Automatic Phrase Recognition in Historical German

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Abstract

Due to a lack of annotated data, theories of historical syntax are often based on very small, manually compiled data sets. To enable the empirical evaluation of existing hypotheses, the present study explores the automatic recognition of phrases in historical German. Using modern and historical treebanks, training data for a neural sequence labeling tool and a probabilistic parser is created, and both methods are compared on a variety of data sets. The evaluation shows that the unlexicalized parser outperforms the sequence labeling approach, achieving $F_1$-scores of 87%–91% on modern German and between 73% and 85% on different historical corpora. An error analysis indicates that accuracy decreases especially for longer phrases, but most of the errors concern incorrect phrase boundaries, suggesting further potential for improvement.

1 Introduction

In recent years, the availability of ever-larger data sets and increasing computational power have led to major changes in the way language is analyzed. Today, NLP tools can automatically enrich large amounts of text quickly and accurately with linguistic annotations needed for commercial or research purposes. When it comes to non-standard data like historical language, though, the availability of models and annotated corpora is still limited compared to modern language and hypotheses are often based on qualitative analyses of very small data sets. For example, Speyer (2011) investigates object order in the middle field of Early New High German sentences based on a total of 70 pairs of direct and indirect objects from three centuries. Similarly, Light (2012) grounds her study of extraposition, i.e. the movement of elements behind the clause-final verb, on 115 cases of extraposed subjects in one Early New High German bible translation, while Sapp (2014) analyzes 683 extraposed phrases spread over texts from five centuries. Although data-driven qualitative analyses like these provide valuable insights for linguistic research, they require a lot of manual effort and cannot achieve the same statistical significance as studies of modern language.

Recently, there have been several attempts to address the lack of annotated historical data and provide a basis for the empirical evaluation of existing hypotheses by automatically identifying relevant syntactic units in historical text (e.g. Chiarcos et al., 2018; Ortmann, 2020, 2021). The present paper takes a similar approach and looks explicitly at the units targeted by the qualitative studies mentioned above, namely phrases.

In the context of this study, phrases are understood as continuous, non-overlapping constituents from a sentence’s parse tree. Since the concrete definition of constituents may vary depending on the annotation scheme and not all constituents are equally relevant for linguistic studies like the ones mentioned above, this paper focuses on four main phrase types: noun phrases (NP), prepositional phrases (PP), adjective phrases (AP), and adverb phrases (ADVP). For each sentence, only the highest non-terminal nodes of the given types are considered, ignoring the internal structure of phrases. This means that phrases may dominate other phrases of the same or different types, but the dominated phrases are not evaluated here. Example (1) shows an annotated sentence from a 1731 theological text.

(1) [NP Der kräftigste Bewegungs-Grund] nimmt [NP seinen Ursprung] [PP aus einer zärtlichen Leydenchaft meines Gemühts].

The most powerful motive takes its origin from a tender passion of my heart.

To enable research on phenomena like extraposition, phrases may not cross topological field bound-
aries. For example, a prepositional phrase in the middle field is considered separate from an adjacent modifying relative clause in the post-field, as shown in example (2) from a chemistry essay (field boundaries are indicated by vertical pipes). Also, discontinuous structures as they exist in some German corpora are not allowed here.

(2) Erhebt l [NP es] [NP sich] [PP mit dem Waﬀerstoﬀgas], l [NP welches] l [NP die Moräfte] [PP in Ueberfluß] l ausdunften?

Does it rise with the hydrogen gas that the swamps evaporate in abundance?

The goal of this study is to automatically recognize phrases that meet the aforementioned requirements in historical German texts. The remainder of the paper is structured as follows: Section 2 presents related work on the syntactic analysis of (historical) German before Section 3 introduces the data sets used in this study. In Section 4, two different methods for the automatic recognition of phrases are selected based on the findings of previous studies and their performance is evaluated in Section 5. The paper concludes with a discussion in Section 6.

2 Related Work

The recognition of phrases as defined in the previous section is related to chunking as well as (constituency) parsing and can be located somewhere in between the two tasks regarding its complexity.

Chunking refers to the identification of non-overlapping, non-recursive phrases from a sentence’s parse tree, ending with the head token (Sang and Buchholz, 2000). As a consequence, chunks are often shorter than phrases because post-modifying elements form separate chunks. For simple cases without pre- or post-modifying elements, however, the definitions of chunks and phrases overlap and methods that are successful at chunking may also be useful for phrase recognition.

Parsing, on the other hand, aims at a complete syntactic analysis of the sentence. Hence, the resulting constituency tree includes more information than just the phrase annotation, e.g. dominance relations, which are not considered in this study. As a result, phrase annotations can be derived from the more complex parse output, but the complexity of the task may also reduce overall accuracy.

3 Data

The data sets for the experiments are taken from a previous chunking study (Ortmann, 2021). The training data consists of two modern and two historical text corpora. The TüBa-D/Z corpus (Telljohann et al., 2017) and the Tiger corpus (Brants et al., 2004) contain modern German newspaper articles, whereas the Mercurius corpus (Demske, 2005) and the ReF.UP corpus (Demske, 2019) comprise Early New High German texts from the 14th to 17th century. All four data sets are annotated with constituency trees, but before they can be used to train a parser or extract phrase annotations for sequence labeling, a few modifications are necessary.

While studies on chunking observe \(F_1\)-scores >95% for modern German (cf. Müller, 2005; Ortmann, 2021), the highest \(F_1\)-scores for constituency parsing of German are reported with approx. 90%, compared to 95% for English (Kitaev et al., 2019). In general, parsing results heavily depend on the selected treebank and the inclusion of grammatical functions (Dakota and Kübler, 2017) and discontinuous structures (cf. Vilares and Gómez-Rodríguez, 2020). Also, all of these results are obtained for standard language like newspaper text. For non-standard data, performance drops must be expected (Pinto et al., 2016; Jamshid Lou et al., 2019).

For historical German, so far, there have been experiments on chunking (Petran, 2012; Ortmann, 2021) and topological field parsing (Chiarcos et al., 2018; Ortmann, 2020). For chunking, the best results are observed for CRF-based sequence labeling with overall \(F_1\)-scores between 90% and 94% (Ortmann, 2021). For topological field identification, the application of a probabilistic parser yields overall \(F_1\)-scores >92% (Ortmann, 2020). In the present study, both of these approaches will be explored for the purpose of phrase recognition in historical German.

1 For an overview of the topological field model, see e.g. Cheung and Penn (2009) or Wöllstein (2018, in German)

2 https://github.com/rubcompling/nodalida2021

3 Release 11.0, http://www.sfs.uni-tuebingen.de/ascl/ressourcen/korpora/tueba-dz.html

4 Version 2.2, http://www.ims.uni-stuttgart.de/forschung/ressourcen/korpora/tiger

5Mercurius Baumbank (version 1.1), https://doi.org/10.34644/laudatio-dev-VyQlChMB7CarrQ9cjF30

6 ReF.UP is a subcorpus of the Reference Corpus of Early New High German (Wegera et al., 2021), https://www.linguistics.rub.de/ref
The underlying annotation scheme of the Tiger corpus and the two historical treebanks allows for discontinuous annotations, which must be removed to enable the use of standard chunking and parsing methods. Here, a combination of the raising and splitting approaches described by Hsu (2010) is applied to the trees until no crossing branches remain.7

Since German exhibits a relatively free word order, grammatical functions like subject and object play an important role in the syntactic analysis of sentences, especially for the reduction of ambiguity (Fraser et al., 2013). For the purpose of phrase recognition, however, they are not relevant and, therefore, mostly excluded from the trees to reduce the size of the tagset and improve parsing performance (Rafferty and Manning, 2008; Dakota and Kübler, 2017).8

The modified trees can serve as training input for a parser, or they can be used to extract phrase annotations. Contrary to chunking studies, where the lowest non-terminal nodes are converted to chunks (Kübler et al., 2010; Ortmann, 2021), here, the highest non-terminal nodes of the relevant types correspond to the desired phrases.9 Before the extracted phrases can be used for evaluation or to train a sequence labeling tool, another difference between the annotation schemes of the treebanks regarding topological fields must be taken into account, though.

While the TüBa-D/Z trees represent a combination of constituency and topological field annotations, the other three corpora that follow the Tiger scheme do not include topological fields. This means that constituents in the TüBa-D/Z data are already bound to the corresponding fields as required by the phrase preserved: KONJ, OS, R-SIMPX, NX:HD within PX, and NX:APP within NX. Also, one-word children of sentence nodes that only receive a grammatical function according to the Tiger scheme are assigned a phrase type NP, PP, AP, AVP, VP, or SVP based on their POS tag.

8The only exception are GFs that are needed to extract correct phrases from the trees. For the Tiger scheme, these are S:RC and S:OC. For TüBa-D/Z, the following GFs are preserved: KONJ, OS, R-SIMPX, NX:HD within PX, and NX:APP within NX. Also, one-word children of sentence nodes that only receive a grammatical function according to the Tiger scheme are assigned a phrase type NP, PP, AP, AVP, VP, or SVP based on their POS tag.

9Again, phrases of the four types are added for one-word constituents from Tiger-scheme trees based on the POS tag of the word.
The resulting data sets are used to build four distinct wards.

Table 2: Overview of the test data. The number of sentences with a gold parse are included, and the number of phrases refers to phrases of the four relevant types. The Mix set is a combination of the News2 and Hist sets.

| Corpus      | #Docs | #Sents | #Toks  | #Phrases |
|-------------|-------|--------|--------|----------|
| TuBa-D/Z    | 364   | 10,488 | 196,630| 49,329   |
| Tiger       | 200   | 4,445  | 78,018 | 17,622   |
| Modern      | 78    | 547    | 7,605  | 2,240    |
| Mercurius   | 2     | 818    | 18,740 | 4,401    |
| HIPKON      | 53    | 342    | 4,210  | 1,146    |
| DTA         | 29    | 608    | 18,515 | 4,068    |

Table 2: Overview of the test data. The number of phrases includes NP, PP, AP, and ADVP phrases as described in Section 1. Only sentences containing at least one of the four phrase types are considered.

An example of the different modifications of the trees and extracted phrases can be found in Figure 1. The resulting data sets are used to build four distinct training sets: News1 corresponds to the TuBa-D/Z data, News2 is based on the Tiger treebank, Hist contains the historical data, and a joined set Mix includes all data sets that follow the Tiger annotation scheme. Table 1 gives a summary of the four training sets.

For evaluation, the test sections of the four treebanks are processed in the same way as the training data, and phrases of the four types are extracted and split at topological field boundaries if necessary. In addition, the chunking study (Ortmann, 2021) provides three other test sets, which were annotated with phrases for the present paper: a corpus of modern non-newspaper data with texts from different registers and two historical data sets from the HIPKON corpus (Coniglio et al., 2014) and the German Text Archive DTA (BBAW, 2021) covering different genres and time periods. Table 2 gives an overview of the test data.

In Table 3, the distribution of the phrase types in the data sets is displayed. The most frequent phrase type are NPs with 50% to over 60% in the modern non-newspaper data, followed by PPs with 18% to 28%. ADVPs make up for 11% to 19%, while APs that are not dominated by other phrases are rare with 6% or less.

4 Methods

So far, the automatic syntactic analysis of historical German has been focused on the identification of chunks and topological fields. As described in Section 2, the best results for these tasks are reported for sequence labeling and statistical parsing. In the following, both approaches are applied to the recognition of phrases.

For sequence labeling, the neural CRF-based sequence labeling tool nCRF++ (Yang and Zhang, 2018) is selected. It achieves state-of-the-art performance for several tasks, including tagging, chunking, and named entity recognition in English (Yang et al., 2018). When POS tags are used as features, it also proves successful at identifying chunks in historical German with $F_1$-scores $>90$% (Ortmann, 2021). The default configuration consists of a three-layer architecture with a character and a word sequence development, and test sections, for the other three corpora, the same splits into training (80%), development (10%), and test set (10%) as in the chunking study (Ortmann, 2021) are used.

The manually annotated data sets can be found in this paper’s repository at https://github.com/rubcompling/konvens2021.
quence layer plus a CRF-based inference layer. For the present study, the toolkit is trained on the extracted phrases from the four training sets, where phrases are represented as BIO tags. POS tags are included as additional feature and, during training, the tool is also provided with the development sections of the training corpora. For every word, NCRF++ outputs the single most likely BIO tag, i.e. B-XP (beginning of phrase), I-XP (inside of phrase), or O (outside of phrase). For evaluation, the labels are converted to phrases, and the best result over five runs with different random seeds is reported.

For parsing, the unlexicalized Berkeley parser (Petrov et al., 2006) is selected. It achieves a parsing $F_1$-score of 91.8% on the TüBa-D/Z corpus and 72% on the Tiger corpus (Dakota and Kübler, 2017) and has also been successfully applied to topological field parsing of historical German with overall $F_1$-scores >92% (Ortmann, 2020). In the present study, it is trained with default settings on the four training sets, where the modified constituency trees are used as training input. For annotation, the parser is invoked in interactive mode and given a sentence annotated with POS tags, it returns the single best parse. For evaluation, the constituency trees are then converted to phrases as described in the previous section.

5 Evaluation

To evaluate the performance of the selected approaches on the task of phrase recognition, the output of the trained systems is compared to the gold standard annotation. However, the evaluation of sequence annotations like phrases with standard metrics faces the problem of double penalties, meaning that one unit can count as two errors. For example, and adjective phrase that is recognized as adverb phrase would correspond to a false negative AP and, at the same time, a false positive ADVP. Similarly, if a system misses the initial preposition of a PP and instead annotates the rest as an NP, this would result in a false negative PP and a false positive NP. There have been different suggestions on how to deal with this problem. For word tokenization, Shao et al. (2017) argue that recall should be used as the only evaluation metric. While precision favors under-splitting systems, recall values clearly show the percentage of correctly recognized units that are relevant for higher-level tasks. However, in the case of segmentation tasks that include labeling, identifying entities with almost correct boundaries may also be useful (cf. Ortmann, 2021). For example, the studies on extrapolation mentioned in Section 1 would still benefit greatly from the recognition of incomplete phrases, if not for a complete automatic analysis, then at least for an easier and faster compilation of much larger data sets (see also Eckhoff and Berdičevskis (2016) for a study on using automatic dependency parsing for pre-annotation of historical data to speed up manual annotation). Hence, precision values should not be disregarded entirely. Instead, in Ortmann (2021), I proposed a more fine-grained error analysis that takes into account different types of possible errors while at the same time circumventing the problem of multiply penalizing errors in a single unit.

In the following, this error analysis is adopted for the evaluation of phrase recognition and the output of the different models and models is compared phrase-wise to the gold standard annotation, grouping phrases into one of seven classes: true positives (TP), false positives (FP), labeling errors (LE), boundary errors (BE), labeling-boundary errors (LBE) and false negatives (FN). In addition to the standard categories, labeling errors refer to phrases that cover the same token span but are labeled with a different phrase type. Boundary errors are phrases of the correct type but with incorrect boundaries, and labeling-boundary errors are a combination of the former two error types. Since the three error types indicate an existing and not a missing annotation, they are counted as false positives for the calculation of $F$-scores. Only sentences containing at least one of the four phrase types are evaluated, and punctuation at phrase boundaries is ignored.

Sequence labeling As already mentioned, the neural sequence labeling tool NCRF++ has been applied successfully to the identification of chunks in German, reaching $F_1$-scores between 90% and 94% for different historical data sets (Ortmann, 2021). As could be expected from previous studies (e.g., Petran, 2012), the accuracy for the recognition of phrases, i.e. longer units, with CRF-based sequence labeling is considerably lower. Table 4 gives a sum-

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14 https://github.com/slavpetrov/berkeleyparser
15 java -cp BerkeleyParser-1.7.jar edu.berkeley.nlp.PCFGLA.GrammarTrainer -treebank SINGLEFILE -out grammar.gr -path treebank.txt
16 java -jar BerkeleyParser-1.7.jar -gr grammar.gr -maxLength 1000 -useGoldPOS

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Table 4: Overall $F_1$-scores of the sequence labeling approach. Models trained on historical data are only applied to the historical test sets. The table reports the highest $F_1$-score over five runs and the best result for each corpus is highlighted in bold.

| Corpus   | News1  | News2  | Hist | Mix |
|----------|--------|--------|------|-----|
| TuBia-D/Z| 85.18  | 76.82  | n.a. | n.a.|
| Tiger    | 78.93  | 79.69  | n.a. | n.a.|
| Modern   | 86.80  | 83.10  | n.a. | n.a.|
| Mercurius| 70.25  | 67.83  | 9.05 | 8.93|
| ReF.UP   | 70.62  | 67.91  | 8.80 | 9.90|
| HIPKON   | 80.13  | 81.18  | 8.17 | 7.99|
| DTA      | 72.02  | 68.89  | 6.93 | 7.78|

Table 5: Overall $F_1$-scores (in percent) for the four parser models on each data set. Models trained on historical data are only applied to the historical test sets, and the highest $F_1$-score for each corpus is highlighted in bold.

| Corpus   | News1  | News2  | Hist | Mix |
|----------|--------|--------|------|-----|
| TuBia-D/Z| 91.30  | 81.50  | n.a. | n.a.|
| Tiger    | 82.73  | 87.81  | n.a. | n.a.|
| Modern   | 88.27  | 84.44  | n.a. | n.a.|
| Mercurius| 60.32  | 65.72  | 81.50| 81.06|
| ReF.UP   | 56.44  | 58.86  | 84.15| 84.05|
| HIPKON   | 74.44  | 75.13  | 85.05| 85.12|
| DTA      | 73.66  | 69.44  | 69.07| 70.63|
Table 6: Overall labeled $F_1$-score for the four trained parser models on the test data, excluding virtual root nodes. Training and test trees are modified as described in Section 3, and models are only evaluated on test data that follows the same syntactic annotation scheme as the training data.

| Corpus   | NP  | PP  | AP  | ADVP |
|----------|-----|-----|-----|------|
| TüBa-D/Z | 89.03 | 83.26 | 86.99 | 91.40 |
| Tiger    | 86.60 | 79.28 | 75.80 | 82.35 |
| Modern   | 87.35 | 76.37 | 80.60 | 79.94 |
| Mercurius| 77.96 | 70.47 | 62.61 | 82.59 |
| ReF.UP   | 82.72 | 75.21 | 63.31 | 81.77 |
| HIPKON   | 80.49 | 77.62 | 60.00 | 84.49 |
| DTA      | 66.53 | 64.98 | 67.98 | 72.06 |

Table 7: Overall $F_1$-scores for the best performing parser model on each data set.

| Corpus   | FP  | LE  | BE  | LBE | FN |
|----------|-----|-----|-----|-----|----|
| TüBa-D/Z | 22.47 | 0.96 | 62.85 | 0.75 | 12.97 |
| Tiger    | 20.15 | 1.08 | 59.22 | 1.15 | 18.41 |
| Modern   | 19.12 | 1.99 | 64.34 | 0.40 | 14.14 |
| Mercurius| 26.84 | 1.23 | 51.94 | 1.49 | 18.50 |
| ReF.UP   | 22.74 | 1.53 | 53.20 | 1.23 | 21.30 |
| HIPKON   | 20.00 | 3.03 | 66.36 | 1.21 | 9.39 |
| DTA      | 17.73 | 1.01 | 60.91 | 2.47 | 17.88 |

Table 8: Proportion of the five error types: false positives (FP), labeling errors (LE), boundary errors (BE), labeling-boundary errors (LBE), and false negatives (FN). Numbers are given in percent for the best parser model on each data set.

6 Discussion

The present study has explored the automatic recognition of phrases in historical German. Two tools that proved successful in previous studies on chunking and topological field parsing were selected and trained on modern and historical treebanks. The evaluation has shown that the Berkeley parser outperforms the neural CRF-based sequence labeling tool NCRF++ on all data sets, reaching overall $F_1$-scores of 87.8% to 91.3% on modern German and 73.7%–85.1% on different historical corpora. Parsing results are most accurate for simple phrases while scores decline with increasing phrase length. Since the majority of errors turn out to be boundary errors, the results leave room for further improve-
ment of annotation precision.

Interestingly, the inclusion of historical training data improves the results of the parser, whereas the sequence labeling tool did not benefit from it. One possible explanation could be too much variation in the data due to the non-standardized spelling in historical German, which does not affect the unlexicalized parser. Future studies could experiment with spelling normalization, which was observed to improve the annotation results of modern NLP tools for parsing Middle English (Schneider et al., 2015) or tagging historical German (Bollmann, 2013) and Dutch (Tjong Kim Sang et al., 2017).

The normalized data could then also be used to explore lexicalized parsing, e.g. with the neural Berkeley parser (Kitaev and Klein, 2018). Although parsers do not necessarily need lexical information for good performance (Coavoux et al., 2019), studies on modern English show that the application of neural parsing methods in combination with pre-trained word embeddings can further improve the results (cf. e.g. Vilares and Gómez-Rodríguez, 2020). For morphologically more complex languages like German, this should be even more relevant (Fraser et al., 2013) and could also help in cases where lexical information is necessary to decide about the correct phrase boundaries.

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