Neural End-to-end Coreference Resolution for German in Different Domains

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Abstract

We apply neural coreference resolution to German, surpassing the previous state-of-the-art performance by a wide margin of 10–30 points F1 across three established datasets for German. This is achieved by a neural end-to-end approach, training contextual word-embeddings jointly with mention and entity similarity scores. We explore the impact of various parameters such as language models, pre-training and computational limits with respect to German data. In an effort to support datasets representing the domains of both news and literature, we make use of two distinct model architectures: a mention linking-based and an incremental entity-based approach that should scale to very long documents such as literary works. Our code and ready-to-use models are publicly available.

1 Introduction

Coreference resolution is the task of resolving text spans in documents that refer to the same entities. These are grouped into mention-clusters with each cluster representing one entity. Figure 1 shows coreference annotations on a literary text with different entities being denoted by both subscripts and colors. Tasks such as question answering (Morton, 1999) or text summarization (Steinberger et al., 2007) can rely on coreference resolution as part of the language processing pipeline. Bamman et al. (2014) demonstrated that coreference resolution is also applicable to literary analysis. The task has recently seen large improvements as systems moved from rule-based (e.g. Roesiger and Kuhn, 2016; Lee et al., 2011) to neural approaches (e.g. Lee et al., 2017; Joshi et al., 2019). This advancement from a CoNLL-F1-score of 57.8, achieved by a rule-based system in the original CoNLL-2012 shared task (Pradhan et al., 2012), to 67.2 in the first end-to-end neural system (Lee et al., 2017) has shown that neural systems are key to state-of-the-art performance.

Coreference resolution on German using neural networks has received little attention. There has, to our knowledge, no work been reported on German news datasets using neural networks yet. This work is also the first to use cross-task learning to improve performance on German literary datasets.

We apply and adapt exiting approaches to coreference on German, making our code and models publicly available.¹ There are two approaches to neural coreference resolution that we consider: A mention linking-based and an entity-linking-based approach. Both have an initial mention proposal step, finding text spans that are likely to represent mentions. In mention-linking approaches, out of the cross-products of mentions, those mentions with the highest likelihood are considered. Each such mention is connected to its highest-scoring antecedent with transitively connected mentions forming entities.

The entity-representation-based approach also involves the initial mention proposal step. However, rather then creating links on a per-mention basis, initial mentions are considered to be entity representations, with each subsequent mention be-

¹https://github.com/uhh-lt/neural-coref/tree/konvens
ing compared to existing entity representations and assigned to those that match them best. This way memory usage and computational effort can be reduced, as it is proportional to the number of entities, rather than the square of the number of mentions.

2 Related Work

Relevant prior work can be put into two distinct categories: (a) Neural, state-of-the-art coreference resolution developed primarily on English (b) Coreference resolution applied to German.

Most neural coreference resolution models perform a ranking of antecedents based on the pairwise scores of mention candidates (Wiseman et al., 2015; Clark and Manning, 2016a; Lee et al., 2017), at this only relying on local decisions that may not be globally optimal to form coherent entities (Lee et al., 2018). This general architecture has been improved on in multiple ways.

To address the issue of global optimization, Clark and Manning (2016b) and Wiseman et al. (2016) create entity representations during the ranking step. Lee et al. (2018); Kantor and Globerson (2019) iteratively refine mention representations with associated antecedent information, performing what they refer to as higher-order inference. While the end-to-end coreference model of Lee et al. (2017) uses a bidirectional LSTM (Hochreiter and Schmidhuber, 1997) to produce span representations, Lee et al. (2018) see a 3.2 F1 score increase on the English CoNLL-2012 shared task by additionally using ELMo (Peters et al., 2018) embeddings. Lee et al. (2018) also modify the model to perform coarse-to-fine antecedent pruning enabling an efficient computation and potentially allowing the processing of longer documents. Joshi et al. (2019) and Kantor and Globerson (2019) improve upon this by using BERT (Devlin et al., 2019) embeddings instead of the LSTM-based representations and gain another 3.3 F1 points.

Recently, Joshi et al. (2020) presented a model optimized for span representations named SpanBERT and saw another 2.5 point increase in F1 score, which has been reproduced by Xu and Choi (2020). Wu et al. (2020) have taken a different approach to coreference resolution; they outperform previous state of the art by 3.5 F1 points in part due to the ability to recover missed mentions by framing the task as a question-answering problem. Toshniwal et al. (2020); Xia et al. (2020) both introduce incremental approaches to coreference resolution. Instead of comparing mention pairs like Lee et al. (2017), they compare mentions with entity representations, with the entity representations being produced from a linear combination of their mentions. Both approaches work by iteratively processing all mentions and scoring each mention with regard to a set of entities; as a result, an evaluation of the full cross-product of mentions is not necessary. The two approaches differ slightly in how they handle the introduction of new entities.

For coreference resolution on German texts, published work predates the age of neural networks in natural language processing. The CorZu system (Klenner and Tuggener, 2011; Tuggener and Klenner, 2014) is a rule-based incremental entity-mention model that has been extended with Markov Logic Networks for the antecedent selection. Roesiger and Kuhn (2016) adapted the English system of Björkelund and Kuhn (2014) to German. A directed tree where each node represents a mention is used to model the coreferences in a document. For determining antecedents, both local and non-local handcrafted features are employed. They created the current state-of-the-art approach for German news datasets, evaluating their system on the SemEval-2010 shared task and on version 10 of the TüBa-D/Z dataset.

The domain of literature has, for both German and English, received increased attention in recent years with regard to coreference resolution. Roesiger et al. (2018) considered the domain specific challenges and phenomena of literature. Bamman et al. (2020) released an English dataset and Krug et al. (2018) released a German dataset (see Section 3.2 for details). While Krug (2020) performed coreference resolution on German literary data, Toshniwal et al. (2020) used the English dataset. Krug (2020) compare various approaches to coreference resolution on German historic novels using the DROC dataset (Krug et al., 2018). Their best-performing system in a gold-mention scenario uses a rule-based Stanford Sieve approach (Lee et al., 2011), iteratively applying rules starting from the most precise rule, going to less precise rules. When mention spans are generated by the model, the end-to-end neural network, based on the approach by Lee et al. (2017), performs about on par with the rule-based systems in conjunction with preprocessing pipelines.

Evaluation of coreference data presents a challenge, different proposed metrics emphasise differ-
ent aspects of a model’s performance. An average of the three metrics \( MUC, B^3 \), and \( CEAF_{\phi^4} \) has been used in the CoNLL-2012 task (Pradhan et al., 2012). As these metrics are widely used we focus on them for reporting our results, including an average of the three, the CoNLL-F1 score.

3 German Coreference Datasets

3.1 News

The standard corpus for coreference resolution in German is TüBa-D/Z (Telljohann et al., 2017; Naumann and Möller, 2006), a manually annotated collection of newspaper articles released in multiple versions that incrementally add more documents. It was also used as the data source for the German part of the SemEval-2010 shared task on coreference resolution (Recasens et al., 2010).

To be comparable with previous work, we chose to use SemEval-2010 and TüBa-D/Z release 10.0 instead of the marginally larger 11.0 for most of our experiments. As there is no official split for the TüBa-D/Z, we use the same splits as previous work (Roesiger and Kuhn, 2016).

While TüBa-D/Z does not contain singletons (on average 3.65 mentions per entity, 10.89 entities per article), these mentions are annotated in SemEval-2010 (on average 1.34 mentions per entity, 73.07 entities per article). Across the dataset, 84.6% of all entities and 64.1% of all mentions are singletons.

Compared to the standard English coreference corpus, OntoNotes (Weischedel et al., 2013), used in the CoNLL-2012 shared task on coreference resolution (Pradhan et al., 2012), TüBa-D/Z neither contains different genres of texts nor additional metadata such as speaker information. Regarding statistics such as average mentions per entity, mentions/sentence length and tokens/sentences/entities per document, German TüBa-D/Z 10.0 and English OntoNotes 5.0 are remarkably similar.

3.2 Literature

The DROC dataset (Krug et al., 2018) contains 90 coreference annotated literary documents where each document comprises one chapter with an average length of 4369.49 tokens. We use the splits established by Krug (2020), i.e. 58 training, 14 development and 18 test documents. There is a total of 51 797 mentions in 5365 clusters, 2409 of these are singleton clusters. As a result, while 45% of clusters are singleton clusters, only 4.7% of mentions are singletons. Our calculations for the performance of human annotators on the subset of DROC are listed in Table 1, providing an upper bound for our performance expectations. In contrast to other datasets (e.g. Bamman et al., 2020), only mention heads are annotated, rather than whole nominal phrases. This means that in the sentence, “and [the driver] was none other than [that cursed Englishman]” (from the dataset by Bamman et al. (2020) “The Scarlet Pimpernel”), only the spans “Englishman” and “driver” would be annotated as coreferring instead. Thus, only spans up to a short length need to be considered in the mention proposal step. DROC also differentiates itself from other datasets in that it only annotates references to characters.

More generally, literary data, when compared to news texts, comes with the added challenge of document length. Longer documents tend to come with more mentions, DROC, for example, contains an average of 575.52 mentions per document whereas SemEval only has an average of 97.79. In general, increased document length lead to longer processing time, larger computational effort and higher memory requirements.

4 Model

In this section, we describe our German coreference resolution models in detail. We build on the widely adapted neural end-to-end architecture developed by Lee et al. (2017, 2018), improved by Joshi et al. (2019) and re-implemented in PyTorch (Paszke et al., 2019) by Xu and Choi (2020). Although the CorefQA system (Wu et al., 2020) is currently the top-performing system for English, we chose to not build upon it because it is more complex and requires vastly more computational resources than our chosen approach.

The general idea of our models is to first detect mentions and then to link them. Each document is processed individually during both training and inference; Figure 2 visualizes a single document being processed by both model variants. First, contextual ELECTRA (Clark et al., 2020) embeddings are obtained for each token and all possible

| Mention-F1 | MUC-F1 | B^3-F1 | CEAF_{\phi^4}-F1 | CoNLL-F1 |
|------------|--------|--------|------------------|----------|
| 97.05      | 93.67  | 84.69  | 69.25            | 82.54    |

Table 1: Inter-annotator F1 scores for DROC as calculated using the scorer by Pradhan et al. (2012) based on the individual annotator’s data by Krug et al. (2018).

2 for corpus statistics, see Table 9 in the appendix
mention spans up to a configurable length are enumerated. Mention embeddings are created, containing start and end token embeddings and the attention-weighted average of all span tokens. In contrast to the English models, our models contain neither genre nor speaker embeddings as the German datasets do not supply this information.

A naïve approach of comparing each mention candidate with every other to find links between them raises computational issues, quickly becoming infeasible to compute as it requires $O(M^2)$ comparisons for $M = \max_{\text{mention length}} \cdot |D|$ mention candidates, for a document $D$ where $|D|$ is the document length in word-piece tokens. To reduce computational effort over a naïve approach to find the best antecedent for each mention, we employ two established strategies: A coarse-to-fine and an incremental approach, with the incremental approach being able to handle documents of arbitrary length with limited memory.

### 4.1 Coarse-to-fine

Our model is based on the implementation by Xu and Choi (2020). For each mention span, the model learns a distribution over its antecedents based on how likely both individual spans are to be valid mentions and how likely they refer to the same entity. Two pruning steps are used to make this mention linking computationally feasible.

To reduce the number of mentions, all mention embeddings are scored individually with a feed-forward neural network (FFNN). For each document $D$ only the top $n = \min(4096, 0.4 \cdot |D|)$ mentions are kept after pruning. Instead of performing a pairwise comparison of all $N$ mentions, only a fraction is used. Thus, removing obvious non-mentions and limiting the complexity to $O(n^2 \ll N^2)$, a step that we refer to as mention filtering.

In the coarse antecedent pruning step, the pairwise similarity scores of the remaining mention embeddings are summed with the individual mention scores. A subsequent fine-grained ranking is performed with the top $a = 64$ antecedents per mention; to this effect, pairwise mention-antecedent embeddings consisting of mention, antecedent and similarity embedding are created. These embeddings are scored with a FFNN and combined with scores from the coarse step resulting in scores for the top antecedents per mention. We do not use so-called higher-order inference as this effectively doubles the computational cost of the fine-grained antecedent scoring without improving the quality according to Xu and Choi (2020).

During training, the model learns to optimize the marginal log-likelihood of possibly correct antecedents for each mention, i.e. for each antecedent the score should be 1 if mention and antecedent belong to the same gold entity, 0 otherwise.

During inference, an undirected graph of mentions is created by connecting each mention with its highest-scoring antecedent. In this graph, each connected component of mentions forms an entity.
4.2 Incremental

The general approach of the incremental model follows Xia et al. (2020) and Toshniwal et al. (2020). Mention filtering is performed as in the course-to-fine model. We process the document iteratively, splitting the document into multiple windows for transformer language model inference. Unlike Toshniwal et al. (2020) but following Xia et al. (2020) we reuse all model weights, including both the transformer weights and all task-specific layers.

In a step we call entity assignment, every mention candidate chooses its entity in an iterative fashion. In our standard setup, this is modeled as a classification task with a dynamic number of classes and the initial set of classes, each class representing an entity $C_0 = \{\emptyset\}$. If, for any mention embedding $m$ being processed, $\emptyset$ is selected as the class, the mention is added as a new class. Entity representations are tracked with $R(E_0)$ being set to $m$ when the $n$-th entity is added. As a result, after the first mention is processed the set of classes is always extended: $C_1 = \{\emptyset, E_0\}$. Subsequently, new mentions $E_x$ are added iteratively. Whenever any existing $E_x$ is selected as the best fitting entity, its representation is updated using an update gate: $R(E_x) := (1 - \alpha)m + \alpha R(E_x)$.

Training is done by means of cross entropy loss across all existing entities and the new entity class, with the gold class for each entity being its most recently assigned mention gold class. As a result, early in training many entity representations likely contain mentions that, from a gold label perspective, should not belong together. Toshniwal et al. (2020) use teacher forcing to address this issue and thereby reach earlier convergence; we test this approach in our setup, assigning each mention to its gold class for further computations, rather than relying on predicted classes.

The only way mention candidates can be discarded (either because they are not a mention or because they are singleton mentions) is by means of creating a new entity and never assigning any additional mentions to it, in postprocessing any such singleton entity would be removed, yielding the final output entities. To support detection of singleton mentions, we follow Xia et al. (2020) in adding an additional class representing the discarding of any given entity. In this “discard” scenario, singleton mentions are not removed in postprocessing since non-mentions are modeled explicitly.

| Language Model                      | CoNLL-F1 |
|-------------------------------------|----------|
| BERT-Base, multilingual uncased     | 74.50    |
| BERT-Base, multilingual cased       | 74.60    |
| GBERT base, cased                   | 75.35    |
| GELECTRA base, cased                | 77.01    |
| GNG ELECTRA base, uncased           | 77.86    |
| GBERT large, cased                  | 79.05    |
| GELECTRA large, cased               | 79.24    |

Table 2: TüBa-D/Z 10 development score of coarse-to-fine models with different language models (using 512 as segment size)

5 Experiments: News Domain

We perform preliminary experiments to select the best pre-trained German language model, its best context size and to optimize other hyperparameters. For the main experiments on the news datasets TüBa-D/Z 10 and SemEval-2010, we train and evaluate our coarse-to-fine model as it is easily capable of processing the typically rather short documents. We use the training, development and test splits as described in Section 3.1. The SemEval dataset contains singletons, but our coarse-to-fine model predicts only clusters of at least two entities. Following Roesiger and Kuhn (2016), we ignore singletons when scoring our systems’ predictions.

5.1 Pre-trained Language Models

We evaluated multiple pre-trained language models for our coreference resolution model. As a baseline, we include the multilingual BERT-Base model (in both the cased and uncased variants) by Devlin et al. (2019). Chan et al. (2020) recently published German BERT and ELECTRA (cased, both base and large) denoted as GBERT / GELECTRA in Table 2. In addition, we included another ELECTRA model (uncased, base) by German-NLP-Group denoted as GNG ELECTRA$^3$.

We find that all of the recent German language models perform better than the multilingual BERT. For the base models, ELECTRA outperforms BERT by a substantial margin. Using large models, ELECTRA performs marginally better. Based on the results shown in Table 2, we selected GNG ELECTRA as the base and GELECTRA as the large model for our remaining experiments.

$^3$Model description at https://huggingface.co/german-nlp-group/electra-base-german-uncased
Table 3: TüBa-D/Z 10 development score of coarse-to-fine models GNG, ELECTRA (base) and GELECTRA (large) with different segment lengths.

| Segment Length | F1 (base) | F1 (large) |
|----------------|-----------|------------|
| 128            | 75.69     | 76.28      |
| 256            | 76.56     | 77.29      |
| 384            | 77.01     | 78.51      |
| 512            | 77.50     | 79.27      |

Table 4: The effect of using pre-training on the DROC coarse-to-fine model on data with and without singletons. All results were averaged over 5 runs and the standard deviation is given.

|                  | CoNLL-F1          | News-Pretrain          |
|------------------|-------------------|------------------------|
|                  | ✓                 | ✓                      |
| Singletons       | 61.66 ± 0.52      | 59.93 ± 0.33           |
|                  | ✓                 | ✓                      |
|                  | 65.58 ± 0.46      | 64.26 ± 0.51           |

5.2 ELECTRA Context Size

Following Joshi et al. (2019), we split documents into non-overlapping ELECTRA contexts, evaluating different splits for contexts as shown in Table 3. While Joshi et al. (2019) show that for English BERT-base/large a segment length of 128/384 is optimal, this does not hold true for our German models and dataset where larger segment lengths perform better. Our results are in line with the intuition that larger context sizes provide more contextual information for any given mention. Thus, we use a segment length of 512 in our models.

5.3 Hyperparameters

In general, parameters affecting computational limits have a large impact, all other parameters that we tested had only limited effect. Parameters controlling the pruning (top_span_ratio, max_top_spans and max_top_antecedents) have a strong negative effect when set too low, resulting in too aggressive pruning. Higher values increase evaluation scores with quickly diminishing returns; yet strongly increase computation time and memory.

To reduce GPU memory usage and computation time, we reduced the size of all feed-forward neural networks from 3000 used in previous work to 2048 without seeing distinct score changes on the TüBa-D/Z 10 development set. We also increased the size to 4096, resulting in more memory usage and slower computation, but negligible changes in evaluation performance.

6 Experiments: Literature Domain

For the literary dataset (DROC), we explore the use of both model variants. We initialize the incremental model with weights from the coarse-to-fine variant.

6.1 Coarse-to-fine Model

Given the relatively small size of the DROC dataset, we explore the impact of pretrained weights from the news tasks. We expected that while the different approaches to mention annotation (heads or entire noun phrases) would somewhat limit applicability of existing weights they would still lead to an improvement.

Table 4 shows the development set results for the DROC dataset, with the same set of initial weights that was pretrained on TüBa-D/Z 10 being used for all of our runs. Standard deviation for the ConLL-F1 scores are given, based on five runs with different random initializations. All layer weights, including task specific ones as well as language model ones were reused. The experiment was repeated for a variant of the DROC dataset with all singleton mentions removed.

Using Welch’s t-test we can infer that the pretrained version does, on average, perform better for the no singleton variant ($p < 0.005$). As a result we will use the news-pretrained model variant in all our further experiments. This finding is also supported by the recent publication by (Xia and Durme, 2021) which establishes that, especially for short datasets, using pretrained weights is beneficial. We are unsure if further significant improvements could be gained by pre-training on additional datasets, for example GerDraCor (Pagel and Reiter, 2020), given that TüBa-D/Z is already a large dataset.

Table 5 shows how two configuration parameters affect the coarse-to-fine model’s performance. The two options enable different features, where “segment info” describes how many BERT segments lie between the current and candidate mention while “token info” describes the token distance from the candidate mention to the document start. Further, “token info” encodes the length of the candidate mention span. This experiment was performed as
### Distance Features

| Segment | Token | Coarse-To-Fine | Incremental |
|---------|-------|----------------|-------------|
| ✗       | ✗     | 61.11 ± 0.57   | 65.79       |
| ✓       | ✗     | 62.31 ± 0.27   | 64.20       |
| ✗       | ✓     | 61.70 ± 0.22   | 62.57       |
| ✓       | ✓     | 59.93 ± 0.33   | 65.42       |

Table 5: Performance of the coarse-to-fine and incremental models with respect to two configuration parameters relevant to recency bias.

### 6.2 Incremental Model

The memory usage of the coarse-to-fine approach, while not prohibitive for the DROC dataset, will prevent its application to full length literary documents.

Table 5 illustrates the impact of the same configuration parameters that were used for the coarse-to-fine model. The impact of the parameters appears to be lessened in the incremental case.

Unsurprisingly, due to the possibility of handling singleton mentions, Table 6 clearly shows that the discard functionality is critical to model performance. Teacher forcing appears to have a negative impact on performance; this does come as a surprise but while convergence early in training was faster the final results were slightly worse.

### 6.3 Impact of Document Length

We seek to analyze how well incremental models fare as document length increases. To this end, we split DROC at the nearest sentence boundary into sub documents that are no longer than 512, 1024 and 2048 tokens. Previous work (Krug, 2020; Joshi et al., 2019) has established that, with longer documents, the performance of coreference systems drops. This can be interpreted as the inherent difficulty of the coreference task growing with document length. Figure 3 shows that for longer documents the gap in performance between the model variants increases slightly.

### 7 Results & Error Analysis

Our neural coarse-to-fine models outperform the previous state of the art by a large margin on both SemEval-2010 (+25.85 F1) and TüBa-D/Z (+30.25 F1) as shown in Table 7. In fact, even if the other systems are allowed to use gold mentions, our models still outperform them by more than 10 F1 points. Using ELECTRA large for contextual embeddings yields a small improvement over the base model (+1.58 F1 / +1.92 F1). Figure 4 shows an example of our systems prediction on an unseen document.

We manually analyze the predictions of our
Es war einmal ein gar allerliebstes, niedliches Ding von einem [Mädchen]_1, [das]_1 hatte eine [Mutter]_2 und eine [Großmutter]_2, die waren gar gut und hatten das kleine Ding so lieb. Die [Großmutter]_2 absondernlich, [die]_1 wußte gar nicht, wie gut sie ’s mit dem [Enkelchen]_1 meinen sollte, [...]  

Figure 5a illustrates a recency bias in our model, “grandmother” and “mother” were erroneously combined into one entity, presumably because the distance between the “mother” and “grandmother” mentions were very small. On a larger scale this effect can be observable as long sequences of the same character we find the 212 tokens to occur in 31 different clusters with 4 mentions being assigned to no cluster. Our observation is that this often occurs after a long section of text without explicit mentions of the name, in fact the average distance from one mention of Holmes to the previous is 320.6 tokens whereas it is 655.3 for those cases where a new class is erroneously introduced. We suspect, that this could be attributed to the name taking less prominence in the entity representation after a while.

Figure 5b), an improved result. However, this particular model no longer detects “thing” (Ding) as a more global view, some of our model’s weaknesses are exposed. When searching the token “Holmes” in the German translation of “The Hound of the Baskervilles” 5 which should always refer to the same character we find the 212 tokens to occur in 31 different clusters with 4 mentions being assigned to no cluster. Our observation is that this often occurs after a long section of text without explicit mentions of the name, in fact the average distance from one mention of Holmes to the previous is 320.6 tokens whereas it is 655.3 for those cases where a new class is erroneously introduced. We suspect, that this could be attributed to the name taking less prominence in the entity representation after a while.

Table 8: Final results for the DROC dataset on the test set, with and without singleton mentions included.

| System           | Model       | F1 Score |
|------------------|-------------|----------|
| Krug (2020)      | Sieve       | 51.53    |
|                  | CR          | 51.34    |
|                  | E2E-NN      | 53.17    |
| Ours (with singletons) | Incremental | 64.72    |
|                  | C2F         | 61.66    |
| Ours (no singletons) | C2F        | 65.50    |

Table 8: Final results for the DROC dataset on the test set, with and without singleton mentions included.

coarse-to-fine model and find that it generally produces accurate coreference links both locally and document-wide. While entity assignment of mentions, identified in both prediction and gold data, is typically correct, missed and added mentions are more frequent errors. We assume that one reason is a contradicting training signal, i.e. while some mentions are annotated as such in the gold data, others are not because they are singletons or were missed in the annotation process.

Our incremental model on data including singletons outperforms the existing state of the art for DROC by 11.6 F1 points (see Table 8). Said results were achieved in a setup comparable to ours, with no gold information such as speakers or entity spans being used, except in the case of their end-to-end neural network (E2E-NN), where direct speech and speaker information were used.

We manually evaluate our model on entire literary texts. While we find local coreference relationships to be surprisingly accurate, when taking a

Text from: https://www.projekt-gutenberg.org/bechstei/maerchen/chap053.html

more global view, some of our model’s weaknesses are exposed. When searching the token “Holmes” in the German translation of “The Hound of the Baskervilles” 5 which should always refer to the same character we find the 212 tokens to occur in 31 different clusters with 4 mentions being assigned to no cluster. Our observation is that this often occurs after a long section of text without explicit mentions of the name, in fact the average distance from one mention of Holmes to the previous is 320.6 tokens whereas it is 655.3 for those cases where a new class is erroneously introduced. We suspect, that this could be attributed to the name taking less prominence in the entity representation after a while.

Figure 5a illustrates a recency bias in our model, “grandmother” and “mother” were erroneously combined into one entity, presumably because the distance between the “mother” and “grandmother” mentions were very small. On a larger scale this effect can be observable as long sequences of the same character we find the 212 tokens to occur in 31 different clusters with 4 mentions being assigned to no cluster. Our observation is that this often occurs after a long section of text without explicit mentions of the name, in fact the average distance from one mention of Holmes to the previous is 320.6 tokens whereas it is 655.3 for those cases where a new class is erroneously introduced. We suspect, that this could be attributed to the name taking less prominence in the entity representation after a while.

Figure 5b), an improved result. However, this particular model no longer detects “thing” (Ding) as a
valid mention which could both be a side effect of removing the distance features or an effect of the random initialization and training.

8 Conclusion

We apply recent developments in neural architectures for coreference resolution on German data and achieve a substantial improvement over the previous state of the art on all three established German datasets. We conducted experiments with two variants: a coarse-to-fine model suitable for rather short documents, and an incremental model that should scale to long documents. In our analysis we found that while the task of coreference resolution itself becomes more difficult as document sizes increase, the incremental approach scales worse than the course-to-fine approach in terms of accuracy. While we found local decisions to be accurate, shortcomings of the incremental model in global consistency and recency bias were explored.

In future work, we would especially like to address remaining challenges for the processing of long-form literary documents. In spite of the large improvements we achieved, there is still a considerable headroom for coreference resolution, as reflected by a large performance gap between the human baseline of 82.54 F1 and our best model with 64.7 F1 on the DROC dataset. On a more theoretic note, another extension worth pursuing in the future especially for the literary domain is the notion of subjective coreference. As an example, in the fairy tale "Little Red Riding Hood" (see Figure 5), the girl temporarily perceives a highly plot-relevant coreference between the grandmother and the big bad wolf, which is not reflected in objectivized models.

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### Appendix

| dataset               | articles | sentences | tokens     |
|-----------------------|----------|-----------|------------|
| SemEval-2010          | 1,235    | 26,098    | 455,046    |
| - training            | 900      | 19,233    | 331,614    |
| - develop.            | 199      | 4,129     | 73,145     |
| - test                | 136      | 2,736     | 50,287     |
| TüBa-D/Z 10.0         | 3,644    | 95,595    | 1,787,801  |
| - training            | 2190     | 65,416    | 1,258,514  |
| - develop.            | 727      | 15,593    | 276,635    |
| - test                | 727      | 14,586    | 252,652    |
| TüBa-D/Z 11.0         | 3,816    | 104,787   | 1,959,474  |
| OntoNotes 5.0         | 3,493    | 94,269    | 1,631,995  |
| - training            | 58       | 11,368    | 249,817    |
| - develop.            | 14       | 3,570     | 72,258     |
| - test                | 18       | 3,223     | 70,999     |

Table 9: Overview of the dataset releases referred to in this work.
|                | MUC | B$^3$ | CEAF$_{0.4}$ | CoNLL | LEA |
|----------------|-----|-------|--------------|-------|-----|
|                | R   | P     | F1           | R     | P   | F1  | F1  | R   | P   | F1  |
| **TüBa-D/Z 10.0** |     |       |              |       |     |     |     |     |     |     |
| German c2f base | 81.92 | 79.90 | 80.90        | 77.41 | 73.52 | 75.41 | 75.16 | 75.50 | 75.33 | 77.21 | 74.98 | 70.82 | 72.84 |
| German c2f large | 82.85 | 81.61 | 82.23        | 78.41 | 75.73 | 77.05 | 76.75 | 77.44 | 77.09 | 78.79 | 73.25 | 73.25 | 74.67 |
| IMS HotCoref    |     |       |              |       |     |     |     |     |     | 48.54 |       |       |       |
| + gold mentions |     |       |              |       |     |     |     |     | 65.76 |       |       |       |       |
| **SemEval-2010** |     |       |              |       |     |     |     |     |     |       |       |       |       |
| German c2f base | 76.64 | 76.08 | 76.36        | 71.18 | 69.12 | 70.14 | 71.83 | 70.45 | 71.13 | 72.54 | 67.88 | 65.7  | 66.77 |
| German c2f large | 79.07 | 76.51 | 77.77        | 73.88 | 70.48 | 72.14 | 74.79 | 72.21 | 73.47 | 74.46 | 70.69 | 67.18 | 68.89 |
| IMS HotCoref    |     |       |              |       |     |     |     |     |     | 48.61 |       |       |       |
| + gold mentions |     |       |              |       |     |     |     |     | 63.61 |       |       |       |       |
| CorZu           |     |       |              |       |     |     |     |     | 45.82 |       |       |       |       |
| + gold mentions |     |       |              |       |     |     |     |     | 58.11 |       |       |       |       |

Table 10: Recall, precision and F1 score on the test set of TüBa-D/Z 10 and SemEval-2010 (without singletons). Our coarse-to-fine (c2f) models use either ELECTRA base or large. IMS HotCoref and CorZu system scores as reported by Roesiger and Kuhn (2016).