Error mining in parsing results

Benoît Sagot and Éric de la Clergerie
Projet ATOLL - INRIA
Domaine de Voluceau, B.P. 105
78153 Le Chesnay Cedex, France
{benoit.sagot,eric.de_la_clergerie}@inria.fr

Abstract

We introduce an error mining technique for automatically detecting errors in resources that are used in parsing systems. We applied this technique on parsing results produced on several million words by two distinct parsing systems, which share the syntactic lexicon and the pre-parsing processing chain. We were thus able to identify missing and erroneous information in these resources.

1 Introduction

Natural language parsing is a hard task, partly because of the complexity and the volume of information that have to be taken into account about words and syntactic constructions. However, it is necessary to have access to such information, stored in resources such as lexica and grammars, and to try and minimize the amount of missing and erroneous information in these resources. To achieve this, the use of these resources at a large-scale in parsers is a very promising approach (van Noord, 2004), and in particular the analysis of situations that lead to a parsing failure: one can learn from one’s own mistakes.

We introduce a probabilistic model that allows to identify forms and form bigrams that may be the source of errors, thanks to a corpus of parsed sentences. In order to facilitate the exploitation of forms and form bigrams detected by the model, and in particular to identify causes of errors, we have developed a visualization environment. The whole system has been tested on parsing results produced for several multi-million-word corpora and with two different parsers for French, namely SXLFG and FRMG.

However, the error mining technique which is the topic of this paper is fully system- and language-independent. It could be applied without any change on parsing results produced by any system working on any language. The only information that is needed is a boolean value for each sentence which indicates if it has been successfully parsed or not.

2 Principles

2.1 General idea

The idea we implemented is inspired from (van Noord, 2004). In order to identify missing and erroneous information in a parsing system, one can analyze a large corpus and study with statistical tools what differentiates sentences for which parsing succeeded from sentences for which it failed.

The simplest application of this idea is to look for forms, called suspicious forms, that are found more frequently in sentences that could not be parsed. This is what van Noord (2004) does, without trying to identify a suspicious form in any sentence whose parsing failed, and thus without taking into account the fact that there is (at least) one cause of error in each unparsable sentence. On the contrary, we will look, in each sentence on which parsing failed, for the form that has the highest probability of being the cause of this failure: it is the main suspect of the sentence.

This form may be incorrectly or only partially described in the lexicon, it may take part in constructions that are not described in the grammar, or it may exemplify imperfections of the pre-syntactic processing chain. This idea can be easily extended to sequences of forms, which is what we do by tak-

\[\text{Indeed, he defines the suspicion rate of a form } f \text{ as the rate of unparsable sentences among sentences that contain } f.\]
ing form bigrams into account, but also to lemmas (or sequences of lemmas).

### 2.2 Form-level probabilistic model

We suppose that the corpus is split in sentences, sentences being segmented in forms. We denote by \( s_i \) the \( i \)-th sentence. We denote by \( o_{i,j} \), \( (1 \leq j \leq |s_i|) \) the occurrences of forms that constitute \( s_i \), and by \( F(o_{i,j}) \) the corresponding forms. Finally, we call error the function that associates to each sentence \( s_i \) either 1, if \( s_i \)'s parsing failed, and 0 if it succeeded.

Let \( \mathcal{O}_f \) be the set of the occurrences of a form \( f \) in the corpus: \( \mathcal{O}_f = \{ o_{i,j} | F(o_{i,j}) = f \} \). The number of occurrences of \( f \) in the corpus is therefore \( |\mathcal{O}_f| \).

Let us define at first the **mean global suspicion rate** \( \overline{S} \), that is the mean probability that a given occurrence of a form be the cause of a parsing failure. We make the assumption that the failure of the parsing of a sentence has a unique cause (here, a unique form...). This assumption, which is not necessarily exactly verified, simplifies the model and leads to good results. If we call \( \text{occ}_\text{total} \) the total amount of forms in the corpus, we have then:

\[
\overline{S} = \frac{\sum_i \text{error}(s_i)}{\text{occ}_\text{total}}
\]

Let \( f \) be a form, that occurs as the \( j \)-th form of sentence \( s_i \), which means that \( F(o_{i,j}) = f \). Let us assume that \( s_i \)'s parsing failed: \( \text{error}(s_i) = 1 \). We call **suspicion rate** of the \( j \)-th form \( o_{i,j} \) of sentence \( s_i \) the probability, denoted by \( S_{i,j} \), that the occurrence \( o_{i,j} \) of form \( f \) be the cause of the \( s_i \)'s parsing failure. If, on the contrary, \( s_i \)'s parsing succeeded, its occurrences have a suspicion rate that is equal to zero.

We then define the **mean suspicion rate** \( S_f \) of a form \( f \) as the mean of all suspicion rates of its occurrences:

\[
S_f = \frac{1}{|\mathcal{O}_f|} \sum_{o_{i,j} \in \mathcal{O}_f} S_{i,j}
\]

To compute these rates, we use a fix-point algorithm by iterating a certain amount of times the following computations. Let us assume that we just completed the \( n \)-th iteration: we know, for each sentence \( s_i \), and for each occurrence \( o_{i,j} \) of this sentence, the estimation of its suspicion rate \( S_{i,j} \) as computed by the \( n \)-th iteration, estimation that is denoted by \( S_{i,j}^{(n)} \). From this estimation, we compute the \( n+1 \)-th estimation of the mean suspicion rate of each form \( f \), denoted by \( S_f^{(n+1)} \):

\[
S_f^{(n+1)} = \frac{1}{|\mathcal{O}_f|} \cdot \sum_{o_{i,j} \in \mathcal{O}_f} S_{i,j}^{(n)}
\]

This rate\(^2\) allows us to compute a new estimation of the suspicion rate of all occurrences, by giving to each occurrence if a sentence \( s_i \) a suspicion rate \( S_{i,j}^{(n+1)} \) that is exactly the estimation \( S_f^{(n+1)} \) of the mean suspicion rate of \( S_f \) of the corresponding form, and then to perform a sentence-level normalization. Thus:

\[
S_{i,j}^{(n+1)} = \text{error}(s_i) \cdot \frac{S_f^{(n+1)}(o_{i,j})}{\sum_{1 \leq j \leq |s_i|} S_f^{(n+1)}(o_{i,j})}
\]

At this point, the \( n+1 \)-th iteration is completed, and we can resume again these computations, until convergence on a fix-point. To begin the whole process, we just say, for an occurrence \( o_{i,j} \) of sentence \( s_i \), that \( S_{i,j}^{(0)} = \text{error}(s_i)/|s_i| \). This means that for a non-parsable sentence, we start from a baseline where all of its occurrences have an equal probability of being the cause of the failure.

After a few dozens of iterations, we get stabilized estimations of the mean suspicion rate each form, which allows:

- to identify the forms that most probably cause errors,
- for each form \( f \), to identify non-parsable sentences \( s_i \) where an occurrence \( o_{i,j} \in \mathcal{O}_f \) of \( f \) is a main suspect and where \( o_{i,j} \) has a very

\[\text{\textsuperscript{2}We also performed experiment in which \( S_f \) was estimated by another estimator, namely the smoothed mean suspicion rate, denoted by \( \tilde{S}_f^{(n)} \), that takes into account the number of occurrences of \( f \). Indeed, the confidence we can have in the estimation \( S_f^{(n)} \) is lower if the number of occurrences of \( f \) is less. Hence the idea to smooth \( S_f^{(n)} \) by replacing it with a weighted mean \( \tilde{S}_f^{(n)} \) between \( S_f^{(n)} \) and \( \overline{S} \), where the weights \( \lambda \) and \( 1 - \lambda \) depend on \( |\mathcal{O}_f| \); if \( |\mathcal{O}_f| \) is high, \( \tilde{S}_f^{(n)} \) will be close from \( S_f^{(n)} \); if it is low, it will be closer from \( \overline{S} \):

\[
\tilde{S}_f^{(n)} = \lambda(|\mathcal{O}_f|) \cdot S_f^{(n)} + (1 - \lambda(|\mathcal{O}_f|)) \cdot \overline{S}
\]

In these experiments, we used the smoothing function \( \lambda(|\mathcal{O}_f|) = 1 - e^{-\beta|\mathcal{O}_f|} \) with \( \beta = 0.1 \). But this model, used with the ranking according to \( M_f = S_f \cdot \ln|\mathcal{O}_f| \) (see below), leads results that are very similar to those obtained without smoothing. Therefore, we describe the smoothingless model, which has the advantage not to use an empirically chosen smoothing function.}
high suspicion rate among all occurrences of form $f$.

We implemented this algorithm as a perl script, with strong optimizations of data structures so as to reduce memory and time usage. In particular, form-level structures are shared between sentences.

### 2.3 Extensions of the model

This model gives already very good results, as we shall see in section 4. However, it can be extended in different ways, some of which we already implemented.

First of all, it is possible not to stick to forms. Indeed, we do not only work on forms, but on couples made out of a form (a lexical entry) and one or several token(s) that correspond to this form in the raw text (a token is a portion of text delimited by spaces or punctuation tokens).

Moreover, one can look for the cause of the failure of the parsing of a sentence not only in the presence of a form in this sentence, but also in the presence of a bigram of forms. To perform this, one just needs to extend the notions of form and occurrence, by saying that a (generalized) form is a unigram or a bigram of forms, and that a (generalized) occurrence is an occurrence of a generalized form, i.e., an occurrence of a unigram or a bigram of forms. The results we present in section 4 includes this extension, as well as the previous one.

Another possible generalization would be to take into account facts about the sentence that are not simultaneous (such as form unigrams and form bigrams) but mutually exclusive, and that must therefore be probabilized as well. We have not yet implemented such a mechanism, but it would be very interesting, because it would allow to go beyond forms or $n$-grams of forms, and to manipulate also lemmas (since a given form has usually several possible lemmas).

### 3 Experiments

In order to validate our approach, we applied these principles to look for error causes in parsing results given by two deep parsing systems for French, FRMG and SxLFG, on large corpora.

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3 One could generalize this to $n$-grams, but as $n$ gets higher the number of occurrences of $n$-grams gets lower, hence leading to non-significant statistics.
useless for the experiments described here, since we want only to distinguish sentences that receive a full parse (without any recovery technique) from those that do not.

3.2 Corpora

We parsed with these two systems the following corpora:

MD corpus: This corpus is made out of 14.5 million words (570,000 sentences) of general journalistic corpus that are articles from the Monde diplomatique.

EASy corpus: This is the 40,000-sentence corpus that has been built for the EASy parsing evaluation campaign for French (Paroubek et al., 2005). We only used the raw corpus (without taking into account the fact that a manual parse is available for 10% of all sentences). The EASy corpus contains several sub-corpora of varied style: journalistic, literacy, legal, medical, transcription of oral, email, questions, etc.

Both corpora are raw in the sense that no cleaning whatsoever has been performed so as to eliminate some sequences of characters that can not really be considered as sentences.

Table 1 gives some general information on these corpora as well as the results we got with both parsing systems. It shall be noticed that both parsers did not parse exactly the same set and the same number of sentences for the MD corpus, and that they do not define in the exactly same way the notion of sentence.

| corpus         | #sentences | #success (%) | #forms | #occ | S (%) | Date   |
|----------------|------------|--------------|--------|------|-------|--------|
| MD/FRMG       | 330,938    | 136,885 (41.30%) | 255,616 | 10,422,926 | 1.86% | Jul. 05 |
| MD/SXLF G     | 567,039    | 343,988 (60.66%)  | 327,785 | 14,482,059 | 1.54% | Mar. 05 |
| EASy/FRMG     | 39,872     | 16,477 (41.32%)  | 61,135  | 878,156 | 2.66% | Dec. 05 |
| EASy/SXLF G   | 39,872     | 21,067 (52.84%)  | 61,135  | 878,156 | 2.15% | Dec. 05 |

Table 1: General information on corpora and parsing results

3.3 Results visualization environment

We developed a visualization tool for the results of the error mining, that allows to examine and annotate them. It has the form of an HTML page that uses dynamic generation methods, in particular javascript. An example is shown on Figure 1.

To achieve this, suspicious forms are ranked according to a measure $M_f$ that models, for a given form $f$, the benefit there is to try and correct the (potential) corresponding error in the resources. A user who wants to concentrate on almost certain errors rather than on most frequent ones can visualize suspicious forms ranked according to $M_f = S_f$. On the contrary, a user who wants to concentrate on most frequent potential errors, rather than on the confidence that the algorithm has given to errors, can visualize suspicious forms ranked according to $M_f = S_f |O_f|$. The default choice, which is adopted to produce all tables shown in this paper, is a balance between these two possibilities, and ranks suspicious forms according to $M_f = S_f \cdot \ln |O_f|$.

The visualization environment allows to browse through (ranked) suspicious forms in a scrolling list on the left part of the page (A). When the suspicious form is associated to a token that is the same as the form, only the form is shown. Otherwise, the token is separated from the form by the symbol “/”. The right part of the page shows various pieces of information about the currently selected form. After having given its rank according to the ranking measure $M_f$ that has been chosen (B), a field is available to add or edit an annotation associated with the suspicious form (D). These annotations, aimed to ease the analysis of the error mining results by linguists and by the developers of parsers and resources (lexica, grammars), are saved in a database (SQLITE). Statistical information is also given about $f$ (E), including its number of occurrences $occ_f$, the number of occurrences of $f$ in non-parsable sentences, the final estimation of its mean suspicion rate $S_f$ and the rate $err(f)$ of non-parsable sentences among those where $f$ appears. This indications are complemented by a brief summary of the iterative process that shows the convergence of the successive estimations of $S_f$. The lower part of the page gives a mean to identify the cause of $f$-related errors by showing

\[ f \]
f’s entries in the Leff lexicon (G) as well as non-parsable sentences where f is the main suspect and where one of its occurrences has a particularly high suspicion rate (H).

The whole page (with annotations) can be sent by e-mail, for example to the developer of the lexicon or to the developer of one parser or the other (C).

4 Results

In this section, we mostly focus on the results of our error mining algorithm on the parsing results provided by SXLFG on the MD corpus. We first present results when only forms are taken into account, and then give an insight on results when both forms and form bigrams are considered.

Such an information, which is extremely valuable for the developers of the resources, can not be obtained by global (form-level and not occurrence-level) approaches such as the err(f)-based approach of (van Noord, 2004). Indeed, enumerating all sentences which include a given form f, and which did not receive a full parse, is not precise enough: it would show at the same time sentences which fail because of f (e.g., because its lexical entry lacks a given subcategorization frame) and sentences which fail for an other independent reason.

4.1 Finding suspicious forms

The execution of our error mining script on MD/SXLFG, with $i_{\text{max}} = 50$ iterations and when only (isolated) forms are taken into account, takes less than one hour on a 3.2 GHz PC running Linux with a 1.5 Go RAM. It outputs 18,334 relevant suspicious forms (out of the 327,785 possible ones), where a relevant suspicious form is defined as a form f that satisfies the following arbitrary constraints:

$$S_f > 1, 5 \cdot S \quad \text{and} \quad |O_f| > 5.$$  

We still can not prove theoretically the convergence of the algorithm. But among the 1000 best-ranked forms, the last iteration induces a mean variation of the suspicion rate that is less than 0.01%.

On a smaller corpus like the EASy corpus, 200 iterations take 260s. The algorithm outputs less than 3,000 relevant suspicious forms (out of the 61,125 possible ones). Convergence information

These constraints filter results, but all forms are taken into account during all iterations of the algorithm.
is the same as what has been said above for the
MD corpus.
Table 2 gives an idea of the repartition of sus-
picious forms w.r.t. their frequency (for FRMG on
MD), showing that rare forms have a greater prob-
ability to be suspicious. The most frequent suspi-
cious form is the double-quote, with (only) $S_f =\ 9\%$, partly because of segmentation problems.

4.2 Analyzing results
Table 3 gives an insight on the output of our algo-
rithm on parsing results obtained by SXLFG on the
MD corpus. For each form $f$ (in fact, for each cou-
ples of the form $(token,form)$), this table displays its
suspicion rate and its number of occurrences, as
well as the rate $\text{err}(f)$ of non-parsable sentences
among those where $f$ appears and a short manual
analysis of the underlying error.

In fact, a more in-depth manual analysis of the
results shows that they are very good: errors are
correctly identified, that can be associated with
four error sources: (1) the Leff lexicon, (2) the
SxPipe pre-syntactic processing chain, (3) imper-
fecions of the grammar, but also (4) problems re-
lated to the corpus itself (and to the fact that it
is a raw corpus, with meta-data and typographic
noise).

On the EASy corpus, results are also relevant,
but sometimes more difficult to interpret, because
of the relative small size of the corpus and because
of its heterogeneity. In particular, it contains e-
-mail and oral transcriptions sub-corpora that in-
troduce a lot of noise. Segmentation problems
(caused both by SxPipe and by the corpus itself,
which is already segmented) play an especially
important role.

4.3 Comparing results with results of other
algorithms
In order to validate our approach, we compared
our results with results given by two other relevant
algorithms:

• van Noord’s (van Noord, 2004) (form-level
and non-iterative) evaluation of $\text{err}(f)$ (the
rate of non-parsable sentences among sen-
tences containing the form $f$),

• a standard (occurrence-level and iterative)
maximum entropy evaluation of each form’s con-
tribution to the success or the failure of
a sentence (we used the MEGAM package
(Daumé III, 2004)).

As done for our algorithm, we do not rank forms
directly according to the suspicion rate $S_f$ com-
putated by these algorithms. Instead, we use the $M_f$
measure presented above ($M_f = S_f \cdot \ln |O_f|$). Us-
ing directly van Noord’s measure selects as most
suspicious words very rare words, which shows
the importance of a good balance between suspi-
cion rate and frequency (as noted by (van Noord,
2004) in the discussion of his results). This remark
applies to the maximum entropy measure as well.

Table 4 shows for all algorithms the 10 best-
ranked suspicious forms, complemented by a man-
ual evaluation of their relevance. One clearly sees
that our approach leads to the best results. Van
Noord’s technique has been initially designed to
find errors in resources that already ensured a very
high coverage. On our systems, whose develop-
ment is less advanced, this technique ranks as most
suspicious forms those which are simply the most
frequent ones. It seems to be the case for the stan-
dard maximum entropy algorithm, thus showing
the importance to take into account the fact that
there is at least one cause of error in any sentence
whose parsing failed, not only to identify a main
suspicious form in each sentence, but also to get
relevant global results.

4.4 Comparing results for both parsers
We complemented the separated study of error
mining results on the output of both parsers by
an analysis of merged results. We computed for
each form the harmonic mean of both measures
$M_f = S_f \cdot \ln |O_f|$ obtained for each parsing sys-

tem. Results (not shown here) are very interest-
ing, because they identify errors that come mostly
from resources that are shared by both systems
(the Leff lexicon and the pre-syntactic processing
chain SxPipe). Although some errors come from
common lacks of coverage in both grammars, it
is nevertheless a very efficient mean to get a first
repartition between error sources.

4.5 Introducing form bigrams
As said before, we also performed experiments
where not only forms but also form bigrams are
treated as potential causes of errors. This approach
allows to identify situations where a form is not in
itself a relevant cause of error, but leads often to
a parse failure when immediately followed or pre-
ceded by an other form.

Table 5 shows best-ranked form bigrams (forms
that are ranked in-between are not shown, to em-
| #occ | > 100 000 | > 10 000 | > 1000 | > 100 | > 10 |
|---|---|---|---|---|---|
| #forms | 13 | 84 | 947 | 8345 | 40 393 |
| #suspicious forms (%) | 1 (7.6%) | 13 (15.5%) | 177 (18.7%) | 1919 (23%) | 12 022 (29.8%) |

Table 2: Suspicious forms repartition for MD/FRMG

| Rank | Token(s)/form | $S_f^{(m)}$ | $|O_f|$ | err($f$) | $M_f$ | Error cause |
|---|---|---|---|---|---|---|
| 1 | _____ / UNDERSCORE | 100% | 4804 | 100% | 8.45 | corpus: typographic noise |
| 2 | poussé | 76% | 91 | 94% | 3.41 | Lefff: misses as an adjective |
| 3 | (...) | 46% | 1216 | 74% | 3.27 | SXPipe: should be treated as skippable words |
| 4 | fallu | 55% | 215 | 93% | 2.94 | Lefff: should allow nominal object (not only infinitive) |
| 5 | organisés | 62% | 89 | 94% | 2.78 | Lefff: misses as an adjective |
| 7 | puisse | 48% | 287 | 95% | 2.74 | grammar: construction missing (aussi adj que puisse inf...) |
| 8 | fallait | 51% | 221 | 91% | 2.73 | as for falla |
| 9 | décentralisée | 55% | 128 | 88% | 2.68 | Lefff: misses as an adjective |
| 10 | généralisé | 56% | 115 | 96% | 2.64 | Lefff: misses as an adjective |
| 11 | spécialisées | 58% | 90 | 94% | 2.63 | Lefff: misses as an adjective |

Table 3: Analysis of the 10 best-ranked forms (ranked according to $M_f = S_f \cdot \ln |O_f|$)

| Rank | Token(s)/form | Eval | global | Token(s)/form | Eval | maxent |
|---|---|---|---|---|---|---|
| 1 | _____ / UNDERSCORE | ++ | " | + | pour | - |
| 2 | (...) | ++ | - | - | - | - |
| 3 | 2_/NUMBER | ++ | livre | - | a | - |
| 4 | privées | ++ | - | - | qu’il/que | - |
| 5 | Haaretz/_Uw | ++ | de | - | sont | - |
| 6 | contesté | ++ | - | - | le | - |
| 7 | occupés | ++ | - | - | qu’un/que | + |
| 8 | privée | ++ | la | - | qu’un/en | + |
| 9 | [...] | ++ | étrangères | - | que | - |
| 10 | faudrait | ++ | lecteurs | - | pourrait | - |

Table 4: The 10 best-ranked suspicious forms, according to the $M_f$ measure, as computed by different algorithms: ours ($this$ paper), a standard maximum entropy algorithm ($maxent$) and van Noord’s rate $err(f)$ ($global$).

| Rank | Tokens and forms | $M_f$ | Error cause |
|---|---|---|---|
| 4 | Toutes/toutes les | 2.73 | grammar: badly treated pre-determiner adjective |
| 6 | y en | 2.34 | grammar: problem with the construction il y en a... |
| 7 | in " | 1.81 | Lefff: in misses as a preposition, which happens before book titles (hence the ") |
| 10 | donne a | 1.44 | Lefff: donner should sub-categorise a-vcomps (donner a voir...) |
| 11 | de demain | 1.19 | Lefff: demain misses as common noun (standard adv are not preceded by prep) |
| 16 | ( 22_/NUMBER | 0.86 | grammar: footnote references not treated |
| 16 | 22_/NUMBER ) | 0.86 | as above |

Table 5: Best ranked form bigrams (forms ranked inbetween are not shown; ranked according to $M_f = S_f \cdot \ln |O_f|$). These results have been computed on a subset of the MD corpus (60,000 sentences).
phasize bigram results), with the same data as in table 3.

5 Conclusions and perspectives

As we have shown, parsing large corpora allows to set up error mining techniques, so as to identify missing and erroneous information in the different resources that are used by full-featured parsing systems. The technique described in this paper and its implementation on forms and form bigrams has already allowed us to detect many errors and omissions in the Lefff lexicon, to point out inappropriate behaviors of the SxPipe pre-syntactic processing chain, and to reveal the lack of coverage of the grammars for certain phenomena.

We intend to carry on and extend this work. First of all, the visualization environment can be enhanced, as is the case for the implementation of the algorithm itself.

We would also like to integrate to the model the possibility that facts taken into account (today, forms and form bigrams) are not necessarily certain, because some of them could be the consequence of an ambiguity. For example, for a given form, several lemmas are often possible. The probabilization of these lemmas would thus allow to look for most suspicious lemmas.

We are already working on a module that will allow not only to detect errors, for example in the lexicon, but also to propose a correction. To achieve this, we want to parse anew all non-parsable sentences, after having replaced their main suspects by a special form that receives under-specifed lexical information. These information can be either very general, or can be computed by appropriate generalization patterns applied on the information associated by the lexicon with the original form. A statistical study of the new parsing results will make it possible to propose corrections concerning the involved forms.

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