Learning to Assign Grammatical Function Labels

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Outline

1. Motivation
2. Learning Function Labels
3. Evaluation

Outline

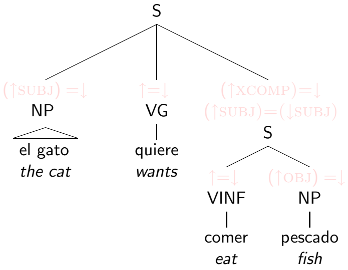
GramLab project

- Treebank-based Multilingual Lexical Functional Grammar induction for English, Chinese, Japanese, Arabic, German, French and **Spanish**
- Leverage successful data-driven approaches to parsing
- Core idea: automatic annotation of constituent trees (c-structures) to obtain LFG f-structures

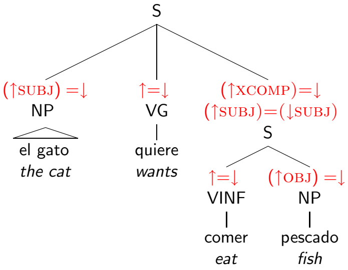
What are f-structures

- F-structures encode grammatical relations such as Subject, Object, Sentential Complement etc.
- Less interlanguage variability than c-structure
- Explicit representation of
  - control and raising constructions
  - pro-drop
  - long distance dependencies
- Syntactic interface to predicate structure and semantics

C-structure to f-structure mapping



C-structure to f-structure mapping



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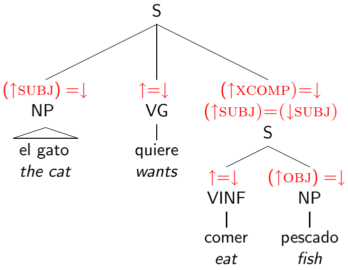


$$\left[\begin{array}{ll} \text{SUBJ} & \left[\begin{array}{ll}\text{PRED} & \text{`gato'}\end{array}\right] \\ \text{PRED} & \text{`querer}\langle\text{SUBJ,XCOMP}\rangle\text{'} \\ \text{XCOMP} & \left[\begin{array}{ll} \text{SUBJ} & [\ \ ] \\ \text{PRED} & \text{`comer}\langle\text{SUBJ,OBJ}\rangle\text{'} \\ \text{OBJ} & \left[\begin{array}{ll}\text{PRED} & \text{`pescado'}\end{array}\right] \end{array}\right] \end{array}\right]$$

Automatic functional annotation

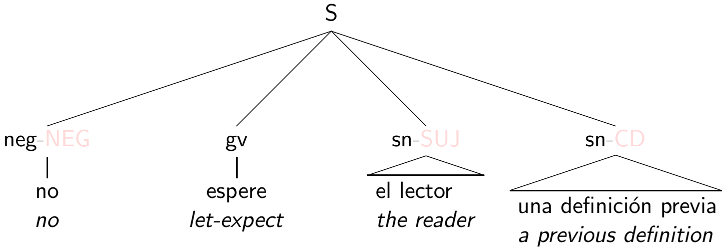
Initial work done on English Penn II Treebank

- Extract most common CFG rules from treebank
- Write annotation rules based on node context:
  - Node category
  - Node's mother's category
  - Position relative to head: head / left / right
- Apply to treebank trees or to parser output
- Collect and solve functional equations

Issues with Spanish

Difficulties in applying this approach to Spanish and Cast3LB

- flexible order of sentence constituents
- information encoded in terms of tree configurations in Penn, but in function tags in Cast3LB



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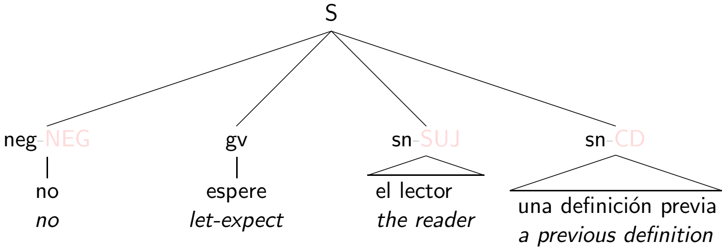

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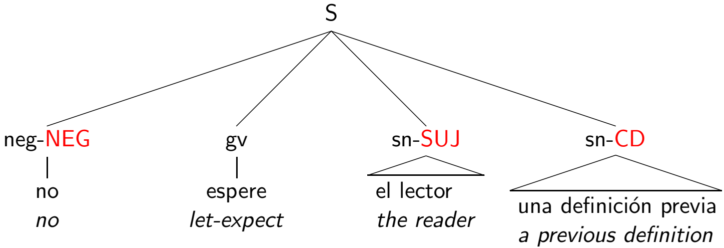

Arguments vs adjuncts

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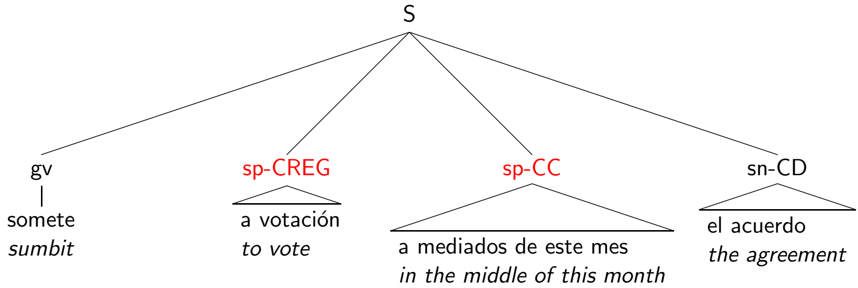

Previous work on automatic functional annotation for Cast3LB

- O'Donovan et al. 2005 decided to rely on Cast3LB functional tags.
- Bikel's parser trained to output function tags by treating compound labels as atomic
- Reasonable results, but maybe we can do better.

Outline

Adding function tags to parse trees

- Can better results be obtained if function tags are added in a postprocess? Advantages:
  - Smaller category label set resulting in reduction of data sparseness
  - Control over learning algorithm and feature set used
- Previous work, Penn Treebank, Charniak's and Collins's parsers
  - Blaheta and Charniak, Assigning function tags to parsed text, *NAACL 2000*
  - Jijkoun and de Rijke, Enriching the output of a parser using memory-based learning, *ACL 2004*

Machine-learning approach

- Adding function tags as a classification task
  - Classes: corresponding to the 24 Cast3LB tags plus the null class for untagged nodes
  - Candidate nodes: sisters to nodes labelled **gv** (Verb Group), **infinitiu** (Infinitive) and **gerundi** (Gerund)
- Experiments with two algorithms: memory-based (Timbl) and Support Vector Machines (R interface to LIBSVM)

Node Features

Nine features: configurational, morphological and lexical information about candidate node

- Position relative to head
- Node head lemma
- Alternative head lemma
- Node head POS
- Node label
- Is definite NP
- Is NP and agrees with head verb
- No. of terminal descendents
- Head lemma +human

Local and Context Features

Four **local** features (head verb and parent information)

- Head verb lemma,
- Head verb person,
- Head verb number,
- Parent node label

8×4 **context** features (= node features of two previous and two following nodes in linear order)

For SVM, feature values of frequency < 20 were replaced with a dummy value

Outline

Evaluation metrics

- Accuracy: proportion of **candidate** nodes that were assigned correct label
- Precision, Recall and F-score defined on sets of tuples: $\langle GF, i, j \rangle$, where
  - GF – grammatical function
  - $\langle w_i, \ldots, w_j \rangle$ – subsequence of tokens spanned by **function-tagged node**

Example:

$[_{NEG}$ No $]$ espere $[_{SUJ}$ el lector $]$ $[_{CD}$ una definición previa $]$

no let-expect the reader a previous definition

$\{\langle NEG, 1, 1 \rangle, \langle SUJ, 3, 4 \rangle, \langle CD, 5, 7 \rangle\}$

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  no *let-expect* *the reader* *a previous definition*

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Results for gold-standard trees

	Accuracy	Precision	Recall	F-score
Timbl	87.55	88.06	87.66	87.86
SVM	**87.64**	88.15	87.75	**87.95**

Results for parser output

Parser performance

	Labelled Bracket P	Labelled Bracket R	F
All	79.52	79.10	79.30
< 40	82.09	81.49	81.78

Labelling

	Precision	Recall	F-score
Baseline	51.97	51.68	51.82
Timbl	56.54	56.57	56.55
SVM	56.91	56.78	**56.84**

Baseline – parser treating compound category-function labels as atomic.

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Parse quality influence

- Features used refer not only to candidate node but to mother and sister nodes
- Small constituency misconfiguration may influence classification decision of several nodes
- But, small improvements in parse quality may give greater improvements in function tag assigment :-)
- In a recent experiment:
  - Evalb f-score went up to **80.68 (+1.38)**.
  - Labelling f-score went up to **59.6 (+2.76)**.

F-Structure evaluation

Cast3LB tags to LFG functions is not a one-to-one mapping, eg.:

- CD $\rightarrow$ {OBJ, COMP, XCOMP}
- {CC, MOD, ET} $\rightarrow$ ADJUNCT

F-structure evaluation less sensitive to slightly incorrect parse trees.

Results for parser output with SVM tags – 100 gold standard f-structure-derived dependencies

Precision	Recall	F-score
76.6	75.58	76.09

Error analysis

Simplified confusion matrix for SVM predictions on gold trees

	SUJ	**CD**	**CI**	**CC**	**CREG**	**ATR**
SUJ	464	29	1	10	0	0
CD	29	410	5	22	4	1
CI	0	1	44	8	0	0
CC	5	15	12	539	29	5
CREG	0	0	0	8	39	0
ATR	5	0	0	3	0	137

Subject vs Direct Object

- Over 55% of mistakenly tagging CD as SUJ are daughters of relative clause nodes (S.R), against 16% of all candidate nodes.
- Subject - Direct Object ambiguity in relative clauses

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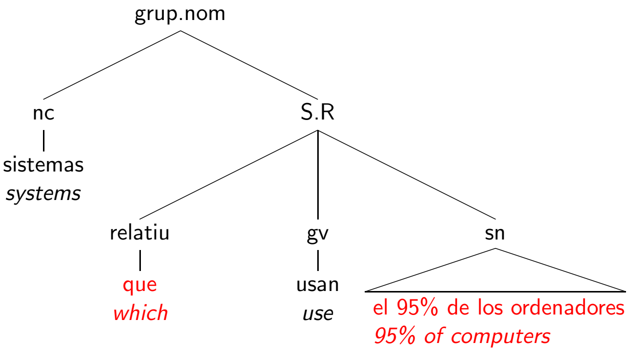

Adjunct vs Prepositional Object

In addition to cases of ambiguity

- Training set too small to learn many lexical dependencies
- Inherently fuzzy distinction
- Subtle semantic distinctions and/or a degree of arbitrariness
- Compare
  - Llegar [$_{CREG}$ a un acuerdo]
    arrive *at an agreement*
  - Llegar [$_{CC}$ a Estados Unidos]
    arrive *in the US*

Further work

- Unbounded dependencies between argument and verb
- Inter-annotator agreement for function would give us an idea of where the upper bound is.
- What to do about arbitary distinctions and inconsistencies in human annotation?