WikiCREM: A Large Unsupervised Corpus for Coreference Resolution

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Abstract
Pronoun resolution is a major area of natural language understanding. However, large-scale training sets are still scarce, since manually labelling data is costly. In this work, we introduce WikiCREM (Wikipedia CoREferences Masked) a large-scale, yet accurate dataset of pronoun disambiguation instances. We use a language-model-based approach for pronoun resolution in combination with our WikiCREM dataset. We compare a series of models on a collection of diverse and challenging coreference resolution problems, where we match or outperform previous state-of-the-art approaches on 6 out of 7 datasets, such as GAP, DPR, WNLI, PDP, WINOBIAS, and WINOGENDER. We release our model to be used off-the-shelf for solving pronoun disambiguation.

1 Introduction
Pronoun resolution, also called coreference or anaphora resolution, is a natural language processing (NLP) task, which aims to link the pronouns with their referents. This task is of crucial importance in various other NLP tasks, such as information extraction (Nakayama, 2019) and machine translation (Guillou, 2012). Due to its importance, pronoun resolution has seen a series of different approaches, such as rule-based systems (Lee et al., 2013) and end-to-end-trained neural models (Lee et al., 2017; Liu et al., 2019). However, the recently released dataset GAP (Webster et al., 2018) shows that most of these solutions perform worse than naïve baselines when the answer cannot be deduced from the syntax. Addressing this drawback is difficult, partially due to the lack of large-scale challenging datasets needed to train the data-hungry neural models.

As observed by Trinh and Le (2018), language models are a natural approach to pronoun resolution, by selecting the replacement for a pronoun that forms the sentence with highest probability. Additionally, language models have the advantage of being pre-trained on a large collection of unstructured text and then fine-tuned on a specific task using much less training data. This procedure has obtained state-of-the-art results on a series of natural language understanding tasks (Devlin et al., 2018).

In this work, we address the lack of large training sets for pronoun disambiguation by introducing a large dataset that can be easily extended. To generate this dataset, we find passages of text where a personal name appears at least twice and mask one of its non-first occurrences. To make the disambiguation task more challenging, we also ensure that at least one other distinct personal name is present in the text in a position before the masked occurrence. We instantiate our method on English Wikipedia and generate the Wikipedia CoREferences Masked (WikiCREM) dataset with 2.4M examples, which we make publicly available for further usage. We show its value by using it to fine-tune the BERT language model (Devlin et al., 2018) for pronoun resolution.

To show the usefulness of our dataset, we train several models that cover three real-world scenarios: (1) when the target data distribution is completely unknown, (2) when training data from the target distribution is available, and (3) the transductive scenario, where the unlabeled test data is available at the training time. We show that fine-tuning BERT with WikiCREM consistently improves the model in each of the three scenarios, when evaluated on a collection of 7 datasets. For example, we outperform the state-of-
the-art approaches on GAP (Webster et al., 2018), DPR (Rahman and Ng, 2012), and PDP (Davis et al., 2017) by 5.9%, 8.4%, and 12.7%, respectively. Additionally, models trained with WIKICREM show increased performance and reduced bias on the gender diagnostic datasets WINOGEN- DER (Rudinger et al., 2018) and WINOBIAS (Zhao et al., 2018).

2 Related Work

There are several large and commonly used benchmarks for coreference resolution, such as (Pradhan et al., 2012; Schäfer et al., 2012; Ghaddar and Langlais, 2016). However, Webster et al. (2018) argue that a high performance on these datasets does not correlate with a high accuracy in practice, because examples where the answer cannot be deduced from the syntax (we refer to them as hard pronoun resolution) are underrepresented. Therefore, several hard pronoun resolution datasets have been introduced (Webster et al., 2018; Rahman and Ng, 2012; Rudinger et al., 2018; Davis et al., 2017; Zhao et al., 2018; Emami et al., 2019). However, they are all relatively small, often created only as a test set.

Therefore, most of the pronoun resolution models that address hard pronoun resolution rely on little (Liu et al., 2019) or no training data, via unsupervised pre-training (Trinh and Le, 2018; Radford et al., 2019). Another approach involves using external knowledge bases (Emami et al., 2018; Fähndrich et al., 2018), however, the accuracy of these models still lags behind that of the aforementioned pre-trained models.

A similar approach to ours for unsupervised data generation and language-model-based evaluation has been recently presented in our previous work (Kocijan et al., 2019). We generated MASKEDWIKI, a large unsupervised dataset created by searching for repeated occurrences of nouns. However, training on MASKEDWIKI on its own is not always enough and sometimes makes a difference only in combination with additional training on the DPR dataset (called WSCR) (Rahman and Ng, 2012). In contrast, WIKICREM brings a much more consistent improvement over a wider range of datasets, strongly improving models’ performance even when they are not fine-tuned on additional data. As opposed to our previous work (Kocijan et al., 2019), we evaluate models on a larger collection of test sets, showing the usefulness of WIKICREM beyond the Winograd Schema Challenge.

Moreover, a manual comparison of WIKICREM and MASKEDWIKI (Kocijan et al., 2019) shows a significant difference in the quality of the examples. We annotated 100 random examples from MASKEDWIKI and WIKICREM. In MASKEDWIKI, we looked for examples where masked nouns can be replaced with a pronoun, and only in 7 examples, we obtained a natural-sounding and grammatically correct sentence. In contrast, we estimated that 63% of the annotated examples in WIKICREM form a natural-sounding sentence when the appropriate pronoun is inserted, showing that WIKICREM consists of examples that are much closer to the target data. We highlight that pronouns are not actually inserted into the sentences and thus none of the examples sound unnatural. This analysis was performed to show that WIKICREM consists of examples with data distribution closer to the target tasks than MASKEDWIKI.

3 The WIKICREM Dataset

In this section, we describe how we obtained WIKICREM. Starting from English Wikipedia2, we search for sentences and pairs of sentences with the following properties: at least two distinct personal names appear in the text, and one of them is repeated. We do not use pieces of text with more than two sentences to collect concise examples only. Personal names in the text are called “candidates”. One non-first occurrence of the repeated candidate is masked, and the goal is to predict the masked name, given the correct and one incorrect candidate. In case of more than one incorrect candidate in the sentence, several datapoints are constructed, one for each incorrect candidate.

We ensure that the alternative candidate appears before the masked-out name in the text, in order to avoid trivial examples. Thus, the example is retained in the dataset if:

(a) the repeated name appears after both candidates, all in a single sentence; or
(b) both candidates appear in a single sentence, and the repeated name appears in a sentence directly following.

Examples where one of the candidates appears in the same sentence as the repeated name, while the

2https://dumps.wikimedia.org/enwiki/ dump id: enwiki-20181201
other candidate does not, are discarded, as they are often too trivial.

We illustrate the procedure with the following example:

When asked about Adams’ report, Powell found many of the statements to be inaccurate, including a claim that Adams first surveyed an area that was surveyed in 1857 by Joseph C.

The second occurrence of “Adams” is masked. The goal is to determine which of the two candidates (“Adams”, “Powell”) has been masked out. The masking process resembles replacing a name with a pronoun, but the pronoun is not inserted to keep the process fully unsupervised and error-free.

We used the Spacy Named Entity Recognition library\(^3\) to find the occurrences of names in the text. The resulting dataset consists of 2,438,897 samples. 10,000 examples are held out to serve as the validation set. Two examples from our dataset can be found on Figure 1.

Gina arrives and she is furious with Denise for not protecting Jody from Kingsley, as [MASK] was meant to be the parent.

**Candidates:** Gina, Denise

When Ashley falls pregnant with Victor’s child, Nikki is diagnosed with cancer, causing Victor to leave [MASK], who secretly has an abortion.

**Candidates:** Ashley, Nikki

![Figure 1: WIKICREM examples. Correct answers are given in bold.](https://spacy.io/usage/linguistic-features#named-entities)

We note that our dataset contains hard examples. To resolve the first example, one needs to understand that Denise was assigned a task and “meant to be the parent” thus refers to her. To resolve the second example, one needs to understand that having an abortion can only happen if one falls pregnant first. Since both candidates have feminine names, the answer cannot be deduced just on the common co-occurrence of female names and the word “abortion”.

We highlight that our example generation method, while having the advantage of being unsupervised, also does not give incorrect signals, since we know the ground truth reference.

Even though WIKICREM and GAP both use text from English Wikipedia, they produce differing examples, because their generating processes differ. In GAP, passages with pronouns are collected and the pronouns are manually annotated, while WIKICREM is generated by masking names that appear in the text. Even if the same text is used, different masking process will result in different inputs and outputs, making the examples different under the transductive hypothesis.

**WIKICREM statistics.** We analyze our dataset for gender bias. We use the Gender guesser library\(^4\) to determine the gender of the candidates. To mimic the analysis of pronoun genders performed in the related works (Webster et al., 2018; Rudinger et al., 2018; Zhao et al., 2018), we observe the gender of the correct candidates only. There were 0.8M “male” or “mostly_male” names and 0.42M “female” or “mostly_female” names, the rest were classified as “unknown”. The ratio between female and male candidates is thus estimated around 0.53 in favour of male candidates. We will see that this gender imbalance does not have any negative impact on bias, as shown in Section 6.2.

However, our unsupervised generating procedure sometimes yields examples where the correct answer cannot be deduced given the available information, we refer to these as unsolvable examples. To estimate the percentage of unsolvable examples, we manually annotated 100 randomly selected examples from the WIKICREM dataset. In order to prevent guessing, the candidates were not visible to the annotators. For each example, we asked them to state whether it was solvable or not, and to answer the solvable examples. In 100 examples, we found 18 unsolvable examples and achieved 95.1% accuracy on the rest, showing that the annotation error rate is tolerable. These annotations can be found in Appendix A.

However, as shown in Section 6.2, training on WIKICREM alone does not match the performance of training on the data from the target distribution. The data distribution of WIKICREM differs from the data distribution of the datasets for evaluation. If we replace the [MASK] token with a pronoun instead of the correct candidate, the resulting sentence sometimes sounds unnatural and would not occur in a human-written text. On the annotated 100 examples, we estimated the percentage of natural-sounding sentences to be 63%. While these sentences are not incorrect, the

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\(^3\)https://pypi.org/project/gender-guesser/

\(^4\)https://spacy.io/usage/linguistic-features#named-entities
4 Model

We use a simple language-model-based approach to anaphora resolution to show the value of the introduced dataset. In this section, we first introduce BERT (Devlin et al., 2018), a language model that we use throughout this work. In the second part, we describe the utilization of BERT and the fine-tuning procedures employed.

4.1 BERT

The Bidirectional Encoder Representations from Transformers (BERT) language model is based on the transformer architecture (Vaswani et al., 2017). We choose this model due to its strong language-modeling abilities and high performance on several NLU tasks (Devlin et al., 2018).

BERT is initially trained on two tasks: next sentence prediction and masked token prediction. In the next sentence prediction task, the model is given two sentences and is asked to predict whether the second sentence follows the first one. In the masked token prediction task, the model is given text with approximately 15% of the input tokens masked, and it is asked to predict these tokens. The details of the pre-training procedure can be found in Devlin et al. (2018).

In this work, we only focus on the masked token prediction. We use the PyTorch implementation of BERT and the pre-trained weights for BERT-large released by Devlin et al. (2018).

4.2 Pronoun Resolution with BERT

This section introduces the procedure for pronoun resolution used throughout this work. Let $S$ be the sentence with a pronoun that has to be resolved. Let $a$ be a candidate for pronoun resolution. The pronoun in $S$ is replaced with a [MASK] token and used as the input to the model to compute the log-probability $\log P(a|S)$. If $a$ consists of more than one token, the same number of [MASK] tokens is inserted into $S$, and the log-probability $\log P(a|S)$ is computed as the average of log-probabilities of all tokens in $a$.

The candidate-finding procedures are dataset-specific and are described in Section 6. Given a sentence $S$ and several candidates $a_1, \ldots, a_n$, we select the candidate $a_i$ with the largest $\log P(a_i|S)$.

4.3 Training

When training the model, the setup is similar to testing. We are given a sentence with a name or a pronoun masked out, together with two candidates. The goal is to determine which of the candidates is a better fit. Let $a$ be the correct candidate, and $b$ be an incorrect candidate. Following our previous work (Kocijan et al., 2019) we minimize the negative log-likelihood of the correct candidate, while additionally imposing a max-margin between the log-likelihood of the correct and incorrect terms. We observe that this combined loss consistently yields better results on validation sets of all experiments than negative log-likelihood or max-margin loss on their own.

$$\mathcal{L} = -\log P(a|S) + \alpha \cdot \max(0, \log P(b|S) - \log P(a|S) + \beta),$$

where $\alpha$ and $\beta$ are hyperparameters controlling the influence of the max-margin loss term and the margin between the log-likelihood of the correct and incorrect candidates, respectively.

The hyperparameter settings for fine-tuning BERT on WIKICRE\textemdash were the same as by Devlin et al. (2018), except for the learning rate and introduced constants $\alpha$ and $\beta$. For our hyperparameter search, we used learning rate $lr \in \{3 \cdot 10^{-5}, 1 \cdot 10^{-5}, 5 \cdot 10^{-6}, 3 \cdot 10^{-6}\}$ and hyperparameters $\alpha \in \{5, 10, 20\}, \beta \in \{0.1, 0.2, 0.4\}$ with grid search. The hyperparameter search is performed on a subset of WIKICRE\textemdash 10^5 datapoints with 10^5 hyperparameters on the validation set of WIKICRE\textemdash. The best validation score was achieved with $lr = 1 \cdot 10^{-5}, \alpha = 10$, and $\beta = 0.2$. We used batches of size 64.

Since WIKICRE\textemdash is large and one epoch takes around two days even when parallelized on 8 Tesla P100 GPUs, we only fine-tune BERT on WIKICRE\textemdash for a single epoch. We note that better results may be achieved with further fine-tuning and improved hyperparameter search.

Fine-tuning on other datasets is performed in the same way as training except for two differences. Firstly, in fine-tuning, the model is trained for 30 epochs due to the smaller size of datasets. Secondly, we do not sub-sample the training set for hyperparameter search. We validate the model
after every epoch, retaining the model that performs best on the WIKICREM validation set.

5 Evaluation Datasets

We now introduce the 7 datasets that were used to evaluate the models. We decide not to use the CoNLL2012 and WinoCOREF (Pradhan et al., 2012; Peng et al., 2015) datasets, because they contain more general coreference examples than just pronouns. We did not evaluate on the KNOW-REF dataset (Emami et al., 2019), since it was not yet publicly available at the time of writing.

GAP. GAP (Webster et al., 2018) is a collection of 4,454 passages from Wikipedia containing ambiguous pronouns. It focuses on the resolution of personal pronouns referring to human names and has a 1 : 1 ratio between masculine and feminine pronouns. In addition to the overall performance on the dataset, each model is evaluated also on its performance on the masculine subset \( F_1^M \), feminine subset \( F_1^F \), and its gender bias \( \frac{F_1^F}{F_1^M} \). The best performance was exhibited by the Referential Reader (Liu et al., 2019), a GRU-based model with additional external memory cells.

For each example, two candidates are given with the goal of determining whether they are the referent. In approximately 10% of the training examples, none of the candidates are correct. When training on the GAP dataset, we discard such examples from the training set. We do not discard any examples from the validation or test set.

When testing the model, we use the Spacy NER library to find all candidates in the sentence. Since the GAP dataset mainly contains examples with human names, we only retain named entities with the tag PERSON. We observe that in 18.5% of the test samples, the Spacy NER library fails to extract the candidate in question, making the answer for that candidate “FALSE” by default, putting our models at disadvantage. Because of this, 7.25% of answers are always false negatives, and 11.25% are always true negatives, regardless of the model. Taking this into account, we compute that the maximal \( F_1 \)-score achievable by our models is capped at 91.1%.

We highlight that, when evaluating our models, we are stricter than previous approaches (Liu et al., 2019; Webster et al., 2018). While they count the answer as “correct” if the model returns a substring of the correct answer, we only accept the full answer. The aforementioned models return the exact location of the correct candidate in the input sentence, while our approach does not. This strictness is necessary, because a substring of a correct answer could be a substring of several answers at once, making it ambiguous.

Wsc. The Winograd Schema Challenge (Levesque et al., 2011) is a hard pronoun resolution challenge inspired by the example from Winograd (1972):

The city councilmen refused the demonstrators a permit because they [feared/advocated] violence.

Question: Who [feared/advocated] violence?

Answer: the city councilmen / the demonstrators

A change of a single word in the sentence changes the referent of the pronoun, making it very hard to resolve. An example of a Winograd Schema must meet the following criteria (Levesque et al., 2011):

1. Two entities appear in the text.
2. A pronoun or a possessive adjective appears in the sentence and refers to one of the entities. It would be grammatically correct if it referred to the other entity.
3. The goal is to find the referent of the pronoun or possessive adjective.
4. The text contains a “special word”. When switched for the “alternative word”, the sentence remains grammatically correct, but the referent of the pronoun changes.

The Winograd Schema Challenge is specifically made up from challenging examples that require commonsense reasoning for resolution and should not be solvable with statistical analysis of co-occurrence and association.

We evaluate the models on the collection of 273 problems used for the 2016 Winograd Schema Challenge (Davis et al., 2017), also known as Wsc273. The best known approach to this problem uses the BERT language model, fine-tuned on the DPR dataset (Kociej et al., 2019).

DPR. The Definite Pronoun Resolution (DPR) corpus (Rahman and Ng, 2012) is a collection of problems that resemble the Winograd Schema Challenge. The criteria for this dataset have been relaxed, and it contains examples that might not require commonsense reasoning or examples where the “special word” is actually a whole phrase. We remove 6 examples in the DPR training set that overlap with the Wsc dataset. The
dataset was constructed manually and consists of 1,316 training and 564 test samples after we removed the overlapping examples. The best result on the dataset was reported by Peng et al. (2015) using external knowledge sources and integer linear programming.

**PDP.** The Pronoun Disambiguation Problem (PDP) is a small collection of 60 problems that was used as the first round of the Winograd Schema Challenge in 2016 (Davis et al., 2017). Unlike WSC, the examples do not contain a “special word”, however, they do require commonsense reasoning to be answered. The examples were manually collected from books. Despite its small size, there have been several attempts at solving this challenge (Fähndrich et al., 2018; Trinh and Le, 2018), the best result being held by the Marker Passing algorithm (Fähndrich et al., 2018).

**WNLI.** The Winograd Natural Language Inference (WNLI) is an inference task inspired by the Winograd Schema Challenge and is one of the 9 tasks on the GLUE benchmark (Wang et al., 2019). WNLI examples are obtained by rephrasing Winograd Schemas. The Winograd Schema is given as the “premise”. A “hypothesis” is constructed by repeating the part of the premise with the pronoun and replacing the pronoun with one of the candidates. The goal is to classify whether the hypothesis follows from the premise.

A WNLI example obtained by rephrasing one of the WSC examples looks like this:

**Premise:** The city councilmen refused the demonstrators a permit because they feared violence.

**Hypothesis:** The demonstrators feared violence.

**Answer:** true / false

The WNLI dataset is constructed manually. Since the WNLI training and validation sets overlap with WSC, we use the WNLI test set only. The test set of WNLI comes from a separate source and does not overlap with any other dataset.

The currently best approach transforms examples back into the Winograd Schemas and solves them as a coreference problem (Kocijan et al., 2019). Following our previous work (Kocijan et al., 2019), we reverse the process of example generation in the same way. We automatically detect which part of the premise has been copied to construct the hypothesis. This locates the pronoun that has to be resolved, and the candidate in question. All other nouns in the premise are treated as alternative candidates. We find nouns in the premise with the Stanford POS tagger (Manning et al., 2014).

**WINOGENDER.** WINOGENDER (Rudinger et al., 2018) is a dataset that follows the WSC format and is aimed to measure gender bias. One of the candidates is always an occupation, while the other is a participant, both selected to be gender neutral. Examples intentionally contain occupations with strong imbalance in the gender ratio. Participant can be replaced with the neutral “someone”, and three different pronouns (he/she/they) can be used. The aim of this dataset is to measure how the change of the pronoun gender affects the accuracy of the model.

Our models mask the pronoun and are thus not affected by the pronoun gender. They exhibit no bias on this dataset by design. We mainly use this dataset to measure the accuracy of different models on the entire dataset. According to Rudinger et al. (2018), the best performance is exhibited by Durrett and Klein (2013) when used on the male subset of the dataset. We use this result as the baseline.

**WINOBIAS.** Similarly to the WINOGENDER dataset, WINOBIAS (Zhao et al., 2018) is a WSC-inspired dataset that measures gender bias in the coreference resolution algorithms. Similarly to WINOGENDER, it contains instances of occupations with high gender imbalance. It contains 3,160 examples of Winograd Schemas, equally split into validation and test set. The test set samples are split into 2 types, where examples of type 1 are “harder” and should not be solvable using the analysis of co-occurrence, and examples of type 2 are easier. Additionally, each of these subsets is split into anti-stereotypical and pro-stereotypical subsets, depending on whether the gender of the pronoun matches the most common gender in the occupation. The difference in performance between pro- and anti-stereotypical examples shows how biased the model is. The best performance is exhibited by Lee et al. (2017) and Durrett and Klein (2013), as reported by Zhao et al. (2018).

6 Evaluation

We quantify the impact of WIKICREM on the introduced datasets.
6.1 Experiments

We train several different models to evaluate the contribution of the WikiCREM dataset in different real-world scenarios. In Scenario A, no information of the target distribution is available. In Scenario B, the distribution of the target data is known and a sample of training data from the target distribution is available. Finally, Scenario C is the transductive scenario where the unlabeled test samples are known in advance. All evaluations on the GAP test-set are considered to be Scenario C, because BERT has been pre-trained on the English Wikipedia and has thus seen the text in the GAP dataset at the pre-training time.

We describe the evaluated models below.

**BERT.** This model, pretrained by Devlin et al. (2018), is the starting point for all models and serves as the soft baseline for Scenario A.

**BERT_WIKIRAND.** This model serves as an additional baseline for Scenario A and aims to eliminate external factors that might have worked against the performance of BERT. To eliminate the effect of sentence lengths, loss function, and the percentage of masked tokens during the training time, we generate the RANDOMWIKI dataset. It consists of random passages from Wikipedia and has the same sentence-length distribution and number of datapoints as WikiCREM. However, the masked-out word from the sentence is selected randomly, while the alternative candidate is selected randomly from the vocabulary. BERT is then trained on this dataset in the same way as BERT_WIKICREM, as described in Section 4.3.

**BERT_WIKICREM.** BERT, additionally trained on WikiCREM. Its evaluation on non-GAP datasets serves as the evaluation of WikiCREM under Scenario A.

**BERT_DPR.** BERT, fine-tuned on DPR. We hold out 10% of the DPR train set (131 examples) to use them as the validation set. All datasets, other than GAP, were inspired by the Winograd Schema Challenge and come from a similar distribution. We use this model as the baseline for Scenario B.

**BERT_WIKICREM_DPR.** This model is obtained by fine-tuning BERT_WIKICREM on DPR using the same split as for BERT_DPR. It serves as the evaluation of WikiCREM under Scenario B.

**BERT_GAP_DPR.** This model serves as an additional comparison to the BERT_WIKICREM_DPR model. It is obtained by fine-tuning BERT_GAP on the DPR dataset.

**BERT_GAP.** This model is obtained by fine-tuning BERT on the GAP dataset. It serves as the baseline for Scenario C, as explained at the beginning of Section 6.1.

**BERT_WIKICREM_GAP.** This model serves as the evaluation of WikiCREM for Scenario C and is obtained by fine-tuning BERT_WIKICREM on GAP.

**BERT_ALL.** This model is obtained by fine-tuning BERT on all the available data from the target datasets at once. Combined GAP-train and DPR-train data are used for training. The model is validated on the GAP-validation set and the WinOBias-validation set separately. Scores on both sets are then averaged to obtain the validation performance. Since both training sets and both validation sets have roughly the same size, both tasks are represented equally.

**BERT_WIKICREM_ALL.** This model is obtained in the same way as the BERT_ALL model, but starting from BERT_WIKICREM instead.

6.2 Results

The results of the evaluation of the models on the test sets are shown in Table 1. We notice that additional training on WikiCREM consistently improves the performance of the models in all scenarios and on most tests. Due to the small size of some test sets, some of the results are subject to deviation. This especially applies to PDP (60 test samples) and WNLI (145 test samples).

We observe that BERT_WIKIRAND generally performs worse than BERT, with GAP and PDP being notable exceptions. This shows that BERT is a strong baseline and that improved performance of BERT_WIKICREM is not a consequence of training on shorter sentences or with different loss function. BERT_WIKICREM consistently outperforms both baselines on all tests, showing that WikiCREM can be used as a standalone dataset.

We observe that training on the data from the target distribution improves the performance the most. Models trained on GAP-train usually show more than a 20% increase in their $F_1$-score on GAP-test. Still, BERT_WIKICREM_GAP shows...
### Table 1: Evaluation of trained models on all test sets. GAP and WINOBIAS (abbreviated WB) are additionally split into subsets, as introduced in Section 5. Double lines in the table separate results from three different scenarios: when no training data is available, when additional training data exists, and the transductive scenario. The table is further split into sections separated with single horizontal lines. Each section contains a model that has been trained, and sets the new state-of-the-art on the PDP data.

| Model | GAP $F_1$ | GAP $F_1$ | GAP $F_1^M$ | Bias $F_1^M - F_1^G$ | DPR | WSc | WNL1 |
|-------|-----------|-----------|--------------|----------------------|-----|-----|------|
| SOTA  | 72.1%     | 71.4%     | 72.8%        | 0.98                 |     |     |      |
| BERT  | 50.0%     | 47.2%     | 52.7%        | 0.90                 | 59.8% | 61.9% | 65.8% | no train |
| BERT_WikiRand | 55.1%     | 51.8%     | 58.2%        | 0.89                 | 59.2% | 59.3% | 65.8% |
| BERT_WikiCREM | 59.0%     | 57.5%     | 60.5%        | 0.95                 | 67.4% | 63.4% | 67.1% | data |
| BERT_GAP | 75.2%     | 75.1%     | 75.3%        | 1.00                 | 66.8% | 63.0% | 68.5% | |
| BERT_WikiCREM_GAP | 77.4%     | 78.4%     | 76.4%        | 1.03                 | 71.1% | 64.1% | 70.5% |
| BERT_DPR | 60.9%     | 61.3%     | 60.6%        | 1.01                 | 83.3% | 67.0% | 71.9% | existing data |
| BERT_GAP_DPR | 70.0%     | 70.4%     | 69.5%        | 1.01                 | 79.4% | 65.6% | 72.6% | |
| BERT_WikiCREM_DPR | 64.2%     | 64.2%     | 64.1%        | 1.00                 | 80.0% | 71.8% | 74.7% |
| BERT_all | 76.0%     | 77.4%     | 74.7%        | 1.04                 | 80.1% | 70.0% | 74.0% |
| BERT_WikiCREM_all | 78.0%     | 79.4%     | 76.7%        | 1.04                 | 84.8% | 70.0% | 74.7% |

| WB T1-a | WB T1-p | WB T2-a | WB T2-p | WINOGENDER | PDP |
|---------|---------|---------|---------|------------|-----|
| SOTA    | 60.6%   | 74.9%   | 78.0%   | 88.6%      | 50.9% | 74.0% |
| BERT    | 61.3%   | 60.3%   | 76.2%   | 75.8%      | 59.2% | 71.7% | no train |
| BERT_WikiRand | 53.5%     | 52.5%     | 64.6%    | 65.2%      | 57.9% | 73.3% |
| BERT_WikiCREM | 65.2%     | 64.9%     | 95.7%    | 94.9%      | 66.7% | 76.7% |
| BERT_GAP | 64.6%   | 63.8%   | 88.1%   | 87.9%      | 67.5% | 85.0% |
| BERT_WikiCREM_GAP | 72.2%     | 70.5%     | 97.2%    | 98.2%      | 75.4% | 83.3% |
| BERT_DPR | 78.0%   | 78.2%   | 85.6%   | 86.4%      | 79.2% | 81.7% |
| BERT_GAP_DPR | 77.8%     | 76.5%     | 89.6%    | 89.1%      | 75.8% | 86.7% |
| BERT_WikiCREM_DPR | 76.0%     | 76.3%     | 81.3%    | 80.3%      | 82.1% | 76.7% |
| BERT_all | 77.9%   | 77.3%   | 94.7%   | 94.9%      | 78.0% | 81.7% |
| BERT_WikiCREM_all | 76.8%     | 75.8%     | 98.7%    | 99.0%      | 76.7% | 86.7% |

A consistent improvement over BERT_GAP on all subsets of the GAP test set. This confirms that WikiCREM works not just as a standalone dataset, but also as an additional pre-training in the transductive scenario.

Similarly, BERT_WikiCREM_DPR outperforms BERT_DPR on the majority of tasks, showing the applicability of WikiCREM to the scenario where additional training data is available. However, good results of BERT_GAP_DPR show that additional training on a manually constructed dataset, such as GAP, can yield similar results as additional training on WikiCREM. The reason behind this difference is the impact of the data distribution. GAP, DPR, and WikiCREM contain data that follows different distributions which strongly impacts the trained models. This can be seen when we fine-tune BERT_GAP on DPR to obtain BERT_GAP_DPR, as the model’s performance on GAP-test drops by 8.2%. WikiCREM’s data distribution strongly differs from the test sets’ as described in Section 3.

However, the best results are achieved when all available data is combined, as shown by the models BERT_all and BERT_WikiCREM_all. BERT_WikiCREM_all achieves the highest performance on GAP, DPR, WNL1, and WINOBIAS among the models, and sets the new state-of-the-art result on GAP, DPR, and WINOBIAS. The new state-of-the-art result on the WINOGENDER dataset is achieved by the BERT_WikiCREM_DPR model, while BERT_WikiCREM_all and BERT_GAP_DPR set the new state-of-the-art on the PDP dataset.
7 Conclusions and Future Work

In this work, we introduced WikiCREM, a large dataset of training instances for pronoun resolution. We use our dataset to fine-tune the BERT language model. Our results match or outperform state-of-the-art models on 6 out of 7 evaluated datasets.

The employed data-generating procedure can be further applied to other large sources of text to generate more training sets for pronoun resolution. In addition, both variety and size of the generated datasets can be increased if we do not restrict ourselves to personal names. We hope that the community will make use of our released WikiCREM dataset to further improve the pronoun resolution task.

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A Annotated WikiCREM Examples

The appendix contains the 100 manually annotated examples.

1. Throughout training camp, Jackson competed to be the Bengals’ third cornerback on the depth chart against Darqueze Dennard. On August 2, 2016, it was announced that [MASK] had suffered a torn pectoral muscle and would have to undergo surgery.

   ambiguous
   Pronoun in place of [MASK]? : No
   Annotator’s answer: N/A
   Correct?: N/A

2. The Ark “consisted of a giant rowboat with a small engine which Beek used as his first ferry vessel.” The [MASK] “carried oars in the event of engine failure.

   not ambiguous
   Pronoun in place of [MASK]? : no
   Annotator’s answer: Ark
   Correct?: yes

3. However, John was able to gain the lost estates by a marriage to Joanna of Urgell, granddaughter of Peter IV of Aragon. [MASK] fought with Aragon against Castile, but helped his brother Peter, Cardinal of Foix and Arles, to crush insurgents from Aragon.

   not ambiguous
   Pronoun in place of [MASK]? : yes
   Annotator’s answer: John
   Correct?: yes

4. Ultravox had gone on to greater success with Midge Ure fronting the band, but when Simon left the band in 1988, Billy Currie formed a new band which later included [MASK].

   not ambiguous
   Pronoun in place of [MASK]? : no
   Annotator’s answer: Midge Ure
   Correct?: no

5. The poem describes the poet’s idyllic family life with his own three daughters, Alice, Edith, and Anne Allegra; "grave [MASK], and laughing Allegra, and Edith with golden hair."

   not ambiguous
   Pronoun in place of [MASK]? : no
   Annotator’s answer: Alice
   Correct?: yes

6. Koch and Eide searched Cho’s belongings and found a pocket knife, but they did not find any items that they deemed threatening. [MASK] also described a telephone call that he received from Cho during the Thanksgiving holiday break from school.

   ambiguous
   Pronoun in place of [MASK]? : no
   Annotator’s answer: N/A
   Correct?: N/A

7. As Rajveer was able to successfully lead the escape of them both, Harleen now entrusts Rajveer, subsequently falling in love with him. When Rajveer goes out of his hotel with [MASK], he sees that they are wanted by Interpol.

   not ambiguous
   Pronoun in place of [MASK]? : yes
   Annotator’s answer: Harleen
   Correct?: yes

8. Elmas, Su Masu in Sardinian language, is a “comune” of the Metropolitan City of Cagliari in the Italian region of Sardinia, located about northwest of Cagliari. Until 1989 [MASK] was a district of Cagliari.

   not ambiguous
   Pronoun in place of [MASK]? : yes
   Annotator’s answer: Elmas
   Correct?: yes

9. Later in the year, Li Keyong did send Li Sizhao and Zhou to capture Xi and Ci Prefectures, which had become under Zhu’s control when [MASK] conquered Huguo earlier in 901.

   not ambiguous
   Pronoun in place of [MASK]? : yes
   Annotator’s answer: Zhu
   Correct?: yes

10. Elisha told Hazael to tell Hadadezer that he would recover, and he revealed to Hazael that the king would recover but would die of other means. The day after he returned to Hadadezer in Damascus, [MASK] suffocated him and seized power himself.

    not ambiguous
    Pronoun in place of [MASK]? : yes
11. In 1946, Hill and Knowlton dissolved their partnership, and Knowlton took over the direction of Hill & Knowlton Cleveland, which closed shortly after Knowlton’s retirement in 1962. [MASK] also maintained an interest in music.

12. First, God is revealed with Law, and secondly, God is revealed as Person. [MASK]’s anger at Moses for not speaking to the rock on the second occasion, highlights that this is not the spiritual picture He wanted portrayed.

13. He now said he had seen Acreman follow Cheryl Fergeson up a staircase leading to the auditorium and then heard her scream, “No” and “Don’t.” Later that day, [MASK] warned Sessum not to tell anyone what he had seen.

14. Meidi finally figures it out, but does not reveal to Qi Yue and Ah Meng until [MASK] confesses.

15. Brett went back to Leary, expecting to be turned down again, but this time, Leary gave Brett the aircraft he wanted. “Perhaps”, [MASK] speculated, “Leary had heard from Washington”.

16. Maurice White spoke to Stepney on the morning of May 17, 1976, but later that day, Earth, Wind & Fire keyboardist Larry Dunn received a phone call, informing him that [MASK] had died of a heart attack.

17. Li Yi sought aid from Gao, who personally led two thousand cavalry soldiers to aid Li Yi, causing Dou to withdraw. Gao thereafter sought to submit to Tang, through [MASK].

18. At Cambridge, Rose studied under Hubert Middleton and Edward Joseph Dent from 1935 to 1939. [MASK] started his academic career at The Queen’s College, Oxford.

19. Brady and Bolger leave with Rothbaum, and Rothbaum demands the money Brady owes him. When Rothbaum threatens to kill them if they don’t pay up, Bolger shoots Rothbaum’s thugs, and Brady stabs [MASK], killing him.

20. In the reception room, a boy named Billy won’t stop staring at Don. [MASK] is drawing a picture and then rips it out of his book and hands it to Billy, getting up and leaving.

21. Hasan and Stein agree that Harsa became king in 1089. Utkarsa was disliked and soon deposed, with a half-brother called Vijayamalla supporting [MASK] and being at the
forefront of the rebellion against the king. ambiguous
Pronoun in place of [MASK]?: no
Annotator’s answer: N/A
Correct?: N/A

22. Yet this did not prevent Leisegang from reasserting that Aristotle’s own pattern of thinking was incompatible with a proper understanding of Plato. “Therein Cherniss believed Jaeger to be contrary to [MASK], and Leisegang was unsympathetic to compatibility between Plato and Aristotle in both and above.
not ambiguous
Pronoun in place of [MASK]?: no
Annotator’s answer: Leisegang
Correct?: yes

23. Aska later decides not to rule Cephiro because Fuu told her that the Pillar can think only of Cephiro, but since Lady Aska loves the people of Fahrenheit, she cannot complete the task of Pillar in [MASK].
not ambiguous
Pronoun in place of [MASK]?: yes
Annotator’s answer: Cephiro
Correct?: yes

24. As the weeks wore on, it became evident that Nick could be Lujack’s twin brother, hence, Alex’s son. [MASK] soon became obsessed with Nick and Mindy warned him that Alex wouldn’t give up until she got him.
not ambiguous
Pronoun in place of [MASK]?: yes
Annotator’s answer: Alex
Correct?: yes

25. Due to Jijii’s psychological manipulation, Ichi believes that Kaneko is his brother and confronts him. Kaneko shoots the side of [MASK]’s leg, causing Ichi to slit Kaneko’s throat in front of Takeshi.
not ambiguous
Pronoun in place of [MASK]?: yes
Annotator’s answer: Ichi
Correct?: yes

26. Frank, Jump and other members of the gang go to Clay’s social club, where Frank tells Clay that he wants a percentage of all Clay’s profits. When Clay insults him, [MASK] shoots the Mafioso.
ambiguous
Pronoun in place of [MASK]?: no
Annotator’s answer: N/A
Correct?: N/A

27. The spoils were to be divided between Shivaji, Kootab Shah and Bijapur. With the agreement concluded and with [MASK] giving him money, horses and artillery, Sivajee set out in March 1677 for his invasions via Kurnool, Cuddapah and Madras.
ambiguous
Pronoun in place of [MASK]?: no
Annotator’s answer: N/A
Correct?: N/A

28. Billingsley’s response was a gift—bow ties for Ace. [MASK]’s reply was to ask Billingsley for some matching socks so he would be well-dressed when he was refused admittance again.
not ambiguous
Pronoun in place of [MASK]?: yes
Annotator’s answer: Ace
Correct?: yes

29. In 890, when Zhu asked Luo Hongxin the military governor of Weibo Circuit for permission to go through Luo’s territory to attack Hedong, Luo refused. [MASK] reacted by sending Ding, Ge, Pang Shigu, and Huo Cun to attack Weibo.
not ambiguous
Pronoun in place of [MASK]?: yes
Annotator’s answer: Zhu
Correct?: yes

30. However, it is recorded that Lewis was born in 1381 and sent to the school at Oxford at age 10; it is also known that Chaucer’s “Treatise on the Astrolabe” was written for [MASK].
not ambiguous
Pronoun in place of [MASK]?: yes
Annotator’s answer: Lewis
Correct?: yes

31. Claiborne and the other survivors are rescued, thanks to quick action by Taylor and Harold. At the interment, [MASK] begs Claiborne to take him and Harold on his expedition to K2, the second highest peak in the world.
32. That year, LONGi signed a contract with Yingli to cooperate on monocrystalline products. In early 2016, [MASK] signed a $1.

33. Katie is taken to Children’s Hospital, and Louise and Wes find themselves being arrested for “what authorities are calling the worst case of child abuse they’ve ever seen.” Shortly before his trial begins, [MASK] kills himself.

34. When it becomes clear that Warren has shifted his interest from Marjorie to Bernice, Marjorie sets about humiliating Bernice by tricking her into going through with bobbing her hair. When [MASK] comes out of the barbershop with the new hairdo, her hair is flat and strange.

35. Rebello defeated David Cho via Unanimous Decision at PXC 26 - Meanest Game Face on August 20, 2011. [MASK] made his WEC debut at WEC 39, losing to Kenji Osawa via split decision.

36. Karen overhears Bermadette talking to Keanu, who [MASK] thinks may be the baby’s father.

37. Murray Abraham, Daphne Rubin-Vega, Henry Minkler, Kathryn Boule and Judy Kuhn also got their start with Theatreworks. [MASK] has won many awards in its long history.

38. In Jacmel, three weeks prior to his reunion with Marie, Paul spends time with his lover and fiancé Natasha. Natasha harbors feelings of mistrust for [MASK], who left for New York after the earthquake, and spent three years there without having ever contacted her.

39. After the match, Deuce ‘n Domino attacked Snuka and Slaughter until Tony Garea and Rick Martel came into the ring to assist Snuka and [MASK].

40. Later, Jude and Noah realize that they will be working together, as [MASK] is a new sideline reporter assigned to the Devils.

41. As such, Michael, Madeline, Sam, Fiona, and Jesse are all hell-bent on exacting revenge for Nate’s murder. Eventually, Michael, with his former mentor Tom Card helping him, tracks [MASK]’s killer, Tyler Grey, to Panama.

42. Eileen later follows Des to Erinsborough to check up on him and she takes an instant dislike to [MASK]’s housemate, Daphne.
43. Although Armstrong was a third party not in privity with Leyland, and a stranger to the car purchase transaction, nonetheless Armstrong was permitted to rely on the non-derogation rights of the car owners relative to [MASK].

44. Its theological center and the Fatima Masumeh Shrine are prominent features of Qom. Another very popular religious site of pilgrimage formerly outside the city of [MASK] but now more of a suburb is called Jamkaran.

45. Schult was married to Elke Koska for 25 years, who Schult considers his muse - she was also his manager, now in cooperation with Anna Zlotovskaya, the Russian classical violinist, [MASK] married in 2010.

46. Gordon wakes up and successfully escapes from Nygma. Shaking off [MASK]'s pursuit, Gordon reaches Bruce and Selina's hideout and collapses.

47. During World War II, Hill, as well as Lewis, filed for conscientious objector status. After the war, [MASK], Hill and a small group of former conscientious objects created the Pacifica Foundation in Pacifica, California.

48. Lana tries to intervene but is punched in the stomach by Dino. Luca lunges at Dino but [MASK] pushes him to the ground.

49. On October 28, 2010, Facebook banned Rapleaf from scraping data on Facebook, and [MASK] said it would delete the Facebook IDs it had collected.

50. After arriving at the camp, Charlie apologizes to Claire, but Claire tells him to leave her and her son alone. [MASK] then goes into the jungle, and opens a hiding place where he is keeping Virgin Mary statues to put the one Eko gave him.

51. When Sylvie belittles Babe, she leaves Sylvie by the canal in the rain, although Sylvie is found and Shirley realizes that Babe left [MASK] to die and disowns her.

52. Gregory, as an infant, drowned in a bathtub when Kay became distracted from a call from Sam. [MASK] and Kay ended up divorcing.

53. Stefanie in Rio is a 1960 West German romantic comedy film directed by Curtis Bernhardt and starring Carlos Thompson, Sabine Sinjen and Andra Parisy. It is a sequel to the 1958 film "[MASK]".
54. Kent Ling and his team of assassins are then forced to rescue Ling Hung, but it involved them and Ling Hung having to be in a very deadly gun battle against Kam Tin ’s henchmen and unfortunately [MASK] ’s team are all killed in the process.

55. On the weekend of January 14, 2017, Walker was planning to compete at the 2016 Montana ProRodeo Circuit Finals in Great Falls. [MASK] was in 2nd place in the circuit standings with $14,351 so far.

56. Samantha, Jennifer, Billy, Taylor and Coop leave by the end of the season. In the season finale, [MASK] gives birth to Michael ’s son and agrees to share motherhood with the returning Jane.

57. Appears in “ ” Bucky was a worker who encountered Michael Myers as he wandered around an electrical power plant. [MASK] told Michael that he was not permitted on the grounds.

58. In August of the same year, Laura came to Coronation Street to tell Alan and Elsie Tanner that she was getting re-married and wanted to drop [MASK] ’s loan - although Elsie refused.

59. When Spike lands, Jerry sticks out his tongue and throws Spike ’s lips over his own face, provoking [MASK] to chase him around the corner.

60. A year later she met Friedrich Schiller and played Luise Miller in his first performance of Kabale und Liebe. Sophie Albrecht and [MASK] had similar interests and became close friends.

61. Walcott lost the count as Ali circled around a floored Liston and [MASK] tried to get him back to a neutral corner.

62. At the World Matchplay, Whitlock recorded wins over Kevin Painter, Raymond van Barneveld and James Wade to reach the semi-finals of the event for the second time, with [MASK] stating he was playing his best darts in five years.

63. In the long period that Lars Semb was manager at Moss Jernverk he traveled almost yearly to the mining areas and he subsequently stayed with the local agents. [MASK] was totally dependent on charcoal that the surrounding farmers produced.

64. Armstrong felt impressed with the style of Hansen ’s work. In June 2002, Armstrong
and [MASK] signed a formal agreement.

**not ambiguous**

Pronoun in place of [MASK]? : yes
Annotator’s answer: Hansen
Correct?: yes

65. In 1235 and 1239 the da Camino managed to obtain the rule in Treviso, but the second time they were betrayed by Alberico da Romano, who expelled the Guelphs from the city. However, with Gherardo III da Camino the [MASK] regained prominence.

**not ambiguous**

Pronoun in place of [MASK]? : yes
Annotator’s answer: Guelphs
Correct?: yes

66. The small forward Shamell Stallworth made a three-pointer with the clock reset already and gave the victory to Pinheiros. This game was extremely important because [MASK] because Pinheiros finished the regular season in front of Flamengo precisely by direct confrontation.

**not ambiguous**

Pronoun in place of [MASK]? : no
Annotator’s answer: Pinheiros
Correct?: yes

67. The Mississippi Department of Transportation calculated an average of 14,000 vehicles passing along the route near [MASK].

**ambiguous**

Pronoun in place of [MASK]? : no
Annotator’s answer: N/A
Correct?: N/A

68. In France, Andrianarivo met with former President Albert Zafy on June 11, 2007; Zafy had also met with Ratsiraka and former Deputy Prime Minister Pierrot Rajaonarivelo in the previous days. [MASK] and Ratsiraka met with Zafy again on June 25.

**not ambiguous**

Pronoun in place of [MASK]? : yes
Annotator’s answer: Andrianarivo
Correct?: yes

69. In the next round, Williams faced Alona Bondarenko and once again won with only dropping 5 games. In the quarterfinals, for the third match in a row, [MASK] only dropped five games this time to Czech Lucie afov.

**not ambiguous**

Pronoun in place of [MASK]? : yes
Annotator’s answer: Williams
Correct?: yes

70. Eventually, Saori and Yoshino rejoin Shuichi’s group of friends, though Saori says she still hates Yoshino and Momoko. Shuichi and Anna start dating, much to the surprise of their friends and [MASK]’s sister.

**ambiguous**

Pronoun in place of [MASK]? : no
Annotator’s answer: N/A
Correct?: N/A
Posučice, Turkw, Uciechowice, Wodzienin, Wdka and Wysoka.

not ambiguous
Pronoun in place of [MASK]?: no
Annotator’s answer: Dzbace
Correct?: yes

75. When she sees Franky getting into Luke’s car, she gets into a van with Matty. Grace joins him, wanting to talk, but Liv rushes up and demands they follow Franky and [MASK].
not ambiguous
Pronoun in place of [MASK]?: no
Annotator’s answer: Luke
Correct?: yes

76. She explained that Laura was frantic and told her that Luis jumped in the water channel and that she was unable to see him anymore. Supposedly, the group of friends met [MASK] at the park and started looking for Luis.
not ambiguous
Pronoun in place of [MASK]?: yes
Annotator’s answer: Laura
Correct?: yes

77. Whether it was Sidney who next challenged Vere to a duel or the other way around, Vere did not take it further, and the Queen personally took Sidney to task for not recognizing the difference between his status and [MASK]’s.
not ambiguous
Pronoun in place of [MASK]?: no
Annotator’s answer: Vere
Correct?: yes

78. Wei attempts to rescue Ku, only to find out that Po deduced Wei’s identity as a cop, since [MASK] was too skilled compared to the rest of his gang.
not ambiguous
Pronoun in place of [MASK]?: yes
Annotator’s answer: Po
Correct?: no

79. After an unsuccessful evening on the town, Clark takes Sarah to the Indian side of Calcutta, where they attend a party at the home of a wealthy socialite. There, [MASK] seduces Sarah by challenging her to taste life.
not ambiguous
Pronoun in place of [MASK]?: yes
Annotator’s answer: Clark
Correct?: yes

80. The incapacitated Mike is stabbed repeatedly by Erin, who ties a rope around his neck, attaches the other end to a tractor, and drives the vehicle until Mike’s neck snaps.[MASK] stumbles outside, and discovers Danny, who is barely alive.
not ambiguous
Pronoun in place of [MASK]?: yes
Annotator’s answer: Erin
Correct?: yes

81. Slingsby was married to the sister of Lawford’s wife, hence why Lawford had to give Slingsby a chance to command the Light Company to prove himself which angered Sharpe.[MASK] was regarded as a poor officer who was often drunk.
ambiguous
Pronoun in place of [MASK]?: no
Annotator’s answer: N/A
Correct?: N/A

82. Hans and Gerda’s mutual attraction is a challenge, as Gerda is navigating her changing relationship to Lili; but Hans’ long-time friendship with and affection for [MASK] cause him to be supportive of both Lili and Gerda.
ambiguous
Pronoun in place of [MASK]?: no
Annotator’s answer: N/A
Correct?: N/A

83. Sirius ”sailed in ballast, having unloaded a cargo of hay at Rsneshavn after departing Troms. She had left [MASK] in the morning of 17 May 1940.”
not ambiguous
Pronoun in place of [MASK]?: Rsneshavn
Annotator’s answer: Rsneshavn
Correct?: yes

84. Harold does not take the news well, but Karl eventually convinces him to fight. [MASK] has an operation and begins chemotherapy after speaking to Stephanie Scully.
not ambiguous
Pronoun in place of [MASK]?: yes
Annotator’s answer: Harold
Correct?: yes
85. Ron knocks Dale out and leaves her in a locked car filling with exhaust, sadistically goading Andrew into braving his agoraphobia in order to save her. Andrew manages to save her and wound Ron; reviving, Dale deals [MASK] a death blow.

not ambiguous
Pronoun in place of [MASK]?: no
Annotator’s answer: Ron
Correct?: yes

86. Evans introduced two romantic interests for Corrigan: Anina Kreemar, the wealthy niece of Corrigan’s bureau chief, and [MASK]’s friendly rival Jennever Brand, a spirited female agent of a rival clandestine spy agency.

not ambiguous
Pronoun in place of [MASK]?: yes
Annotator’s answer: Corrigan
Correct?: yes

87. Her fifth victim was Pillama, aged 60, and killed at Maddur Vyadyanathapura. [MASK] was a temple priest at Hebbal temple.

not ambiguous
Pronoun in place of [MASK]?: yes
Annotator’s answer: Pillama
Correct?: yes

88. Sandy tells Rizzo she plans to watch the race and offers to help [MASK] despite the rumors about Rizzo’s character that have been spread around school.

not ambiguous
Pronoun in place of [MASK]?: yes
Annotator’s answer: Rizzo
Correct?: yes

89. Qianru’s mother, Fengyi tries to talk her into accepting the fact that Huanhuan is autistic but Qianru is unwilling to face reality. After some time, under Wenxin’s patient persuasion, [MASK] finally agrees to send Huanhuan to a school for children with special needs.

not ambiguous
Pronoun in place of [MASK]?: yes
Annotator’s answer: Qianru
Correct?: yes

90. After Trey pushes away Guy, Trey finally realized that Alex was right all along and that Guy has been trying to break them up. Trey and Alex kick [MASK] out of their home and later apologizes to Alex.

not ambiguous
Pronoun in place of [MASK]?: yes
Annotator’s answer: Guy
Correct?: yes

91. Burns’s clashes with Smith was perhaps most obvious at the notorious New York City concert in 1998 where Burns attacked [MASK] after the vocalist repeatedly and deliberately knocked one of Burns’s cymbal stands to the floor.

not ambiguous
Pronoun in place of [MASK]?: yes
Annotator’s answer: Smith
Correct?: yes

92. When Viki asks if he loves Echo, Charlie hesitates, and Viki storms off. On April 12, Viki asks [MASK] again whether or not he loves Echo; he says he does.

not ambiguous
Pronoun in place of [MASK]?: yes
Annotator’s answer: Charlie
Correct?: yes

93. In pre-sentence proceedings, Chen’s father, Edward Chen, was reported as saying: During his final plea on 2 February 2006, Chen said: On 15 February 2006 [MASK] was sentenced to life imprisonment.

not ambiguous
Pronoun in place of [MASK]?: yes
Annotator’s answer: Chen
Correct?: yes

94. Andrea considers assassinating the Governor, but Milton knows that his second-in-command, Martinez, will follow through on the Governor’s plans. Instead, [MASK] urges Andrea to escape and warn Rick and the others.

not ambiguous
Pronoun in place of [MASK]?: yes
Annotator’s answer: Milton
Correct?: yes

95. Patterson took the communiqué to the White House, where Truman and Attlee signed it on 16 November 1945. The next meeting of the Combined Policy Committee on 15
April 1946 produced no accord on collaboration, and resulted in an exchange of cables between Truman and [MASK].

**ambiguous**
Pronoun in place of [MASK]?: no
Annotator’s answer: N/A
Correct?: N/A

96. In any case, Baldwin’s other brother Philip of Namur remained as regent, and eventually both of [MASK]’s daughters, Joan and Margaret II, were to rule as countesses of Flanders.

**not ambiguous**
Pronoun in place of [MASK]?: no
Annotator’s answer: Baldwin
Correct?: yes

97. In the late 1990s, Luis Rossi, Ivan Fernandez, and Mercedes Fernandez purchased the Aragon. In September 2014, [MASK] sold all her interests in the Aragon.

**not ambiguous**
Pronoun in place of [MASK]?: no
Annotator’s answer: Mercedes Fernandez
Correct?: yes

98. Peschko also played chamber music; best known are his projects with violinist Georg Kulenkampff and cellists Enrico Mainardi and Hans Adomeit. From 1953 to 1958 [MASK] was responsible for lieder, choir and church music at Radio Bremen.

**not ambiguous**
Pronoun in place of [MASK]?: yes
Annotator’s answer: Peschko
Correct?: yes

99. Realising the war was lost, Himmler attempted to open peace talks with the western Allies without Hitler’s knowledge, shortly before the end of the war. Hearing of this, [MASK] dismissed him from all his posts in April 1945 and ordered his arrest.

**not ambiguous**
Pronoun in place of [MASK]?: yes
Annotator’s answer: Hitler
Correct?: yes

100. Dein was behind the appointment of the then little known Arsne Wenger to the manager’s job in 1996; under Wenger, Arsenal have won the Premier League three times and the FA Cup seven times, and [MASK] strongly backed him and his transfer wishes throughout.