Grammar Based Generation: Algorithm Optimisation and Performance Improvement through Error Mining

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Grammar-Based Surface Realisation (SR)

Efficiency and Coverage

- **XTAG and Top-Down, Bottom-Up SR algorithm** generates Penn Tree Bank sentences in 2.57 seconds
  Average (maximum) word length: 22 (134)

Correctness

- **Error Mining** permits improving correctness and adapting the grammar to the PTB input yielding a BLEU score on covered input of 0.73
A TD/BU algorithm for Grammar Based Surface Realisation

What is Surface Realisation?

Structured Input from the Generation Challenge Surface Realisation Task

Feature-Based Tree Adjoining Grammar

The Algorithm

Evaluation and Results

S. Narayan and C. Gardent
Structure-Driven Lexicalist Generation
Proceedings of COLING 2012, pp 2027 - 2041, Mumbai, India
What is Surface Realisation?

SR maps INPUT DATA to SENTENCES

The input data can be more syntactic or more semantic; a tree or a graph:

- Dependency trees (SR Task)
- OWL triples
- First Order Logic (FOL) Formulae
- Flat semantics (MRSs)
- ...

$$\exists x. (\text{Man}(x) \land \exists y. (\text{Apple}(y) \land \text{eat}(e, x, y) \land \text{now}(e)))$$

$$\Rightarrow \text{A man eats an apple}$$
The SR Shared Task Input Representations

Surface Realisation Task organised by the Generation Challenges 2011

Input derived from the PennTreebank

Shallow dependency structures

- Unordered trees
- Edges are labelled with syntactic functions
- Nodes labelled with lemmas, part of speech tags and partial morphosyntactic information

All words of the original sentence are represented by a node in the tree
The most troublesome report may be the August merchandise trade deficit due out tomorrow.
Grammar

Feature-Based Lexicalised Tree Adjoining Grammar (FB-LTAG)

- A set of trees, lexicalised with one or more words and decorated with feature structures
- 2 combining operations: substitution and adjunction
- XMG Reimplementation of XTAG (large coverage of English)
Example FB-LTAG

(a) Derived tree

(b) Derivation tree
# Grammar-Based Surface Realisation Algorithms

## Two main approaches

<table>
<thead>
<tr>
<th>Head-Driven algorithm</th>
<th>Cons: Logical Form Equivalence Problem</th>
</tr>
</thead>
<tbody>
<tr>
<td>Used for recursively structured input data e.g., logical formulae</td>
<td></td>
</tr>
<tr>
<td>Use input structure to guide the search</td>
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<table>
<thead>
<tr>
<th>Lexicalist</th>
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<tbody>
<tr>
<td>Used for unstructured input data (e.g., MRS formula)</td>
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<tr>
<td>Selects lexical entries bottom-up from the input semantic literals</td>
</tr>
<tr>
<td>Cons: Computationally expensive (Unordered input, Lexical ambiguity, Intersective modifiers)</td>
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Structure-Driven Lexicalist Surface Realisation

Combines techniques and ideas from the head-driven and the lexicalist approach.

- Select grammar rules bottom up for each input tree node (Lexicalist)
- Uses the structure of the input to guide the search and prune the search space (Structure Driven)

Integrates various optimisations previously proposed for parsing/generation

Parallelised
Structure-Driven Lexicalist Generation

- FB-LTAG converted to FB-RTG to construct derivation rather than derived trees (Koller and Striegnitz, 2002; Gardent and Perez-Beltrachini 2010)
- Top-down filter using the structure of the input (Head-Driven algorithm, Shieber et al. 1990)
- Bottom-up polarity filter on local input trees. (Bonfante 2004; Gardent and Kow 2007).
- Language model used to prune competing intermediate structures (Bangalore and Rambow 2000; White 2004)
- Parallelism used to explore the possible completions of the top-down predictions simultaneously rather than sequentially.
Converting a TAG to an RTG

\[
\begin{align*}
& \text{r1. } NP_S \rightarrow \text{john}(NPA) \\
& \text{r2. } S_S \rightarrow \text{runs}(S_A NP_S VP_A V_A) \\
& \text{r3. } VP_A \rightarrow \text{often}(VP_A) \\
& \text{r4. } NP_A \rightarrow \epsilon \\
& \text{r5. } S_A \rightarrow \epsilon \\
& \text{r6. } V_A \rightarrow \epsilon \\
& \text{r7. } VP_A \rightarrow \epsilon \\
\end{align*}
\]
The Algorithm

Starts from the root node of the input tree

Processes all children nodes in parallel spreading lexical selection constraints top-down and combining FB-RTG rules bottom-up

4 main steps

▸ Bottom-Up Lexical Selection and Top-Down Filtering
▸ Bottom-Up Local Polarity Filtering
▸ Bottom-Up Generation
▸ N-Gram Filtering
Example

Input Dependency Tree

eat
fruit
OBJ
John
SBJ
has
VC
which
NMOD
An FB-LTAG
... and the corresponding FB-RTG

\[ NP_{A}^{[t:T]} \rightarrow \text{which}(NP_{A}^{[t:T,b:[wh:+]]}) \]
\[ NP_{A}^{[t:T]} \rightarrow \text{the}(NP_{A}^{[t:T,b:[wh:-]]}) \]
\[ NP_{A}^{[t:T]} \rightarrow \text{fruit}(NP_{A}^{[t:T]}) \]
\[ NP_{A}^{[t:T]} \rightarrow \text{John}(NP_{A}^{[t:T]}) \]
\[ S_{A}^{[t:T]} \rightarrow \text{have}(S_{A}^{[t:T]}) \]
\[ VP_{A}^{[t:T]} \rightarrow \text{have}(VP_{A}^{[t:T]}) \]
\[ S_{S}^{[t:T,b:B]} \rightarrow \text{have}(S_{A}^{[t:T,b:B]} \quad \text{NP}_{S}^{[t:[wh:-]]} \quad \text{VP}_{A} \quad \text{NP}_{S}) \]
\[ S_{S}^{[t:T,b:B]} \rightarrow \text{eat}(S_{A}^{[t:T,b:B]} \quad \text{NP}_{S}^{[t:[wh:-]]} \quad \text{VP}_{A}) \]
\[ S_{S}^{[t:T,b:B]} \rightarrow \text{eat}(S_{A}^{[t:T,b:B]} \quad \text{NP}_{S}^{[t:[wh:-]]} \quad \text{VP}_{A} \quad \text{NP}_{S}) \]
\[ S_{S}^{[t:T,b:B]} \rightarrow \text{eat}(S_{A}^{[t:T,b:B]} \quad \text{NP}_{S}^{[t:[wh:+]]} \quad S_{A} \quad \text{NP}_{S} \quad \text{VP}_{A}) \]
\[ S_{A}^{[t:T,b:B]} \rightarrow \text{eat}(S_{A}^{[t:T,b:B]} \quad \text{NP}_{S}^{[t:[wh:+]]} \quad S_{A} \quad \text{NP}_{S} \quad \text{VP}_{A}) \]
\[ \epsilon \]
Lexical Selection: for each input node $n$ with lemma $w$, selects all FB-RTG rules which can be lexicalised by $w$

Top-Down Filtering: Only keep those rules whose left-hand side category occurs at least once in the right-hand side of the rules selected by the parent node.
Example Top-Down Filtering

Rule selection for *eat*:

\[
\begin{align*}
S_{[t:T,b:B]} & \quad \rightarrow \quad \text{eat}(S_{[t:T,b:B]}^{S} NP_{S}^{[t:[wh:−]]} VP_{A}) \\
S_{[t:T,b:B]} & \quad \rightarrow \quad \text{eat}(S_{[t:T,b:B]}^{S} NP_{S}^{[t:[wh:−]]} VP_{A} NP_{S}) \\
S_{[t:T,b:B]} & \quad \rightarrow \quad \text{eat}(S_{[t:T,b:B]}^{S} NP_{S}^{[t:[wh:+]]} S_{A} NP_{S} VP_{A})
\end{align*}
\]

Rule selection and filtering for *has*:

\[
\begin{align*}
\checkmark & \quad S_{[t:T]}^{A} \quad \rightarrow \quad \text{have}(S_{[t:T]}^{A}) \\
\checkmark & \quad VP_{[t:T]}^{A} \quad \rightarrow \quad \text{have}(VP_{[t:T]}^{A}) \\
\times & \quad S_{[t:T,b:B]}^{S} \quad \rightarrow \quad \text{have}(S_{[t:T,b:B]}^{A} NP_{S}^{[t:[wh:−]]} VP_{A} NP_{S})
\end{align*}
\]
Global Polarity Filtering (Gardent and Kow 2005) filters out

- Sets of rules which cover the input
- but cannot possibly lead to a valid derivation
- either because a substitution node cannot be filled
- or because a root node fails to have a matching substitution site

**Local** (Structure-Driven) Polarity Filtering: on each local tree
Example of Local Polarity Filtering

\[
\times \quad S_{[t:T, b:B]} \rightarrow \text{eat}(S_{A}, NPs_{[t:[wh:−]]} VPA)
\]
\[
\checkmark \quad S_{[t:T, b:B]} \rightarrow \text{eat}(S_{A}, NPs_{[t:[wh:−]]} VPA NPs)
\]
\[
\checkmark \quad S_{[t:T, b:B]} \rightarrow \text{eat}(S_{A}, NPs_{[t:[wh:+]]} S_A NPs VPA)
\]

\[
NP_{S}^{t:[wh:+], b:[wh:+]}
\]
\[
NP_{A}^{t:[wh:+], b:[wh:+]}
\]
\[
NP_{A}^{t:[wh:+]}
\]

\[
\text{fruit-t3} \quad \text{have-t5} \quad \text{John-t4} \quad \text{have-t6}
\]
\[
\text{which-t1} \quad \epsilon \quad \epsilon \quad \epsilon
\]

\[
\epsilon
\]
Bottom-Up Generation and N-Gram filtering

For each local tree in the input, the rule sets passing the local polarity filter are tried out for combination.

Only the \textit{n best scoring n-grams} let through after each bottom-up generation step are kept. The language model helps finding the most likely ordering of modifiers.
Evaluation and Results

Test data: The SR Data
- Dependency trees derived from the Penn Treebank
- 26,725 inputs
- Average (maximum) word length: 22 (134)
- Average (maximum) branching degree: 4 (18)

Algorithms compared:
- Baseline: A strictly top-down algorithm
  (No time information available for systems participating in SR Task, only coverage and BLEU)
- SEQ: The SDL algorithm without parallelism
- PAR: The SDL algorithm with parallelism

Evaluation Focus: Efficiency (Time)
Evaluation and Results

<table>
<thead>
<tr>
<th></th>
<th>S(0−5)</th>
<th>S(6−10)</th>
<th>S(11−20)</th>
<th>S(All)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BL</td>
<td>0.85</td>
<td>10.90</td>
<td>110.07</td>
<td>−</td>
</tr>
<tr>
<td>SEQ</td>
<td>1.49</td>
<td>2.84</td>
<td>4.36</td>
<td>4.52</td>
</tr>
<tr>
<td>PAR</td>
<td>1.53</td>
<td>2.56</td>
<td>2.66</td>
<td>2.57</td>
</tr>
</tbody>
</table>

- Maximum arity = 3. Else BL times out.
- Many time out for BL on input longer than 10
- For short sentences (0−5), BL outperforms SDL
- For sentences with more than 5 words, SDL increasingly outperforms BL
Branching factor and Parallelism

<table>
<thead>
<tr>
<th></th>
<th>Sentences (Arity)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>S(1)</td>
<td>S(3)</td>
</tr>
<tr>
<td>Total</td>
<td>190</td>
<td>3619</td>
</tr>
<tr>
<td>SEQ</td>
<td>0.89</td>
<td>3.65</td>
</tr>
<tr>
<td>PAR</td>
<td>0.97</td>
<td>2.63</td>
</tr>
</tbody>
</table>

The impact of parallelism increases with the branching factor.
Coverage and BLEU score

Coverage: 81.74%

- No robustness mechanism added.

BLEU score: 0.73 (for covered data)

- No ranking module
- Best statistical system in SR Task: 0.88
- Best symbolic system in SR Task: 0.37
Error Mining as a way to Improve Grammar Correctness

March 26, 2014

S. Narayan and C. Gardent
Error Mining with Suspicion Trees
Proceedings of COLING 2012, pp 2011 - 2025, Mumbai, India

C. Gardent and S. Narayan
Error Mining on Dependency Trees
Proceedings of ACL 2012, pp 592 - 600, Jeju Island, Korea
Error Mining (van Noord 2004)

Goal: Identify errors in grammar or lexicon which leads to parsing failure

Method:

- Parse \( n \) sentences \((S)\)
- Divide the input set of sentences \( S \) into the set of sentences for which parsing succeeds (PASS) and the set of sentences for which parsing fails (FAIL)
- Identify n-grams or words that frequently occur in FAIL (high Suspicion Score)

\[
S = \frac{ct(w_i \mid FAIL)}{ct(w_i)}
\]
Error Mining applied to Generation

Input to generation = Unordered Dependency Trees

Search for subtrees (Suspicious Forms) in the input which frequently lead to generation failure and rarely lead to generation success (high Suspicion Score).
Error Mining applied to Generation

Three main modifications w.r.t. Van Noord’s approach

1. The input is a tree. Suspicious forms are subtrees (not strings). We adapt the HybridTreeMiner algorithm to efficiently enumerate subtrees of the input.

2. The suspicion score takes into account both Pass and Fail (not just Pass).

3. The output of error mining is a tree (not a list). This output tree highlights the relations between suspicious forms and facilitates grammar correction.
Example Suspicious Form

Suspicious forms are Suspicious subtrees of the SR dependency trees labelled with lemma, parts-of-speech and/or dependency information.

\[
\begin{align*}
  & sroot \\
  & \quad \text{PLAY/VB} \\
  & \quad \text{suj/NN} \\
  & \quad \text{JOHN/NNP} \\
  & \quad \text{FOOTBALL/NN}
\end{align*}
\]

\((sroot\text{-}\text{PLAY/VB}, (\text{suj-JOHN/NNP}), (\text{obj-FOOTBALL/NN}))\)

<table>
<thead>
<tr>
<th>WORD</th>
<th>((\text{PLAY}, (\text{JOHN}), (\text{FOOTBALL})))</th>
</tr>
</thead>
<tbody>
<tr>
<td>POS</td>
<td>((\text{VB}, (\text{NNP}), (\text{NN})))</td>
</tr>
<tr>
<td>dep</td>
<td>((\text{sroot}, (\text{suj}), (\text{obj})))</td>
</tr>
<tr>
<td>WORD/POS</td>
<td>((\text{PLAY/VB}, (\text{JOHN/NNP}), (\text{FOOTBALL/NN})))</td>
</tr>
<tr>
<td>dep-POS</td>
<td>((\text{sroot-VB}, (\text{suj-NNP}), (\text{obj-NN})))</td>
</tr>
</tbody>
</table>
Enumerating Subtrees

HybridTreeMiner algorithm (Chi et al. 2004): Build an enumeration tree whose nodes are all possible subtrees of $T$ and such that, at depth $d$ of this enumeration tree, all possible frequent subtrees consisting of $d$ nodes are listed.

1. Convert the unordered labelled trees to a canonical form called BFCF (Breadth-First Canonical Form)

2. Enumerate the subtrees of the BFCF trees in increasing order of size using two tree operations called join and extension
Adapting the HybridTreeMiner algorithm for Error Mining

Use **support** (nb of FAIL and PASS sentences for a given form $f$) and suspicion score to prune the search space.

for a larger tree $t$ to be added to the enumeration tree, the suspicion score of all subtrees contained in a new tree $t$ must be smaller or equal to $S(t)$.

$$S(f_n) \geq S(t_{n-1}), \forall t_{n-1} \in t_n$$

Construct the tree breadth first rather than depth first

The enumeration process take 10-15 minutes for a dataset of 123,523 trees.
Suspicion Score, $S_{\text{score}}(f)$

Captures the degree to which a form $f$ is associated with failure. It is high when $f$ is often present in data associated with failure and/or often absent in data associated with success.

$$S_{\text{score}}(f) = \frac{1}{2} (\text{Fail}(f) \ast \ln \text{count}(f) + \text{Pass}(\neg f) \ast \ln \text{count}(\neg f))$$

$$\text{Fail}(f) = \frac{\text{count}(f|\text{FAIL})}{\text{count}(f)}$$

$$\text{Pass}(\neg f) = \frac{\text{count}(\neg f|\text{PASS})}{\text{count}(\neg f)}$$
Constructing the output Suspicion Tree

We adapt the ID3 decision tree algorithm to yield a tree whose nodes are suspicious forms and whose structure highlights the relations between suspicious forms.

The Error Mining algorithm recursively partitions the data by

1. selecting the suspicious form with highest suspicion score (attribute selection).
2. using this attribute to split the data into two subsets, a subset containing that attribute and a subset excluding that attribute (dataset division).
Pruning the Suspicion Tree

1. Only consider those forms whose frequency is above a given threshold.

2. Only consider a larger suspicious form if its suspicion rate is larger than the suspicion rate of all smaller forms it contains.

3. Limit depth of tree (max 10).

Building a suspicion tree for a dataset of 123,523 trees takes about one minute.
Experiments and Results

We applied error mining to the results of our SR algorithm on the SR data.

▶ Corrections:
▶ 11 rewrite rules (Gen-1, Dt-4, Adv-1, Inf-3, Aux-1 and Final-1), to adapt the SR data to the input expect by our generator
▶ 2 grammar corrections and
▶ a few lexicon updates

<table>
<thead>
<tr>
<th>Test Data</th>
<th># Failures Before EM</th>
<th># Failures after EM</th>
<th>Error Reduction</th>
</tr>
</thead>
<tbody>
<tr>
<td>26725</td>
<td>19280 (72.1%)</td>
<td>5157 (19.3%)</td>
<td>-52.8</td>
</tr>
</tbody>
</table>

▶ sentences from minimum size 1 to maximum size 134 with the average size 22 with
▶ the coverage of 81.74% and the BLEU score 0.73 (for the covered data)
Suspicion tree and Grammar Correction

The structure of the suspicion tree helps the linguist correct the grammar by

- ordering suspicious forms from the most to the least suspicious
- showing forms that are suspicious independently of context and require a single correction
- showing forms that are suspicious independently of context and require several corrections (several subcases)
- showing forms that are suspicious in some but not all contexts
From the most to the least Suspicious Form

(POSS)

(CC)

(DT,(IN))

(TO,(VB))

(NN,(RB))

(cont)
Forms that are suspicious independently of context and require a single correction

days/NN. Incorrect TAG family. Lexicon update (DT,(IN)) e.g., *some of us*. DT in Input, PRP in TAG. Rewrite Input
Forms that require several corrections

oprd-TO: Infinitival verbs which complement a control/raising verb.

*He will* try to assuage the fears about finances.

im-VB,(prd-JJ): Inf. verbs subcategorising for an adjectival phrase.

*Amex expects* to be fully operational by tomorrow.

im-VB: Infinitival verbs modifying a noun.

*The ability to trade* without too much difficulty has steadily deteriorated.
Forms that are suspicious in some but not all contexts

CD: noun or determiner. Determiner but not noun in TAG lexicon.
N.B., CD does not appear in suspicion tree as it generates fine when used...
Conclusion

- Proposed a novel approach to error mining which supports a linguistically meaningful error analysis.
- Permits quickly identifying the main sources of errors while providing a detailed description of the various subcases of these sources if any.
- We applied it to the analysis of undergeneration in a grammar based surface realisation algorithm.
- The approach is generic in that permits mining trees and strings for suspicious forms of arbitrary size and arbitrary conjunctions of labelling.