Deep Grammar Error Detection and Automated Lexical Acquisition

Steps towards Wide-Coverage Open Texts Processing

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IGK Colloquium
17^{th} Nov. 2005

Outline

1. Background and Motivation
   - Deep Processing: State-of-the-Art
   - Coverage of Deep Processing
2. Grammar Error Detection
   - Previous Work on Grammar Error Detection
   - Error Mining
3. Automated Lexical Acquisition
   - Previous Work on Lexical Acquisition
   - Statistical Lexical Type Predictor

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What is deep processing?

- Deep processing means to maximally exploit grammatical knowledge for language processing.
- Focus on linguistic precision and semantic modelling
- Grammar-centric approach
- The opposite of deep is not statistical but shallow.

Why we need deep processing?

- Explicit model of grammaticality
- Ability to capture subtle linguistic interactions
- Semantics

Problems with deep processing

Efficiency

- Detailed language modelling creates large search space.
- Alleviated by efficient parsing algorithms and better hardware

Specificity

- Linguistic sound vs. application interesting
- Ranking of the results is necessary.

Robustness/Coverage

- Strict grammaticality metric
- Insufficient coverage of the grammar
- Dynamic nature of language

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Robustness and specificity

Robustness and specificity are a pair of dual problems.

Grammar Engineering

- Overgeneration $\asymp$ specificity
- Undergeneration $\asymp$ robustness

Application

- Ranked output
- High coverag over noisy inputs

- For deep grammars, a balance point should be achieved to maximize linguistic accuracy.
- Robustness and specificity should come with extra mechanism.

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Coverage problem of deep processing

Road-testing ERG over BNC [Baldwin et al., 2004]

- Test on 20,000 strings from BNC
- Full lexical span for only 32%
- Among these
  - 57% are parsed (overall coverage 57% $\times$ 32% $\approx$ 18%)
  - 83% of the parses are correct
  - 40% parsing failures are caused by missing lexical entries
  - 39% parsing failures are caused by missing constructions

The focus of this talk

- Deep grammar error detection
  The lexical coverage is a major problem for deep processing.
- Automated deep lexical acquisition

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Symbolic approach

Inductive Logic Programming

$$\text{Background} \wedge \text{Hypothesis} \models \text{Evidence}$$

ILP based grammar extension [Cussens and Pulman, 2000]

After a failed parse, abduction is used to find needed edges, which, if they existed, would allow a complete parse of the sentence. Linguistic constraints are applied to restrict the generation of implausible edges.

Problems

The generated rules are too general or too specific.

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Error Mining

[van Noord, 2004]

- Large hand-crafted grammars are error-prone.
- Manual detection of errors is time consuming.
- Small test suite based validations are not reliable.
- Parsing failures are good indication of (under-generating) errors.

Parsability

Definition

$$R(w_i \dots w_j) = \frac{C(w_i \dots w_j | OK)}{C(w_i \dots w_j)}$$

- If the parsability of a particular word sequence is (much) lower, it indicates that something is wrong.
- Parsabilities can be calculated efficiently for large corpus with suffix arrays and perfect hashing.

Error mining experiment of ERG with BNC

- 1.8M sentences (21.2M words) with only ASCII characters and no more than 20 words each
- Running *best-only* parsing with PET took less 2 days on *elf*

Status	Num. of Sentence	Percentage
Parsed	301,503	16.74%
No lexical span	1,260,404	69.97%
No parse found	239,272	13.28%
Edge limit reached	96	0.01%

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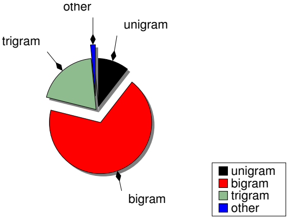
Error analysis

	Number	Percentage
uni-gram	2,336	10.52%
bi-gram	15,183	68.36%
tri-gram	4,349	19.58%

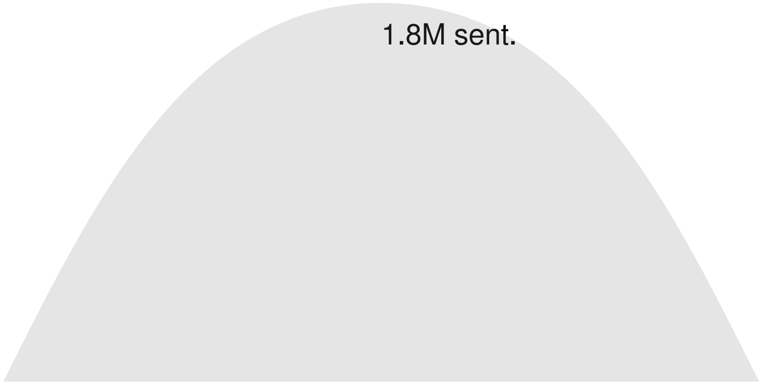
Table: N-grams with $R < 0.1$



N-gram	Count
weed	59
the poor	49
a fight	113
in connection	85
as always	84
peered at	28
the World Cup	57

Table: Examples

Pin down the errors



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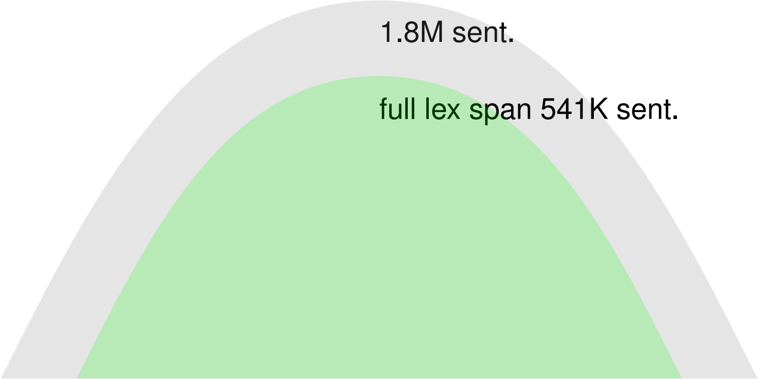

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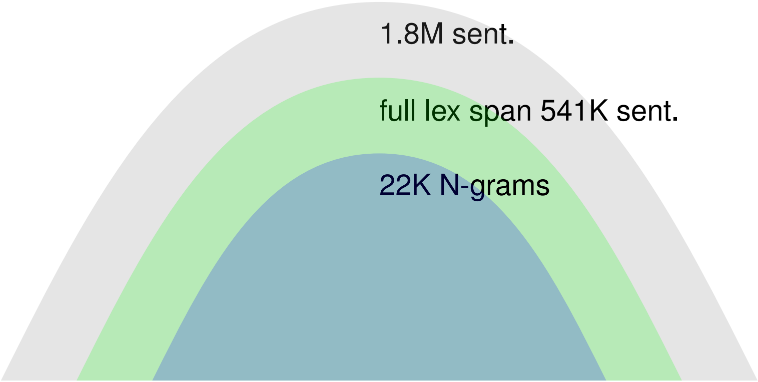

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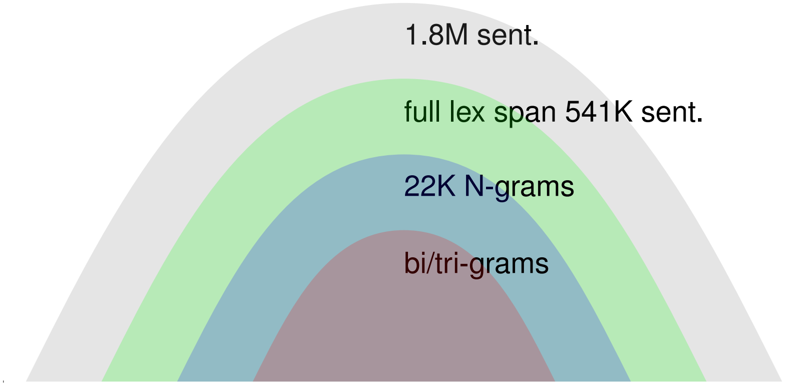

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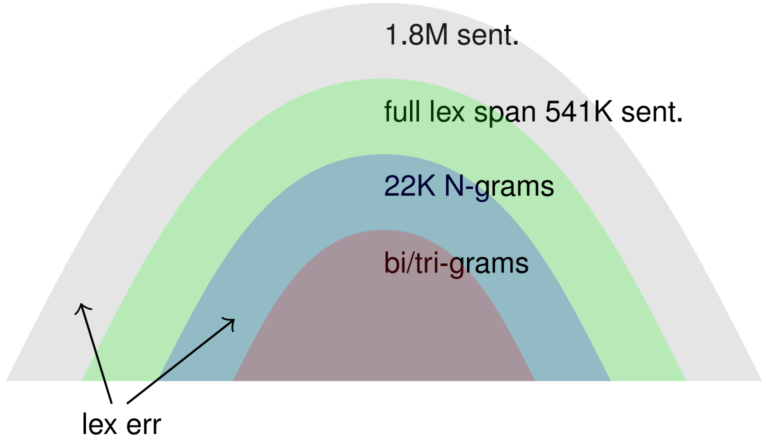

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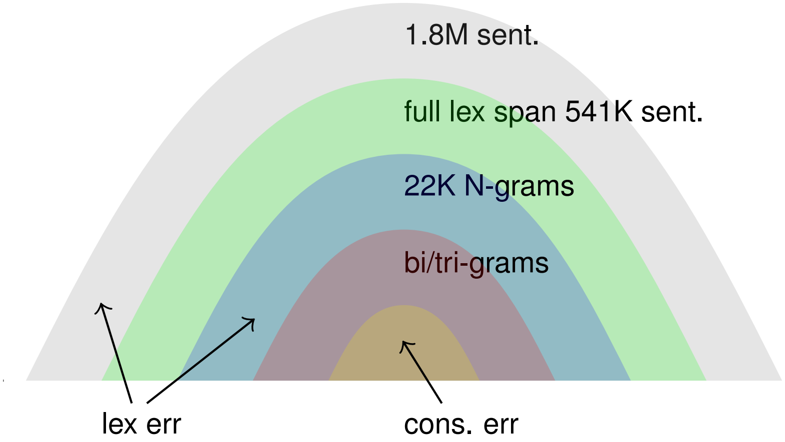

Detecting lexical error

- Missing lexical span
- Low parsability unigrams
- Language dependent heuristics:
  i.e. low parsability bigrams started with determiner like *"the poor"*, *"a fight"*

Outline

Unification-based approach

[Erbach, 1990, Barg and Walther, 1998, Fouvry, 2003]

- Use underspecified lexical entries to parse the whole sentence
- Generate lexical entries afterwards by collecting information from the full parse

An example of how unification-based approach works

the kangaroo jumps

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$$\begin{bmatrix} \text{STEM} & \langle \text{"THE"} \rangle \\ \text{HEAD} & \textit{det} \end{bmatrix}$$

$$\begin{bmatrix} \text{STEM} & \langle \text{"KANGAROO"} \rangle \end{bmatrix}$$

$$\begin{bmatrix} \text{STEM} & \langle \text{"JUMPS"} \rangle \\ \text{HEAD} & {}_{\textit{verb}}\begin{bmatrix} \text{PERSON} & \boxed{2}\ \textit{3rd} \\ \text{NUM} & \boxed{3}\ \textit{sg} \end{bmatrix} \\ \text{SUBJ} & \left\langle \begin{bmatrix} \text{HEAD} & {}_{\textit{noun}}\begin{bmatrix} \text{PERSON} & \boxed{2} \\ \text{NUM} & \boxed{3} \end{bmatrix} \end{bmatrix} \right\rangle \end{bmatrix}$$

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$$\begin{bmatrix} \text{HEAD} & \boxed{5} \\ \text{SPR} & \langle\rangle \\ \text{HEAD-DTR} & \begin{bmatrix}\text{HEAD} & \boxed{5} \\ \text{SPR} & \left\langle \boxed{1} \right\rangle\end{bmatrix} \\ \text{NON-HEAD-DTR} & \boxed{1}\end{bmatrix}$$

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Problems with unification-based approaches

- Generated lexical entries might be:
  - *too general*: overgeneration
  - *too specific*: undergeneration
- Computational complexity increased significantly with underspecified lexical entries, especially when two unknowns occur next to each other.

Outline

Statistical approach

[Baldwin, 2005]

- Based on a set of lexical types
- Treat lexical acquisition as a classification task
- Generalize the acquisition model over various sencondary language resources
  - POS tagger
  - Chunker
  - Treebank
  - Dependency parser
  - Lexical ontology

DELPHIN

Importing lexicon from a semantic lexical ontology

Assumption

There is a strong correlation between the semantic and syntactic similarity of words. [Levin, 1993]

Fact

Above 90% of the synsets in WordNet (2.0) share at least one lexical type among all included words.

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Importing lexicon from WordNet

[Baldwin, 2005]

- Construct semantic neighbours (all synonyms, direct hyponyms, direct hypernyms)
- Take a majority vote across the lexical types of the semantic neighbours

Improvement

Voting is weighted and must exceed a threshold.

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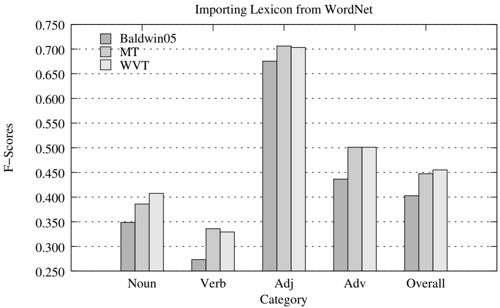
Results



- The sparse ERG lexicon (as compared to WordNet) makes the voting less reliable.

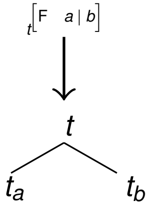
Maximum entropy model based lexical type predictor

$$p(t,c) = \frac{exp(\sum_i \theta_i f_i(t,c))}{\sum_{t' \in T} exp(\sum_i \theta_i f_i(t',c))}$$

- A statistical classifier that predicts for each occurrence of unknown word or missing lexical entry
- Input: features from the context
- Output: atomic lexical types

Atomic lexical types

- The lexical information is encoded in atomic lexical types.
- Attribute-value structures can be decomposed into atomic lexical types.



Baseline models

- Select the majority lexical type for each POS

POS	Majority Lexical Type
noun	n_intr_le
verb	v_np_trans_le
adj.	adj_intrans_le
adv.	adv_int_vp_le

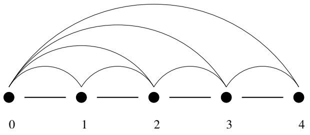
- General purpose POS tagger trained with lexical types: *TnT*, *MXPOST*

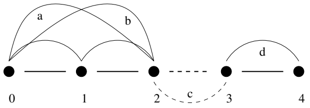
Basic features

- Prefix/suffix of the word
- Context words and their lexical types

Model	Precision
Baseline	30.7%
TnT	40.4%
MXPOST	40.2%
ME basic	50.0%

Partial parsing results





Model	Precision
Baseline	30.7%
TnT	40.4%
MXPOST	40.2%
ME basic	50.0%
ME +pp	50.5%

Turning to the disambiguation model

- Generate top *n* candidate entries for the unknown word
- Parse the sentence with candidate entries
- Use disambiguation model to select the best parse
- Pick the corresponding entry

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Experiment

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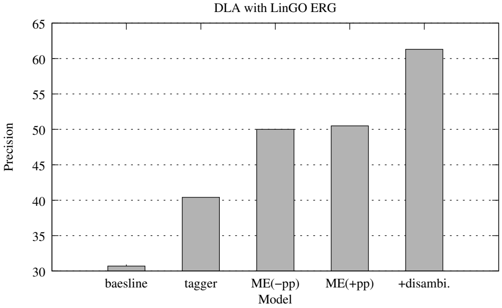

What has been done?

- Error mining based lexical error detection
  - Experiment with ERG and BNC shows a major part of parsing failure is due to missing lexical entries.
  - Some rules are used to discover missing lexical entries.
- Statistical lexical acquisition
  - A maximum entropy based lexical type prediction model is designed and evaluated with various feature templates.
  - Lexical ontology based acquisition method is tried.
  - Disambiguation model is incorporated to enhance robustness.

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