TEXTUAL ENTAILMENT

Lliçons sobre un desastre anunciat

Horacio Rodríguez
Nota previa

• Esta charla está basada en un curso de doctorado con el mismo título (pero sin coda) impartido por Horacio en la Universidad de Sevilla en mayo de 2008.

• El curso inicial ha sufrido un proceso (noisy channel model) de summarization, deformalization y se le ha añadido una moraleja final
Guión

- Textual Entailment Introduction
- RTE in PASCAL
- Techniques
- Systems
- UPC in RTE
  - l'esperança
  - El desastre
  - les lliçons
• **Textual Entailment Community:**
  – El **RTE Resource Pool** se puede acceder desde:
  – El **Textual Entailment Subzone** se puede acceder desde:

• **Textual Entailment Resource Pool**
  – Textual Entailment Resource Pool

• **PASCAL Challenges**
  – RTE-1
  – RTE-2
  – RTE-3

• **Recognizing Textual Entailment (RTE)** ha sido propuesto recientemente como una tarea genérica que captura las necesidades de inferencia semántica en muchas aplicaciones de procesamiento del lenguaje natural.

• **TAC 2008 challenge**
Qué leer

- Workshops
  - ACL 2005 Workshop on Empirical Modeling of Semantic Equivalence
  - First PASCAL Recognising Textual Entailment Challenge (RTE-1), 2001
  - Second PASCAL Recognising Textual Entailment Challenge (RTE-2), 2002
  - Third PASCAL Recognising Textual Entailment Challenge (RTE-3), 2003
  - Answer Validation Exercise at CLEF 2006 (AVE 2006)
  - Answer Validation Exercise at CLEF 2007 (AVE 2007)
Qué leer

• **Thesis**
  – Oren Glickman (PHD, 2006)
  – Idan Szpecktor (MSC, 2005)
  – Regina Barzilay (PHD, 2004)

• **Other material**
  – presentations of RTE 2 online
    • http://videolectures.net/pcw06_rus_trlsa/
Textual Entailment

- **Textual entailment recognition** is the task of deciding, given two text fragments, whether the meaning of one text is entailed (can be inferred) from another text. This task captures generically a broad range of inferences that are relevant for multiple applications.

- For example, a **QA** system has to identify texts that entail the expected answer. Given the question "Who killed Kennedy?", the text "the assassination of Kennedy by Oswald" entails the expected answer form "Oswald killed Kennedy".

- In **IR** the concept denoted by a query expression should be entailed from relevant retrieved documents.
Textual Entailment Applications

- Question-Answering
- Information Extraction
- Information Retrieval
- Multi-Document Summarization
- Named Entity Recognition
- Temporal and Spatial Normalization
- Semantic Parsing
- Natural Language Generation
Textual Entailment

- **Equivalence (Paraphrase)**: \( expr1 \Leftrightarrow expr2 \)
- **Entailment**: \( expr1 \Rightarrow expr2 \) – more general

- Directional relation between two text fragments: *Text* (*t*) and *Hypothesis* (*h*):

\[
\text{t entails h (t} \Rightarrow \text{h) if, typically, a human reading t would infer that h is most likely true}"
\]
Textual Entailment examples

**TEXT**
- Eyeing the huge market potential, currently led by Google, Yahoo took over search company Overture Services Inc last year.
- Microsoft's rival Sun Microsystems Inc. bought Star Office last month and plans to boost its development as a Web-based device running over the Net on personal computers and Internet appliances.
- The National Institute for Psychobiology in Israel was established in May 1971 as the Israel Center for Psychobiology by Prof. Joel.

**HYPOTHESIS**
- Yahoo bought Overture.
- Microsoft bought Star Office.
- Israel was established in May 1971.

**ENTAILMENT**
- TRUE
- FALSE
- FALSE
### Textual Entailment examples

<table>
<thead>
<tr>
<th><strong>TEXT</strong></th>
<th><strong>HYPOTHESIS</strong></th>
<th><strong>ENTAILMENT</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>Since its formation in 1948, Israel fought many wars with neighboring Arab countries.</td>
<td>Israel was established in May 1948.</td>
<td>TRUE</td>
</tr>
<tr>
<td>Putting hoods over prisoners heads was also now banned, he said.</td>
<td>Hoods will no longer be used to blindfold Iraqi prisoners.</td>
<td>FALSE</td>
</tr>
<tr>
<td>The market value of u.s. overseas assets exceeds their book value.</td>
<td>The market value of u.s. overseas assets equals their book value.</td>
<td>FALSE</td>
</tr>
<tr>
<td>First Author (Group)</td>
<td>accuracy</td>
<td>cws</td>
</tr>
<tr>
<td>-----------------------------------</td>
<td>----------</td>
<td>-------</td>
</tr>
<tr>
<td>Akhmatova (Macquarie)</td>
<td>0.519</td>
<td>0.507</td>
</tr>
<tr>
<td>Andreevskai (Concordia)</td>
<td>0.519</td>
<td>0.515</td>
</tr>
<tr>
<td>Bayer (MITRE)</td>
<td>0.586</td>
<td>0.617</td>
</tr>
<tr>
<td></td>
<td>0.516</td>
<td>0.503</td>
</tr>
<tr>
<td>Bos (Edinburgh &amp; Leeds)</td>
<td>0.563</td>
<td>0.593</td>
</tr>
<tr>
<td></td>
<td>0.555</td>
<td>0.586</td>
</tr>
<tr>
<td>Delmonte (Venice &amp; ist)</td>
<td>0.606</td>
<td>0.664</td>
</tr>
<tr>
<td>Fowler (LCC)</td>
<td>0.551</td>
<td>0.56</td>
</tr>
<tr>
<td>Glickman (Bar Ilan)</td>
<td>0.586</td>
<td>0.572</td>
</tr>
<tr>
<td></td>
<td>0.53</td>
<td>0.535</td>
</tr>
<tr>
<td>Herrera (UNED)</td>
<td>0.566</td>
<td>0.575</td>
</tr>
<tr>
<td></td>
<td>0.558</td>
<td>0.571</td>
</tr>
<tr>
<td>Jijkoun (Amsterdam)</td>
<td>0.552</td>
<td>0.559</td>
</tr>
<tr>
<td></td>
<td>0.536</td>
<td>0.553</td>
</tr>
<tr>
<td>Kouylekov (ist)</td>
<td>0.559</td>
<td>0.607</td>
</tr>
<tr>
<td></td>
<td>0.559</td>
<td>0.585</td>
</tr>
<tr>
<td>Newman (Dublin)</td>
<td>0.563</td>
<td>0.592</td>
</tr>
<tr>
<td></td>
<td>0.565</td>
<td>0.6</td>
</tr>
<tr>
<td>Perez (Madrid)</td>
<td>0.495</td>
<td>0.517</td>
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<tr>
<td></td>
<td>0.7</td>
<td>0.782</td>
</tr>
<tr>
<td>Punyakanok (UIUC)</td>
<td>0.561</td>
<td>0.569</td>
</tr>
<tr>
<td>Raina (Stanford)</td>
<td>0.563</td>
<td>0.621</td>
</tr>
<tr>
<td></td>
<td>0.552</td>
<td>0.686</td>
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<tr>
<td>Wu (HKUST)</td>
<td>0.512</td>
<td>0.55</td>
</tr>
<tr>
<td></td>
<td>0.505</td>
<td>0.536</td>
</tr>
<tr>
<td>Zanzotto (Rome-Milan)</td>
<td>0.524</td>
<td>0.557</td>
</tr>
<tr>
<td></td>
<td>0.518</td>
<td>0.559</td>
</tr>
</tbody>
</table>
## Results RTE2

<table>
<thead>
<tr>
<th>First Author (Group)</th>
<th>Accuracy</th>
<th>Average Precision</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hickl (LCC)</td>
<td>75.4%</td>
<td>80.8%</td>
</tr>
<tr>
<td>Tatu (LCC)</td>
<td>73.8%</td>
<td>71.3%</td>
</tr>
<tr>
<td>Zanzotto (Milan &amp; Rome)</td>
<td>63.9%</td>
<td>64.4%</td>
</tr>
<tr>
<td>Adams (Dallas)</td>
<td>62.6%</td>
<td>62.8%</td>
</tr>
<tr>
<td>Bos (Rome &amp; Leeds)</td>
<td>61.6%</td>
<td>66.9%</td>
</tr>
<tr>
<td>11 groups</td>
<td>58.1%-60.5%</td>
<td><strong>Average: 60%</strong></td>
</tr>
<tr>
<td>Median: 59%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>7 groups</td>
<td>52.9%-55.6%</td>
<td></td>
</tr>
</tbody>
</table>
Analysis

- **For the first time:** deep methods (semantic/ syntactic/ logical) clearly outperform shallow methods (lexical/n-gram)
- Still, most systems based on deep analysis did not score significantly better than the lexical baseline
Why?

- System reports point at two directions:
  - Lack of knowledge (syntactic transformation rules, paraphrases, lexical relations, etc.)
  - Lack of training data
- It seems that systems that coped better with these issues performed best:
  - Hickl et al. - acquisition of large entailment corpora for training
  - Tatu et al. – large knowledge bases (linguistic and world knowledge)
Methods and Approaches

• Word overlap
  – lexical, syntactic, and semantic

• Logical approaches
  – Raina et al, 2005
  – Bos et al, 2005, 2006
  – Moldovan et al, 2003

• Graph matching approaches
  – Haghighi et al, 2005
  – de Salvo et al, 2005
  – de Marneffe et al, 2005, 2006

• Paraphrases and Entailment Rules
  – Moldovan and Rus, 2001
  – Lin and Pantel, 2001 QA
  – Shinyama et al, 2002 IE
Methods and Approaches

- Measure similarity between $t$ and $h$ (*coverage of $h$ by $t$)*:
  - Lexical overlap (unigram, N-gram, subsequence)
  - Average Matched Word Displacement
  - Lexical substitution (WordNet, statistical)
  - Syntactic matching/transformations
  - Lexical-syntactic variations ("paraphrases")
  - Semantic role labeling and matching
  - Global similarity parameters (e.g. negation, modality)

- Sentence Alignment
  - Exhaustive Sentence Alignment
    - *parallel corpora*
    - *comparable corpora*
  - Web-based Sentence Alignment

- Cross-pair similarity
- Detect mismatch (for non-entailment)
- Logical inference
Methods and Approaches

- Thesaurus-based Term Expansion
  - WN
- Distributional Similarity
  - Dekang Lin data
  - VerbOcean
- BLEU (BiLingual Evaluation Understudy)
- ROUGE (Recall-Oriented Understudy for Gisting Evaluation)
- classical statistical machine translation model
  - giza++ software (Och and Ney, 2003)
Dominant approach: Supervised Learning

- Features model both similarity and mismatch
- Train on development set and auxiliary $t$-$h$ corpora
<table>
<thead>
<tr>
<th>Name</th>
<th>Institution</th>
<th>Location</th>
</tr>
</thead>
<tbody>
<tr>
<td>Burchart, Frank</td>
<td>Saarbrucken</td>
<td>6262</td>
</tr>
<tr>
<td>Bobrow</td>
<td>Xerox</td>
<td>5150</td>
</tr>
<tr>
<td>Tatu et al</td>
<td>LCC</td>
<td>7225</td>
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<tr>
<td>Wang, Newman</td>
<td>Dublin</td>
<td>6687</td>
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<tr>
<td>Malakasiotis</td>
<td>Athens</td>
<td>6175</td>
</tr>
<tr>
<td>Delmonte et al</td>
<td>Venezia</td>
<td>5875</td>
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<tr>
<td>Clark</td>
<td>Boeing</td>
<td>5088</td>
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<tr>
<td>Ferrés, Rodríguez</td>
<td>UPC</td>
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</tr>
<tr>
<td>Ferrández et al</td>
<td>Alicante</td>
<td>6563</td>
</tr>
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<td>Zanzotto et al</td>
<td>Roma</td>
<td>6675</td>
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<td>Montejo-Ráez</td>
<td>Jaén</td>
<td>6038</td>
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<td>Marsi et al</td>
<td>Tilburg</td>
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<tr>
<td>Rodrigo et al</td>
<td>UNED</td>
<td>6312</td>
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<td>Settembre</td>
<td>Buffalo</td>
<td>6262</td>
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<tr>
<td>Blake</td>
<td>North Carolina</td>
<td>6587</td>
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<td>Roth</td>
<td>Illinois</td>
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<tr>
<td>Burek</td>
<td>Open U. UK</td>
<td>5500</td>
</tr>
<tr>
<td>Adams</td>
<td>Texas</td>
<td>6700</td>
</tr>
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<td>Iftene</td>
<td>Al.I.Cuza</td>
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<td>Bar-Haim</td>
<td>Bar Ilan</td>
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<td>Harmeling</td>
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<tr>
<td>Li</td>
<td>Georgia</td>
<td>6488</td>
</tr>
<tr>
<td>Chambers</td>
<td>Stanford</td>
<td>6362</td>
</tr>
<tr>
<td>Hickl, et al</td>
<td>LCC</td>
<td>8000</td>
</tr>
</tbody>
</table>

2007
PASCAL RTE-3

- Move toward deep approaches, with a general consolidation of approaches based on the syntactic structure of T and H.
- There is an evident increase of systems using some form of logical inferences (at least seven systems).
- A more extensive and fine grained use of specific semantic phenomena is also emerging.
  - As an example, Tatu and Moldovan carry on a sophisticated analysis of named entities
- Relation extraction
- Machine learning using lexical-syntactic features and transformation-based approaches on dependency representations
- WordNet and DIRT
PASCAL RTE-3

- **Verb-oriented** resources are also largely present in several systems
  - Framenet, Verbnet, VerbOcean and Propbank
- **Anaphora resolution**
- **New principled scenarios for RTE**
  - Hickl’s commitment-based approach
  - Bar Haim’s proof system
  - Harmeling’s probabilistic model
  - Standford’s use of Natural Logic
PASCAL RTE-3

Problems, Clark et al, 2007

Diagram showing the frequency of different types of logical errors in natural language processing:
- Syntactic matching
- Synonyms
- Hyponyms
- Noun redundancy
- Noun-Verb Relns
- Compound nouns
- Definitions
- World K: General
- World K: Core
- World K: Scriptal
- Implicative Verbs
- Meyonymy/Transfer
- Idioms/Protocol/Slang
PASCAL RTE-3

- Resources
  - WordNet
  - Extended WordNet
  - WordNet3.0
  - TimeML
  - IKRIS
  - DIRT paraphrase database
  - FrameNet
  - VerbNet
  - VerbOcean
  - Component Library (U. Texas)
  - OpenCyC
  - SUMO
  - Tuple Database (Boeing)
  - Stanford’s additions to Wn
Recursos

ACLWiki Textual Entailment Resources

• **Corpora**
  - Manually Word Aligned RTE 2006 Data Sets. Provided by the Natural Language Processing Group, Microsoft Research.
  - Microsoft Research Paraphrase Corpus.

• **Knowledge Collections**
  - DIRT Paraphrase Collection
  - FrameNet
  - Sekine's Paraphrase Database
  - TEASE
  - VerbOcean
  - WordNet
Recursos

ACLWiki Textual Entailment Resources

• **Tools**
  – Parsers
    • C&C parser for Combinatory Categorial Grammar
    • Minipar
    • Shalmaneser
    • ASSERT
    • CCG Semantic Role Labeller
    • CCG Shallow Parser
  – Entity Recognition Tools
    • CCG Named Entity Tagger
    • CCG Multi-lingual Named Entity Discovery Tool
  – Corpus Readers
    • NLTK provides a corpus reader for the data from RTE Challenges 1, 2, and 3
Recursos

Other resources

- **WN**
  - Extended WN
  - WN 3.0
  - WordNet::SenseRelate::Allwords Package
  - WordNet::Similarity Package

- **Toolbox**
  - Lingpipe
  - NLTK
  - OpenNLP
  - OAK (Sekine)

- **Parsers**
  - Charniak's
  - Stanford
    - Klein, Manning
  - Collins
Recursos

Fracas corpus

- FraCaS test suite
  - There are 346 problems. Each problem contains one or more premises and one question. There are a total of 536 premises, or an average of 1.55 premises per problem

  - # premises  # problems  % problems
    - -------------- --------------  --------------
    - -------------- --------------  --------------
      -  1       192   55.5 %
      -  2       122   35.3 %
      -  3        29    8.4 %
      -  4        2    0.6 %
      -  5        1    0.3 %
Recursos

SIMMETERICS library

- http://www.dcs.shef.ac.uk/~sam/stringmetrics.html
- measures
  - Hamming distance
  - Levenshtein distance
  - Needleman-Wunch distance or Sellers Algorithm
  - Smith-Waterman distance
  - Gotoh Distance or Smith-Waterman-Gotoh distance
  - Block distance or L1 distance or City block distance
  - Monge Elkan distance
  - Jaro distance metric
  - Jaro Winkler
  - SoundEx distance metric
  - Matching Coefficient
  - Dice's Coefficient
  - Jaccard Similarity or Jaccard Coefficient or Tanimoto coefficient
  - Overlap Coefficient
Técnicas basadas en inferencia lógica

- Text
- NLP including Semantic Interpretation
- Logical Representation
- Logical Inference
Técnicas basadas en inferencia lógica

Representación de la semántica

- **FOL**
  - First Order Logic
- **DRT**
  - Discourse Representation Theory
- **DL**
  - Description Logic
- **OWL**
- others
  - ...
Técnicas basadas en inferencia lógica

- **Text:** *Vincent loves Mia.*

- **DRT:**

<table>
<thead>
<tr>
<th>x</th>
<th>y</th>
</tr>
</thead>
<tbody>
<tr>
<td>vincent(x)</td>
<td></td>
</tr>
<tr>
<td>mia(y)</td>
<td></td>
</tr>
<tr>
<td>love(x,y)</td>
<td></td>
</tr>
</tbody>
</table>

- **FOL:** \( \exists x \exists y (vincent(x) \& mia(y) \& love(x,y)) \)

- **BK:**
  - \( \forall x \ (vincent(x) \to man(x)) \)
  - \( \forall x \ (mia(x) \to woman(x)) \)
  - \( \forall x \ (man(x) \to \neg woman(x)) \)

- **Model:** \( D = \{d1,d2\} \)
  - \( F(vincent)=\{d1\} \)
  - \( F(mia)=\{d2\} \)
  - \( F(love)=\{(d1,d2)\} \)
Técnicas basadas en inferencia lógica

Wide-coverage semantics

- **Lingo/LKB**
  - Minimal Recursive Semantics
  - [Copestake 2002]
- **Shalmaneser**
  - Frame Semantics
  - [Erk & Pado 2006]
- **Boxer**
  - Discourse Representation Structures
  - [Bos 2005]
Técnicas basadas en inferencia lógica

C&C

• DRT output

- %%% Authorities in Brazil hold 200 people as hostage.

- %%% (( authority(x1) ; named(x2,brazil,loc) @ in(x1,x2) )

- %%% > 200

- %%% people(x5)

- %%% hold(x3)

- %%% hostage(x4)

- %%% event(x3)

- %%% agent(x3,x1)

- %%% patient(x3,x 5)

- %%% as(x3,x4)
Técnicas basadas en inferencia lógica

**Logical Inference**

- **Theorem provers** check whether a formula is valid
- **Model builders** attempt to construct a model for a formula and thereby show that the formula is satisfiable
  - Domain size must be specified for model builders
    - That a model builder fails to find a model of size $n$ doesn’t mean that the formula is unsatisfiable; there may be a satisfying model of size $n+1$
  - Restricted to finite models
Técnicas basadas en inferencia lógica

Logical Inference

- **Provers** accepting ordinary FOL syntax:
  - PROVER9 (NLTK)
  - OTTER, BLIKSEM, SPASS, Gandalf, Vampire, Equinox, ...

- **Model builders** accepting ordinary FOL syntax:
  - MACE4 (NLTK)
  - KIMBA, Paradox, ...
Johan Bos, 2007

Components of Nutcracker:
- The C&C parser for CCG
- Boxer
- Vampire, a FOL theorem prover
- Paradox and Mace, FOL model builders

Background knowledge
- WordNet [hyponyms, synonyms]
- NomLex [nominalisations]
Técnicas basadas en inferencia lógica

- **DL Reasoners.**
  - Pellet, an open-source Java OWL DL reasoner
  - FaCT, a DL classifier
  - FaCT++, the new generation of FaCT OWL-DL reasoner
- **KAON2** is a free (free for non-commercial usage) Java reasoner
- **RacerPro** is a commercial (free trials and research licenses are available) lisp-based reasoner.

- **Other tools**
  - **Protégé** is a free, open source ontology editor and knowledge-base framework, which can use DL reasoners which offer a DIG interface as backends for consistency checks.
  - DIG Implementation. DIG is an XML interface to DL systems
  - SPARQL Query Language for RDF
UPC 2007

Process
- Linguistic Processing
- Semantic-based distance measures
- Classifier
  - Adaboost
  - SVM

![Diagram](image-url)
Linguistic Processing
- tokenization
- morphologic tagging
- lemmatization
- fine grained Named Entities Recognition and Classification
- syntactic parsing and robust detection of verbal predicate arguments
  - Spear parser (Surdeanu, 2005)
- semantic labeling, with WordNet synsets
- Magnini’s domain markers
- EuroWordNet Top Concept Ontology labels
"Romano Prodi is the prime minister of Italy."

i_en_proper_person(1),
entity_has_quality(2),
entity(5),
quality(4),
which_entity(2,1),
which_quality(2,5),
mod(5,7),
mod(5,4).
<table>
<thead>
<tr>
<th><strong>Type of feature</strong></th>
<th><strong># features</strong></th>
<th><strong>description</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>semantic content of T</td>
<td>12</td>
<td># locations, # persons, # dates, # actions, ...</td>
</tr>
<tr>
<td>semantic content of H</td>
<td>12</td>
<td>...</td>
</tr>
<tr>
<td>intersection of T and H</td>
<td>12</td>
<td>...</td>
</tr>
<tr>
<td>Strict overlapping of unary predicates</td>
<td>5</td>
<td>length of intersection length of intersection score of intersection length of intersection related to shortest env length of intersection related to longest env ratio of intersection related to both (union of)</td>
</tr>
<tr>
<td>Strict overlapping of binary predicates</td>
<td>5</td>
<td>...</td>
</tr>
<tr>
<td>Loose overlapping of unary predicates</td>
<td>5</td>
<td>...</td>
</tr>
<tr>
<td>Loose overlapping of binary predicates</td>
<td>5</td>
<td>...</td>
</tr>
<tr>
<td>Verbal entailment (WordNet)</td>
<td>1</td>
<td>$V_1 \in T$, $V_2 \in H$, such that $V_1$ verbal_entails $V_2$</td>
</tr>
<tr>
<td>Antonymy</td>
<td>1</td>
<td>$A_1 \in T$, $A_2 \in H$, such that $A_1$ and $A_2$ are antonyms and no token compatible with $A_2$ occurs in H</td>
</tr>
<tr>
<td>Negation</td>
<td>1</td>
<td>Difference between # negation tokens in H and T</td>
</tr>
</tbody>
</table>
Problems in LP

- The lack of a coreference component supposed a severe drawback, specially in the case of multi-sentence texts.
- The accuracy of our NERC component was poor.
- The compatible predicate failed to recognize many correct mappings.
- The entails predicate coverage, reduced to verbs having the entailment relation in WN was clearly insufficient.
Solutions

- We included in the LP pipe a simple co-reference solver, reduced to recover pronominal co-references.
- We developed a resegmentation/reclassification component.
- We enriched the set of compatible predicates using additional resources as WN relations and VerbOcean.
- We extended the set of entails predicates.
- We included a H classification component
- We enrich the set of features (25 new)
Results
- 3 runs
  - 1 = baseline UPC-2007
  - 2 = 1 + LP improvements (?)
  - 3 = 1 + new features
- UPC-2008 (1) fall 5 points
- UPC-2008 (2) < UPC-2008 (1)
- UPC-2008 (3) \approx UPC-2008 (1)
UPC 2008

- **Moraleja**
  - Clear objectives:
    - a good system
    - a well scored system
    - focus on some interesting (or new) problem
    - a thesis
    - a publication
  - Learn from errors:
    - accurate analysis of errors
  - Learn from the best
    - Hickl, Tatu, Szpecktor, De Marneffe, Bos
  - Follow your own intuitions or well established opinions
  - Change the approach if needed (or convenient)