



SAARLAND UNIVERSITY  
DEPARTMENT OF COMPUTATIONAL LINGUISTICS

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# Automatic Detection of Linguistic Quality Violations

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*Author:*

Jonathan OBERLÄNDER  
Matriculation: 2539632

*Supervisors:*

Prof. Manfred PINKAL  
Annemarie FRIEDRICH

Date of submission

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# 1 Introduction

Evaluation of automatic summarization systems has largely been done on content coverage, which is why generated summaries often lack linguistic quality (Nenkova et al., 2011), meaning that they contain many errors of various kinds. A new focus on linguistic quality (LQ) evaluation would presumably help decrease these issues and produce overall better summarization systems.

As a first step in this direction, Friedrich et al. (2014) created the *LQVCorpus*, which consists of multi-document summaries from the TAC 2011 shared task on Guided Summarization (Owczarzak and Dang, 2011), annotated manually with LQ violations on entity, clause and discourse level.

Manual annotation is an expensive and time-consuming process, for which an automatic system could be an alternative. Our work deals with creating such a system that manages at least part of the annotation automatically. We develop and evaluate our system on top of the *LQVCorpus*.

## 2 Related Work

Most work in the field of automatic grammar checking seems to have been done in the area of second language learning. Bender et al. (2004) use the LKB parser and generator Copestake (2002) with the English Resource Grammar (Flickinger, 2000) to build *Arboretum*, a system that, when given an erroneous input sentence, detects that error and outputs a corrected version of the sentence. Their method uses manually selected mal-rules (Schneider and McCoy, 1998) to detect error types specific to second language learners of English.

While this seems to work for their specific domain, it does not transform well into ours: The mistakes language learners make, and the kind of ungrammaticality summarization systems produce, are very different. Source texts that are being summarized are usually grammatical, and get their ungrammaticality during summarization from being compressed from two formerly grammatical sentences into one ungrammatical one, for example. Mistakes typical for learners of English as a second language either usually do not occur in automatic summarizations (such as misspelt words), or do happen, but due to a different cause (for example agreement).

Chodorow and Leacock (2000) build *ALEK*, a system to grade TOEFL essays. It does so by viewing the task as an extension of Word Sense Disambiguation, and collecting n-grams of POS-tags and function words, and then classifying using primitive statistical measures like *Mutual Information* and the  $\chi^2$  test. However, only the whole essay is classified into one of six possible scores, and this decision is only made by looking at the test subject’s understanding of the three words *Concentrate*, *Interest* and *Knowledge* in context.

Sun et al. (2007), while also citing second language learning as their primary application, use a different approach: Instead of manually writing rules, they employ a supervised statistical learning method. They extract what they call *labeled sequential patterns* (ngrams associated with a class) from both erroneous and correct sentences in their training corpus, enrich them with other automatically computed features, and use them as input for classification models; an SVM (SVMlight, Joachims, 2002) and a Naïve Bayes classification model. The system achieves F-scores of around 80%.

There also has been work in the area of assessing grammaticality of automatically generated summaries, namely Vadlapudi and Katragadda (2010). They used n-grams on POS-tag level and evaluated their system by looking at how well their classification correlates to ROGUE scores (Lin, 2004). Vadlapudi

and Katragadda achieve a Spearman’s  $\rho$  correlation of up to 77% to ROGUE scores manually assigned by annotators.

Wagner et al. (2007) compare various methods for detecting ungrammaticality: The “flat” method of using n-grams, a parser-based method using the XLE LFG parser (Maxwell and Kaplan, 1996), and using decision trees trained on the output of each of these methods. Their best method achieves an F-score of about 67%.

### 3 Finding Ungrammaticality

As a first step, we inspect the corpus. We find that the type system of the LQVCorpus (Valeeva, 2013) is not detailed enough for our purposes and has a few shortcomings: Especially under the label of `other_ungrammatical_form` many different types of errors are combined. For this reason, we define a number of subtypes for this violation:

#### missing spaces

This is the most common type of error: The sentence contains a word that does not exist. In almost all cases, this happens when whitespace between two words is missing.

Example: *A strong earthquake measuring 7.8 magnitude struck **Wenchuancounty** of Sichuan Province on Monday, leaving at least 12,000people died and thousands more injured.*

#### missing words

One or multiple words are clearly missing. These seem to most often be function words such as articles or pronouns, rather than content words. In the example, an underscore marks the position where a word, probably “was” is missing.

Example: *An Israeli woman \_ killed and 11 others were wounded in the suicide bombing at a shopping mall in southern Israeli town of Dimona.*

#### punctuation error

Most of the time, this means: Punctuation is missing, but it can also mean there is something else wrong with punctuation in that sentence which makes it ungrammatical, as can be seen in the example: Unbalanced parantheses.

Example: *China has allocated 200 million yuan (million dollars for disaster relief work after an earthquake rocked the country’s killing at least seven people, state reported on Tuesday.*

#### capitalization error

A word that should be capitalized is not or one that should not be capitalized is.

Example: *earlier on **m**onday **g**erman chancellor **a**ngela **m**erkel and foreign minister **f**rank **w**alter **s**teinmeier offered their condolences to **c**hina over the heavy loss of life in the powerful earthquake that hit **c**hina’s southwestern province of **s**ichuan.*

#### unparsable

This subtype means that the (human) annotator was unable to make sense of the sentence and considers it not correctly parsable. Most instances of this subtype seem to happen when sentence fusion occurs; the summarization system combined two or more sentences in an ungrammatical or meaningless way.

Example: *All of those provinces and Chongqing, a special municipality – deepest condolences to those who lost their loved ones in the devastating natural disaster.*

#### heading

The sentence contain (usually at the beginning) a sequence of capitalized or otherwise heading-like words.

Example: *THE CURRENT FIX: Internet applications such as firewalls and spam filters attempt to control security threats.*

#### incomplete sentence

The type system of the LQVCorpus (Valeeva, 2013) defines an `incomplete_sentence` violation as words being cut off at the end of a sentence. A couple of times though, this also occurs at the beginning of a sentence. We restructure the type system by treating all types of incomplete sentences as this subtype of `other_ungrammatical_form`.

Example: *A Palestinian suicide bomber detonated an explosive belt at a commercial center in Dimona on.*

#### should be other type

Sometimes sentences that are tagged as `other_ungrammaticality` should (also) be tagged as another type, such as sentences containing datelines. This doesn't necessarily mean that the sentence contains no other ungrammaticalities. This subtype be caused by inconsistencies in the corpus, or from the process of mapping the annotated violations to sentences. While the following example is an `incomplete_sentence`, it also contains a dateline.

Example: *its deepest sympathy to the Israeli people, 00 a.m. local time (0800 GMT) as a suicide bomber detonated an explosive belt in the commercial center, according to local media reports.*

The corpus was split into five parts (*dev-1* through *dev-2*), each containing 8 topics, so that e.g. *dev-1* contains topics D1101 through D1108.

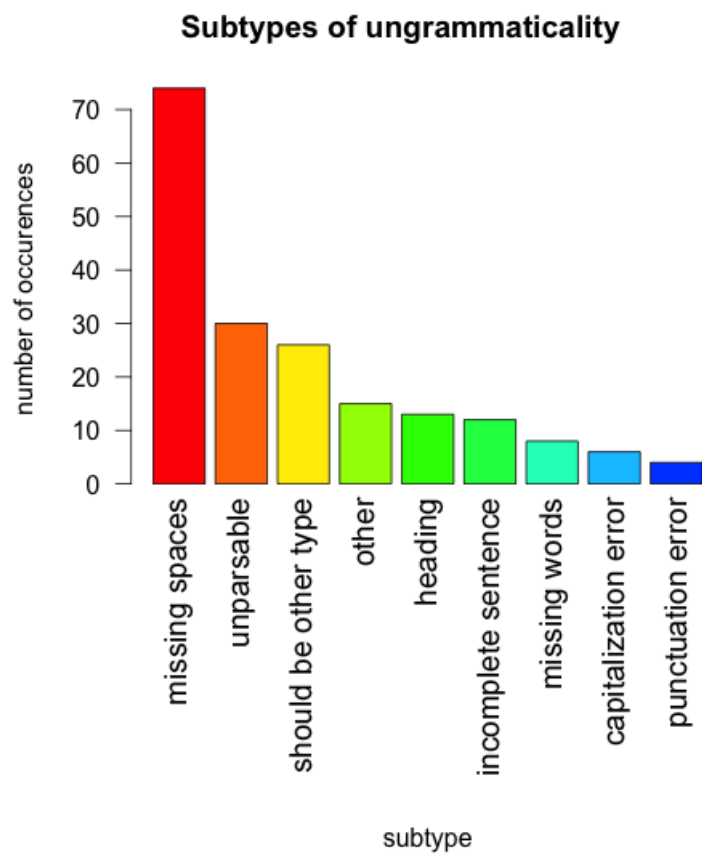
After manually counting and investigating these subtypes on *dev-1* we then mark these types in *dev-2* for every sentence that is tagged as `other_ungrammatical_form` in the corpus. We allow sentences to have multiple subtypes and also annotate `incomplete_sentence` violations with additional (sub)types, if applicable. The frequency distribution of the subtypes in *dev-2* can be seen in Figure 1.

## 4 Experiments

We conduct a number of experiments to find reliable ways to detect different kinds of ungrammaticality. The annotation, our experiments and the evaluation are all done on sentence basis. We use Stanford CoreNLP for sentence splitting.

### 4.1 Detecting Unknown Tokens

Perhaps the most noticeable result is the large portion of *missing spaces* violations, meaning clauses that include tokens which aren't correct words. Almost all of these cases come from a missing space between two words forming tokens such as `reportsreaching` or `Wenchuancounty`. As there is such a large amount of this type, finding a reliable detection method for this subtype would significantly boost detection of ungrammaticality in general.



**Figure 1. Subtypes of ungrammaticality in *dev-2*.** Where the annotator didn't know what subtype to annotate the sentence with, they selected "other".

### 4.1.1 Method

We call our approach to identifying missing spaces **UnknownTokens**: Tagging a sentence as containing a *missing spaces* ungrammaticality if and only if there is a token in the sentence that isn't a "known" token, i.e. one that doesn't exist in a list of known words. In our setting, we can easily deduce such a list from the source documents of the automatic summarization process. If the source document is available and used as a base for our vocabulary, we call that approach **UnknownTokens<sub>source</sub>**.

In case the original documents aren't available or this method should be used in a different setting, we also investigate how to adapt our approach to that. This approach has a few steps, which we will all evaluate individually: First, an initial list of words is created from a large text corpus (**UnknownTokens<sub>wn</sub>**); we use the first 20% of the AFE part of the gigaword corpus (Graff et al., 2003). If the corpus is large and general enough, this will probably cover a large vocabulary.

Because this will not include words for named entities yet, we only consider a token to be an unknown token, if it is not tagged as a Named Entity by a Named Entity Recognizer (**UnknownTokens<sub>ner</sub>**). We employ the Stanford Named Entity Recognizer (Finkel et al., 2005), which is a widely used, state-of-the-art NER that comes with a model for the English language.

In order to improve upon the NER and further increase recall, we use two simple heuristics (**UnknownTokens<sub>heur</sub>**): Firstly, we assume that words that start with a capital letter and are only followed by lower case letters are named entities and therefore no unknown tokens. Finally, we automatically check whether an unknown token has an entry on the online encyclopedia Wikipedia (**UnknownTokens<sub>wiki</sub>**).

We automatically label any tokens that are neither on our list of known tokens from GigaWord, nor tagged as a named entity as "unknown" and tag the sentence as containing unknown tokens. The combined method **UnknownTokens<sub>wn+heur+ner+wiki</sub>** is what we call **UnknownTokens<sub>general</sub>**.

### 4.1.2 Evaluation

We evaluate how effective **UnknownTokens** is in detecting *missing spaces* violations, both with (**UnknownTokens<sub>source</sub>**) and without (**UnknownTokens<sub>general</sub>**) access to the source documents, and compare it to a **baseline**, which always assumes the most common case (no *missing spaces* violation). The standard metrics precision, recall and F-score are used for evaluation.

Table 1 shows the results of the evaluation. Because the amount of sentences not containing a missing spaces violation is much larger than the ones that do, several weighted metrics are provided, too:

The micro-average method consists of summing up the individual values from the confusion matrix (True Positive, False Positive, True Negative and False Negative) and calculating new metrics based on the results. We only display the F-score here, since F-score, recall and precision are identical for a 2-class scenario: Since the true positives of the missing spaces class are identical with the true negatives of the no missing spaces class (and vice versa), the new number of true positives and true negatives (for the micro average) is  $tp + tn$  of any of the two classes. The same goes for false negatives and false positives. That means that when only dealing with two classes, in the micro-average method, the terms *positive* and *negative* can be used interchangeably. As precision is defined as  $\frac{tp}{tp+fp}$  and recall as  $\frac{tp}{tp+fn}$ ; as the equations only differ in whether they use  $fp$  or  $fn$  (which are exactly the same here) in the divisor, precision and recall (and therefore F-score, too, since the F-score is simply the harmonic mean of precision and recall) are identical.



Macro-averages are just arithmetic means of precision and recall. For both micro- and macro-average, the new F-score is calculated from the new scores.

Both **UnknownTokens<sub>general</sub>** and **UnknownTokens<sub>source</sub>** improve vastly over the baseline, but it is clear, that if the source text is available, it should be used to infer known words.

## 4.2 Detecting Ungrammaticality

To detect more general forms of ungrammaticality, several other methods were investigated. Following Wagner et al. (2007), we learn decision trees from outputs of several systems that on their own have not proven sufficient for this task. For this experiment, the development set *dev-1* was used.

### 4.2.1 Method

We train a language model on parts (the same parts we used as a word source in **UnknownTokens<sub>general</sub>** (section 4.1)) of the Gigaword corpus (Graff et al., 2003), extract perplexity scores for the sentences in our test set, and annotate them automatically. For the language model generation and the extraction of perplexity scores, we employ SRILM (Stolcke et al., 2002), a language modeling toolkit.

We then use a RandomForest (Breiman, 2001) to learn decision trees. For this task, we use the machine learning toolkit WEKA (Hall et al., 2009). We use three features for our decision tree:

- **LM\_PP** is the perplexity calculated for a sentence by the language model, following Sun et al. (2007). This is a numeric feature. It proved to not be sufficient for detecting ungrammaticality on its own.
- **missing spaces** is the classification of **UnknownTokens<sub>source</sub>** for a given sentence, as described in section 4.1. This is a binary feature.
- **numberofwords** is the number of words in the sentence. We follow Wagner et al. (2007) here, the intuition is that ungrammatical sentences will often be extraordinarily long, or very short:

*Former US President George W Bush, Who Will attend a memorial service on Tuesday, Virginia, and the university of at least 33 people Were killed, in the Worst shooting rampage in modern history, the White House said.*

*The report of a*

### 4.2.2 Evaluation

We performed 10-fold cross-validation, which lead to a weighted F-score of 86.3%. A total of 1215 (88.1%) instances was classified correctly, 164 (11.9%) incorrectly.

## 4.3 Datelines

Source texts from news articles, like the ones in the TAC dataset, often contain datelines, which sometimes make it into the generated summary. While in the context of the article datelines made sense (often displayed smaller or otherwise visually distinctive), they are not needed, distracting and confusing in the summaries:

	Missing spaces			No missing spaces			Macro-average		Accuracy
	P	R	F	P	R	F	F		
<b>Baseline</b>	0.0	0.0	0.0	94.8	<b>100</b>	97.3	48.7	94.8	
<b>UT<sub>wn</sub></b>	15.0	<b>98.7</b>	26.0	<b>99.9</b>	69.1	81.7	68.2	70.7	
<b>UT<sub>wn+heur</sub></b>	30.5	97.3	46.5	99.8	87.8	93.4	76.5	88.3	
<b>UT<sub>wn+heur+ner</sub></b>	35.5	97.3	52.0	99.8	90.3	94.8	78.6	90.6	
<b>UT<sub>wn+heur+ner+wiki</sub></b>	70.3	96.0	81.2	99.8	97.8	98.8	90.6	97.7	
<b>UT<sub>source</sub></b>	<b>95.9</b>	94.6	<b>95.2</b>	99.7	99.7	<b>99.7</b>	<b>97.5</b>	<b>99.5</b>	

**Table 1.** Evaluation of **UnknownTokens** on *dev-2*, in percent. **UT<sub>wordnet+heur+ner+wiki</sub>** is equivalent to **UnknownTokens<sub>general</sub>**. **wn** = Wordnet-based dictionary, **heur** = title case heuristics, **ner** = Stanford NER, **wiki** = Wikipedia entry check

**BLACKSBURG, Virginia 2007-04-16 18:34: 44 UTC** *A gunman opened fire in a dorm and classroom at Virginia Tech on Monday, killing at least 30 people in the deadliest shooting rampage in U.S. history.*

#### 4.3.1 Method

The emerging patterns are so regular, that we use regular expressions to detect them. A few iterations of the regex were done, but so far the highest results were achieved using the regular expression

```
UTC|^ \d{4}-\d{2}-\d{2} | ^ [A-Z]{3,} | ^ ( Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct  
| Nov | Dec )
```

The expression has four parts, of which only one has to match to make the system classify a sentence as containing datelines: The first part matches the string “UTC” (Coordinated Universal Time, a common fragment in datelines), the second one numeric dates like 2014-04-13, the third one capitalized words that are longer than 4 letters and are therefore expected not to be abbreviations (an example would be LONDON, Feb. 4 (Xinhua)), and the final part matches abbreviated names of months. Only “UTC” can occur anywhere, everything else needs to occur at the beginning of a sentence to be counted.

#### 4.3.2 Evaluation

This very simple approach was evaluated on *dev-2* and leads to good results: The F-score of the class of dateline-containing sentences is 90.7% (precision: 90.3%, recall: 91.1%). When looking into the inaccurately detected instances, the inconsistencies of the LQVCorpus make up most of the misses:

*IVORY TUSKS*

is classified as containing a dateline by the regular expression, but is not annotated as such in the corpus. An example of a false negative would be:

*00 a.m. local time (0800 GMT)*

which our system doesn’t match.

### 4.4 Redundancy

### 4.5 Unrelatedness

## 5 Discussion

## 6 Conclusion

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