# Parsing of Open Domain Text with GF

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- Overview
- 2 Robustness
  - Low-Level API
  - Named Entity Recognizer
  - Chunking
- 3 Disambiguation
- 4 Penn Treebank for GF
- 5 Open-Domain Parsing by Cheating
- 6 Conclusion

# Can we apply GF to open-domain text?

Current state (application grammars)

- Parsing for small controlled languages
- Language Generation from formal representation

### Long-term goal

- Parsing with the resource grammars
- Robustness for out of coverage content
- Statistical disambiguation

# Application Grammars

- domain with constrained language
- requirement for clear semantics
- mission critical quality
- lightweight

#### Resource Grammars

- free unrestricted language
- no need for semantic understanding
- small percentage of **errors** is permissible
- computationally hard

## The Concrete Experiment

We evaluated the combination:

- English Resource Grammar
- Oxford Advanced Learners Dictionary (adapted)
- Simple Named Entities Recognizer

with sections 2-21 from PennTreebank.

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### Robustness

Try to read this:

Lorem ipsum dolor sit amet, consectetur adipiscing elit.

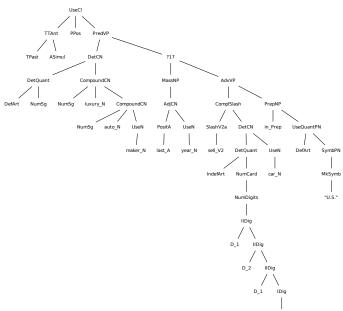
#### Robustness

Try to read this:

Lorem ipsum dolor sit amet, consectetur adipiscing elit.

The Standford Parser reads it as:

## Robustness: Incomplete Abstract Trees in GF



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# Parse State Threading

```
initState :: PGF \rightarrow Language \rightarrow Type \rightarrow ParseState
nextState :: ParseState \rightarrow ParseInput \rightarrow Either ErrorState ParseState
getParseOutput :: ParseState \rightarrow Type \rightarrow Maybe Int
```

 $\rightarrow$  (ParseOutput, BracketedString)

# Reading the Input

```
mkParseInput :: PGF \rightarrow Language
\rightarrow (\textbf{forall } \alpha : \beta \rightarrow Map \ Token \ \alpha \rightarrow Maybe \ \alpha)
\rightarrow [(CId, \beta \rightarrow Maybe \ (Tree, [Token]))]
\rightarrow (\beta \rightarrow ParseInput)
```

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## Design

- we cannot build Named Entity Recognizer directly in GF
- ... but we can complement GF grammars with custom code
  - The user defines some category as "literal"
    - gf make literal = Symb PennTreebankEng.gf
  - and also provides a callback:

 The GF parser doesn't parse literal categories but delegates this to the callback

#### Rules

## Currently very naïve rules:

Every sequence of tokens starting with captial letter is a candidate for name

#### Full Source Code

```
parse :: PGF -> Language -> Type -> Maybe Int -> [Token] -> ParseOutput
parse pgf lang typ dp toks = loop (initState pgf lang typ) toks
 where
   loop ps [] = getParseOutput ps typ dp
    loop ps (t:ts) = case nextState ps (inputWithNames (t:ts)) of
                      Left es → []
                      Right ps -> loop ps ts
    inputWithNames = mkParseInput pgf lang
                                 t.ok
                                 [mkCId "String", name]
     where
       tok (t:ts) = Map.lookup (map toLower t)
       tok _ = Nothing
       name ts = let nts = takeWhile isNameTok ts
                 in if null nts
                      then Nothing
                      else Just (mkStr (unwords nts).nts)
       isNameTok (c:cs) | isUpper c = True
       isNameTok
                            = False
```

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#### Idea

#### Simple:

- When we analize a sentence piece by piece and not as a whole, then the whole process is more robust.
- If a single piece (chunk) is not parseable the rest are still recognized.

For example: We can parse up to 75% of the basic noun phrases in PennTreebank but we can parse only few complete sentences.

## Example

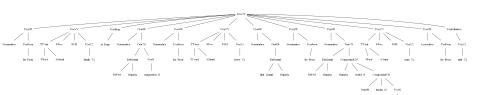
- We import parts of the English RGL + OALD
- ... but we introduce a new category *Chunk* instead of the category for sentences *S*.
- We add the rules:

**fun**  $UseNP : NP \rightarrow Chunk$   $UseAP : AP \rightarrow Chunk$   $UseVX : VX \rightarrow Chunk$  $UsePrep : Prep \rightarrow Chunk$ 

# Parsing Strategy

- Call initState and start parsing from the beginning of the sentence.
- Consume as many tokens as possible by using nextState
- At the first failure, read the abstract syntax trees for the chunk that is recognized so far (getParseOutput).
- Continue again from the next token.

# **Example Output**



## Disadvantages

- Due to ambiguities we might miss the right chunking (works better when it is guided by some statistical chunker)
- Does not recover the structures that are far from the surface
- For disambiguation we might still need the global context

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# Disambiguation

The resource grammars can assign thousands of different analizes for a nontrivial sentence.

- Most alternative are missleading and useless
- Disambiguation is usually done statistically

# Simple Probabilistic Model

• A configuration file assigns probability to every function:

AAnter	0.0074483421432004
ASimul	0.9255165785679962
AdVVP	0.0012515808814756
AdjCN	0.2070667478106594
AdvNP	0.1648705815470020
AdvS	0.0043645480559712
AdvVP	0.2808957930655976
AdvVPSlash	0.0008114836248423
BaseNP	0.6195076570774295
CompAP	0.4186262017838527
CompAdv	0.0099386076682497

• Compile the probabilities into the grammar:

```
> gf -make -probs=PennTreebank.probs PennTreebankCnc.gf
```



## Dependency Model

- The simple model tends to get the PP attachement wrong
- State of the art parsers use head-driven dependency models (Not yet available in GF)
- Ranking should be integrated with the three extraction (Not yet available in GF)

# Training Data?

- All statistical parsers rely on training data (treebank)
- Nothing is available for GF
- Building treebanks from scratch is costly

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### **Grammar Evaluation**

#### Success

- 85% single words
- 75% basic noun phrases
- 0% full sentences

#### **Failure**

- Incomplete patterns for Named Entities (ex: the United States)
- Syntax for dates?
- Missing constructions
- Missing words

# Early Lessons

- Trying to directly parse a treebank is pointless (failure)
- Extending the grammar should not be the ultimate goal (all grammars leak)
- Even if you can parse a sentence this doesn't mean that you do it right (false positives)

## Parsing vs Transformation

Transformation Patterns

$$\frac{ \left( \textit{ADJP ad1} @ (\textit{RB} \dots) \; \textit{ad2} @ (\textit{RB} \dots) \; \dots \; \textit{adj} @ (\textit{JJ} \dots) \right) }{ \textit{AdAP ad1} \; \left( \textit{AdAP ad2} \dots \left( \textit{PositA adj} \right) \dots \right) }$$

...or as Haskell code:

#### Current status

- There is a script which can transform the whole treebank to GF for **few minutes**.
- We have recovered 92% of tree nodes in the treebank
- Manual transformation can be as good as 97%

## Number of Guesses per Sentence

22.7.2.4.5.0.3.2.1.0.0.0.0.0.1

Distribution:
1416,4467,4623,4871,4561,4303,3763,3137,2501,
1857,1353,952,646,483,332,200,116,89,54,41,20,

• Average: 5

# Summary of Grammar Extensions

- Very few syntax extensions (simple and easy things)
- A lot of changes in the lexicon
  - Structural words
  - Irregular verbs
  - Valency frames

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# Robust GF parser by cheating

- Take any statistical parser which produces Penn Treebank trees
- Use the parser to produce the Penn Treebank tree
- Convert the output to GF abstract syntax tree

### Pros and Cons

#### **Pros**

- Simple and easy
- Already possible

### Cons

- Doesn't utilize the GF infrastructure
- It is more interesting to have native GF parser
- The grammar is duplicated in the transformation rules.
- The Stanford Parser skip some annotations

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### Conclusion

# This is only the beginning:

- The first draft import of Penn Treebank to GF
- Named entity recognizer in GF
- Preliminary experiments in robust parsing