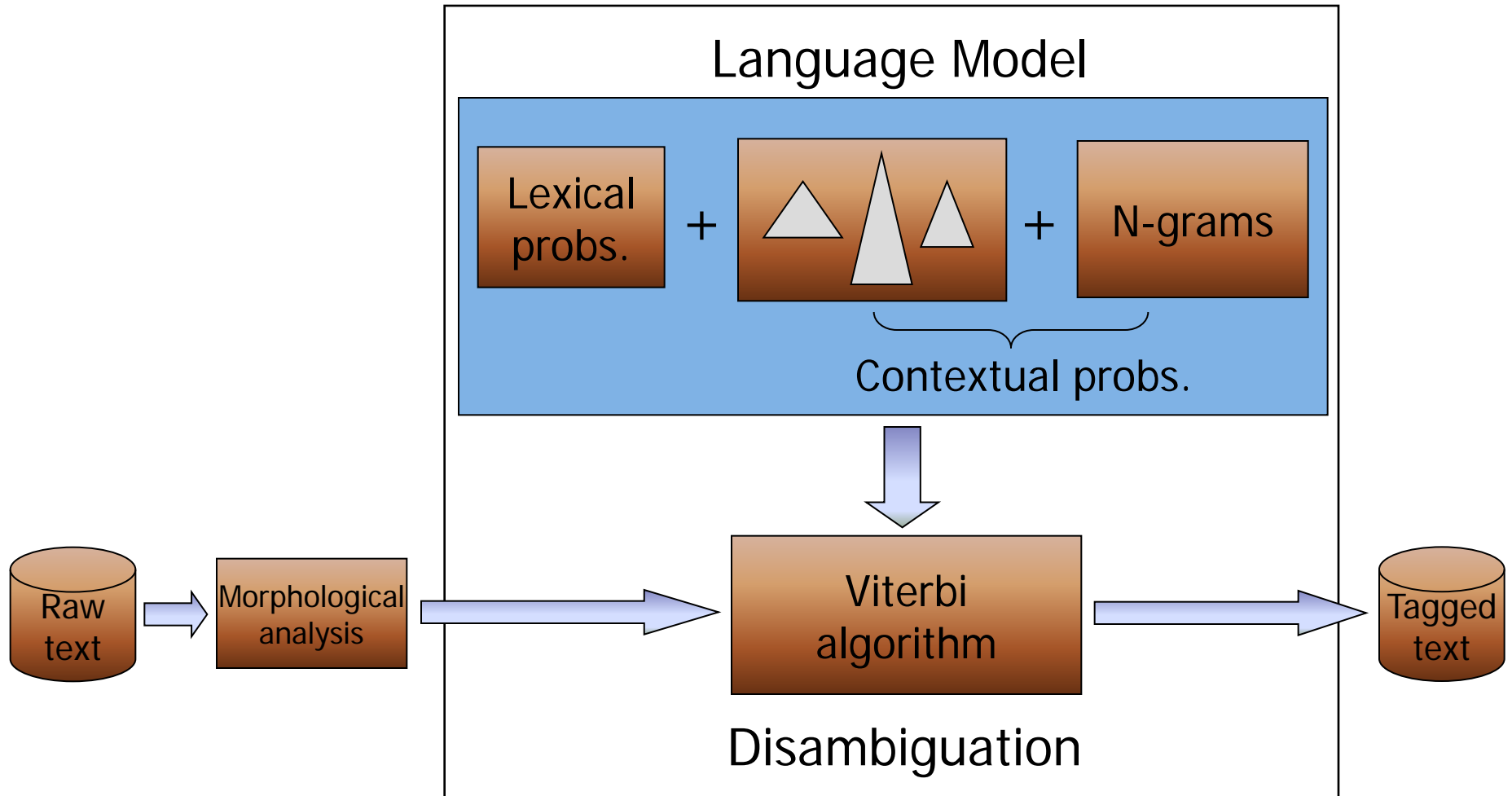
- Combinación of classifiers

- bagging (Breiman, 1996)
- boosting (Freund, Schapire, 1996)

Brill, Wu, 1998  
Màrquez et al, 1999  
Abney et al, 1999

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Màrquez's STT+



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Padró's Relax

