The ApposCorpus: A new multilingual, multi-domain dataset for factual appositive generation

Yova Kementchedjhieva
University of Copenhagen
yova@di.ku.dk

Di Lu
Dataminr, Inc.
dlu@dataminr.com

Joel Tetreault
Dataminr, Inc.
jtetreault@dataminr.com

Abstract

News articles, image captions, product reviews and many other texts mention people and organizations whose name recognition could vary for different audiences. In such cases, background information about the named entities could be provided in the form of an appositive noun phrase, either written by a human or generated automatically. We expand on the previous work in appositive generation with a new, more realistic, end-to-end definition of the task, instantiated by a dataset that spans four languages (English, Spanish, German and Polish), two entity types (person and organization) and two domains (Wikipedia and News). We carry out an extensive analysis of the data and the task, pointing to the various modeling challenges it poses. The results we obtain with standard language generation methods show that the task is indeed non-trivial, and leaves plenty of room for improvement.

1 Introduction

News articles, image captions, product reviews and many other texts mention people and organizations, whose name recognition could vary for different audiences. A piece of news, for example, may concern people and organizations that are known locally, but are not necessarily well-recognized on a global level. In such cases, news pieces targeted at a wider audience would provide background information about the entity in focus, often in the form of an *appositive*. For example:

> In March 2017 , Natalie Jaresko, *former Minister of Finance in Ukraine*, was appointed as the board's executive director.

It is unlikely that many people outside of Ukraine know the name Natalie Jaresko, so a foreign reader would likely benefit from the extra bit of information about her former occupation as justification for her new appointment. An appositive could also be less contextualized and provide information of more general importance, for example:

> The conservation unit is in the Calhau bairro of São Luís, *the state capital.*

In general terms, appositives are phrases that appear next to a noun phrase and serve an explicative function (Bauer, 2017). Adding such explanations to text is a multi-step process. First, one has to decide whether an entity mention needs an appositive. That may not be the case for entities that are sufficiently well-known or that have been introduced earlier in the text. In case an appositive is indeed needed, the next step is to choose what information about the entity to disclose. If the information is to be of a factual nature, the writer needs to have prior knowledge of the entity, or access to an external knowledge resource–Kang et al. (2019) found appositives to be frequently based on facts of particular relevance to the context of the mention. Lastly, the surface form of the appositive, well-fitted to the surrounding context, needs to be produced. Viewed from the perspective of NLP, appositive generation is therefore an

Proceedings of the 28th International Conference on Computational Linguistics, pages 1989–2003
Barcelona, Spain (Online), December 8-13, 2020

interesting and challenging natural language generation problem that involves reasoning over facts from an external knowledge source, with reference to a given context.

The task of appositive generation, first introduced by Kang et al. (2019), is still in its early stages and data resources are limited. We expand on previous work in appositive generation with a new, more realistic, end-to-end definition of the task, instantiated by a dataset, `ApposCorpus`,[1] that spans four languages (English, Spanish, German and Polish), two entity types (person and organization) and two domains (Wikipedia and News). While Wikipedia as a domain is curated for a world-wide audience and as such may not benefit much from appositive generation, we posit that it is a valuable source of abundant cross-lingual data which could be used as the basis for transfer learning. In addition to a large training set automatically sourced from Wikipedia, we therefore also introduce a gold standard test sourced from newswire, one of the true target domains for appositive generation (Kang et al., 2019).

The next section of the paper outlines the theoretical framework behind the task of appositive generation. In Section 3 we describe the automatic data collection procedure used to obtain training data, and in Section 4 we detail the further manual validation performed to obtain quality data for cross-domain evaluation. The properties of the dataset are discussed in detail in Section 5. Sections 6, 7 and 8 describe the experiments we performed and the main findings from them. Section 9 concludes the paper and outlines avenues for future research.

2 The task: Appositive generation

Kang et al. (2019) laid the groundwork for appositive generation and our work can be seen as an expansion of their efforts. Yet, we both rename the task and redefine it in more general terms.

2.1 Prior work

Kang et al. (2019) introduced the task of appositive generation. To date this is the only work on this task. They designed a data collection procedure where appositives are identified by locating instances of the `appos` dependency label (Nivre et al., 2020) in parsed text, and used it to build a dataset of appositives for PERSON entities in English news articles. The candidate appositives were cross-referenced with the WikiData knowledge base (Vrandečić and Krötzsch, 2014) through word matching, and only those appositives were included in the final dataset which matched a fact from WikiData.

More generally, appositive generation relates to work on joint fact selection and generation (Liang et al., 2009; Kim and Mooney, 2010; Angeli et al., 2010; Konstas and Lapata, 2013).

2.2 A shift in terminology

Kang et al. (2019) actually called the phrases in question *post-modifiers*, rather than appositives. The linguistic term *post-modifier* can be seen as subsuming appositives, but it is much broader, including also prepositional, non-finite and dependent clauses that appear in postposition. Meanwhile, appositives come in two forms, nominal appositives, where a single noun identifies or qualifies another noun, e.g. President *Washington*, and explicative appositives, where a pronoun, an infinitive or a noun phrase is used to explain or specify the status of a noun (Bauer, 2017). Explicative appositives are further characterized as *non-essential*, meaning that they are not integral to the grammatical or semantic well-formedness of the sentence it appears in, and as such are often delimited from the rest of the sentence by punctuation marks (Traffis, 2019). For the purposes of providing background information about named entities, we are in particular interested in *explicative appositive noun phrases*, and that is what we refer to as an *appositive* throughout this work.

2.3 Expanding the task definition

Being built with reference to WikiData, the dataset of Kang et al. (2019) creates the illusion that all facts necessary to generate an appositive are available in the knowledge base. Balaraman et al. (2018) studied the relative completeness of WikiData entries and found gaps to be the norm rather than an exception. Moreover, the dataset of Kang et al. (2019) only includes positive samples, i.e. instances where an

[1] Available at `https://yovakem.github.io/#ApposCorpus`.

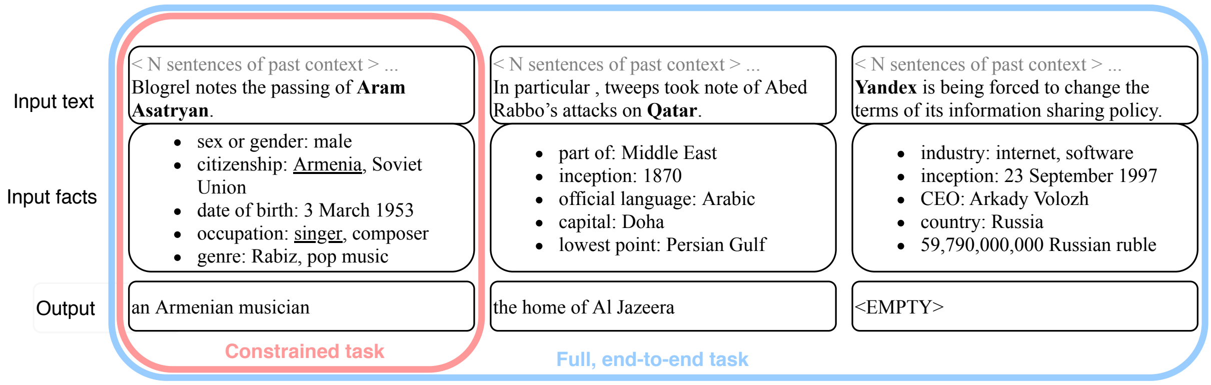

Input text
Input facts
Output
< N sentences of past context > ...
Blogrel notes the passing of **Aram Asatryan**.
sex or gender: male
citizenship: Armenia, Soviet Union
date of birth: 3 March 1953
occupation: singer, composer
genre: Rabiz, pop music
an Armenian musician
< N sentences of past context > ...
In particular , tweeps took note of Abed Rabbo's attacks on **Qatar**.
part of: Middle East
inception: 1870
official language: Arabic
capital: Doha
lowest point: Persian Gulf
the home of Al Jazeera
< N sentences of past context > ...
Yandex is being forced to change the terms of its information sharing policy.
industry: internet, software
inception: 23 September 1997
CEO: Arkady Volozh
country: Russia
59,790,000,000 Russian ruble
<EMPTY>
Constrained task
Full, end-to-end task

Figure 1: Illustration of the task in a *constrained* setting, where an appositive is always due and the facts in it are always available in the knowledge base; and in a *full, end-to-end* setting, where a decision has to be made as to whether or not to generate an appositive, and the facts in the appositive may be missing from the knowledge base. The entity in focus is shown in bold, the relevant facts are underlined (where available), and the <EMPTY> tag means no appositive is needed. Optionally, previous context can be included in the input, e.g. the three previous sentences–this is not shown in the figure.

appositive is due. A more realistic scenario would also require the model to choose whether or not to add an appositive to a given entity mention. `ApposCorpus` is *not* constrained by WikiData in terms of fact matching, and contains positive *and* negative samples, i.e. instances of empty appositives. See Figure 1 for an illustration. Moreover, it is multilingual and covers both PERSON and ORGANIZATION named entities. We built this dataset primarily based on text from Wikipedia, chosen for its rich cross-lingual coverage.

3 Dataset collection: Wikipedia

We used the March 2020 Wikipedia dump[2] for English, Spanish, German and Polish, which we parsed with WikiExtractor,[3] preserving internal links.[4] The choice of these particular languages was mostly based on the availability of good dependency parsers. Since dependency parsing is an integral step of the data collection process (Kang et al., 2019), it has to be as precise as possible, to maximize the quality of the outcome.[5] Below, we describe in detail the data collection procedure.

3.1 Preprocessing

We processed every article as follows: (1) tokenize the text and segment sentences; (2) normalize mentions of the entity in the article's title and annotate them with internal links; (3) identify sentences which contain a linked named entity listed as an instance of type *human* or of (a subclass of) type *organization* in WikiData (corresponding to the PERSON and ORGANIZATION named entity types); (4) run a dependency parser on these sentences. Steps (1) and (4) were performed with Stanza (Qi et al., 2020).

3.2 Detecting appositives

Any instance of the `appos` label that depends on a linked named entity and is separated from it with a comma or an opening parenthesis was considered a valid candidate. In this case, we recorded the source sentence, replacing the appositive with special token <`appos`>, as input data, and the appositive as a target. The beginning of the appositive was taken to be the first token after the comma or opening parenthesis, and the end is taken to be the last token before the next comma/semicolon/full stop (if beginning was marked by a comma) or closing parenthesis (if beginning was marked by an opening parenthesis). We discarded any commas and parenthesis surrounding the appositive, but kept semicolons

[2] `https://dumps.wikimedia.org/`

[3] `https://github.com/attardi/wikiextractor`

[4] These links point to other pages on Wikipedia and allow us to identify the Wikidata entry for the given named entity.

[5] We only considered parsers with labeled accuracy score over 90.0

and full stops as part of the input sentence. We also recorded the three preceding sentences from the article and one following sentence. Similarly to Kang et al. (2019), we process one appositive per sentence, i.e. if there are multiple appositives in a sentence, we select the first one and do not consider the rest.

Appositives containing just dates (usually the date of birth and/or death of a person) are ubiquitous across Wikipedia articles to the point that they constitute up to 30% of the data samples that we get with the procedure described above. We reduced this imbalance in the data by downsampling this type of appositives to only 10% of its occurrences.

3.3 Negative samples

We added negative samples to the dataset, matching the number of positive ones. They were drawn according to the following criteria: (1) there is a PERSON or ORGANIZATION entity in the sentence, (2) it is not followed by a comma or opening parenthesis, and (3) the rest of the sentence does not contain an appositive dependent on the PERSON or ORGANIZATION entity. Condition (2) was used to reduce the chance of including instances of appositives that were not correctly tagged as such by the parser (recall that appositives are often delimited from the rest of the sentence by a punctuation), while (3) was used to ensure that we did not include instances that contain a non-essential appositive, which the author had failed to delimit by any punctuation. In negative samples the input is the original source sentence with an added token `<appos>` just after the PERSON/ORGANIZATION entity, and the target is a special `<EMPTY>` token.

The procedure described above was used to collect *training* data for factual appositive generation. As it is our goal to study the potential of a cross-domain approach to appositive generation, the `ApposCorpus` also contains an out-of-domain test set, sourced from newswire.

4 Dataset collection: News

We sourced our data for cross-domain evaluation from the news domain, following previous work (Kang et al., 2019), using these news corpora: Global Voices (English, Spanish, German, Polish) (Tiedemann, 2012), News Commentary (English, Spanish, German) (Tiedemann, 2012) and Paralela (Pezik, 2016).

4.1 Entity linking

Unlike Wikipedia, where entities are explicitly linked to WikiData entries through internal links, here, we had to perform additional entity linking. We did so in the following manner: (1) extract candidates from WikiData based on exact match between the full span of the named entity and all aliases of entities in the respective subset of WikiData (instances of type *human* if NER label is PERSON , else *organization*), (2) obtain relative alias frequency distributions from Wikipedia, and (3) the candidate entity with the highest relative frequency given the alias is selected. We chose to use this prior-based method instead of a modeling approach since off-the-shelf entity linkers were not available for all the languages involved. Candidate appositives were then identified as described in 3.2.

As errors could occur both in the entity linking and in the appositive detection, we hired manual annotators to verify the output of the two procedures (see details in Appendix A.1). The News portion of the `ApposCorpus` is therefore gold standard and will serve for stable, accurate evaluation.

4.2 Negative samples

We added $1,000 - n$ negative samples to each subset of the data, where n is the number of positive samples. The exact ratio of positive samples in each test set is reflected in the `always yes` baseline shown in the Results section (see Figure 2a), a dummy baseline which always predicts an appositive.

5 Data analysis

This section outlines some findings on the properties of our dataset, based on general statistics and WikiData cross-referencing. The procedure described above yielded less than four thousand samples of ORG appositives for Polish, so this subset is omitted from the `ApposCorpus`.

		en	es	de	pl
PER	Size	559k	164k	269k	14k
	Length	3.4	4.16	2.7	2.67
	WD (%)	25.5	28.1	21.2	22.3
ORG	size	612k	104k	333k	-
	Length	2.19	4.09	1.64	-
	WD (%)	27.8	24.9	22.2	-

(a) Wikipedia data

		en	es	de	pl
PER	size	1k	1k	1k	1k
	Length	4.07	3.51	3.43	2.32
	WD (%)	29.3	30.8	21.7	20.7
ORG	Size	1k	1k	1k	-
	Length	3.31	3.08	1.87	-
	WD (%)	35.4	30.0	22.8	-

(b) News data

Table 1: Dataset statistics. *Size*: full dataset size, *Length*: average appositive length, *WD*: ratio of appositives matching a fact from WikiData.

5.1 General statistics

Table 1 lists some statistics about the two parts of the dataset, one based on Wikipedia (*Wikipedia data*) and the other on news (*News data*). Row *Size* refers to the full size of the data as split into language and entity type. We further split each Wikipedia subset for training (70%), validation (15%) and testing (15%). Size varies greatly across the data, with the Polish PERSON subset being merely 2.5% the size of the English PERSON subset. This relates both to a difference in the Wikipedia sizes for these languages (6M English articles v. 1.4M Polish articles) and to a difference in the frequency of use of appositives across the languages.

Row *Length* in Table 1 lists the average number of tokens per appositive, which varies from two to four tokens, and is generally lower for ORGANIZATION appositives than for PERSON ones.

5.2 Cross-referencing with WikiData

As discussed before, fact matching is not part of our data collection procedure, but at training time it would be beneficial to have access to a knowledge base such as WikiData, and to draw from it, when possible. So we extract the WikiData entries for all named entities in our dataset and perform word matching between facts and appositives in the following way: (1) tokenize the fact and the appositive, (2) remove stopwords, (3) measure token overlap. If the overlap is non-zero, we consider there to be a match and annotate the fact as `used`.[6]

Cross-referencing the data with WikiData is also useful as an insight into the makeup of the data, albeit an insight that is biased the scope and completeness of the knowledge base.

Coverage Row *WD* in Table 1a shows the rather low percentage of appositives from the Wikipedia dataset that are matched to at least one fact from WikiData: from 21.2 for German PERSON appositives to 28.1 for Spanish PERSON appositives. The numbers for the News test set, shown in Table 1b, are mostly similar to those for the WikiData. Another way to view these percentages is as an effective upper bound on the performance of a model trained with WikiData as the source of knowledge. Further work in identifying other sources of facts for appositive generation and new means of integrating them into a model could therefore prove very fruitful.

We manually inspected a random sample of 100 appositives from the English section of the Wikipedia dataset that were not matched to any fact from WikiData. In the majority of cases, the appositives concerned the occupation of a person, their position within an organization, their country of origin, or other type of information that is typically found in WikiData, but was missing for the given named entry.

Composition We studied the composition of the data, as observed with reference to WikiData. We performed our analysis on all languages and found that similar trends hold cross-lingually, so here we discuss the English portion of the data only, and in the Appendix A.2 we include the corresponding tables for Spanish, German and Polish.

We looked at the types of facts that were matched to appositives from the News data. For all fact types that constitute 3% or more of all facts matched, we also looked at their frequency in the Wikipedia data.

[6] We experimented with other thresholds (2 and 3-word overlap) and with fuzzy matching, but found this method to work best.

	Fact type	News (%)	Wiki(%)		Fact type	News (%)	Wiki(%)
PER	position held	20.9	9.4	ORG	instance of	23.1	10.9
	occupation	15.9	10.6		official website	6.3	6.2
	citizenship	10.1	4.3		country	5.9	3.3
	member of party	7.6	1.9		member of	4.2	2.4
	award received	5.2	3.9		subsidiary	3.5	2.1
	nominated for	3.6	0.4		capital of	3.2	0.1
	educated at	3.1	3.1		has quality	3.0	0.0

Table 2: Top fact types. English.

Results are shown in Table 6a. We see that half of the top fact types in the News dataset are also well-attested in the Wikipedia data, i.e. their relative frequency is 3% or more. We can expect that knowledge concerning appositives based on these fact types would trivially transfer from one domain to the other. The low frequency for the remaining fact types (cf. *has quality* and *capital of*), on the other hand, poses a challenge whose solution would require deeper natural language understanding and, possibly, explicit domain transfer techniques.

6 Experiments

To show how the new task formulation can be used, we experiment with three established language generation methods: the main method of Kang et al. (2019), which we refer to as `base`; an extension of `base` with external knowledge injected through embeddings with knowledge-base grounding (`KB`); and a model enhanced with an explicit copy mechanism (`copynet`, Gu et al. (2016)). Notice that our goal here is not to build the best model for this task, but to develop reasonable models which can serve as baselines for future work in this area.[7]

6.1 Architectures

LSTM baseline, `base` Kang et al. (2019) introduced an LSTM-based encoder-decoder architecture with an auxiliary objective used to guide the attention of the decoder towards the WikiData facts that were matched during the data collection process. Input sentences and facts are represented with the same word embeddings and encoded by separate biLSTMs. The decoder is initialized with the encoding of the input and attends over the encodings of the facts. Our only modification here is to add a "None of the above" item to the list of facts about an entity and point the attention to that when no other fact was matched or the appositive was empty (i.e. for negative data instances).

LSTM with external knowledge, `KB` External knowledge can be beneficial to a better understanding of the context and how it relates to the different facts known about an entity. Here, we use the same architecture as above, but initialize the embedding matrix of the model with the NTEE (Neural Text-Entity Encoder) word embeddings, trained on Wikipedia with WikiData grounding (Yamada et al., 2017). They aim to represent a text and its relevant entities close to each other. We deem these embeddings suitable for our modeling setup, where input text and facts are represented in a shared space. Unfortunately, the NTEE embeddings are available only for English. So we used word-level translation to "project" them to Spanish, German and Polish. See more details in Appendix A.4. This approach is likely to introduce some noise, but we only use the projection to initialize the embedding matrix which is then further trained. So any signal coming from the embeddings can be used by the model and any noise can be filtered out during training.

LSTM with a copy mechanism, `copynet` Motivated by the observation that there is an overlap of at least one token between WikiData facts and appositives for about 25% of the datapoints in our dataset, we experiment with a method that allows the decoder to copy tokens directly from the input: Copynet (Gu et al., 2016). Kang et al. (2019) correctly point out that in their constrained data setting, where data points were selected based on word overlap with WikiData facts, using a copy mechanism would

[7] We also experimented with a transformer architecture, but encountered optimization problems. See details in Appendix A.5.

Train setting	Test setting	Dataset	Acc(%)	F1	BLEU	MET.
constrained	constrained	ApposCorpus (News)	-	19.61	7.93	9.12
		PoMo	-	11.21	3.44	5.03
end-to-end	constrained	ApposCorpus (News)	95.0	10.76	3.39	4.41
		PoMo	91.7	4.52	0.57	2.03
	end-to-end	ApposCorpus (News)	72.33	5.97	1.03	2.96

Table 3: Generation of English PERSON appositives in a constrained v. end-to-end train and test setting.

result in double-counting, i.e. artificially boosted results. In our data setting, however, this is not the case.

All three approaches are end-to-end in the sense that we do not split up the classification task of whether or not to predict an appositive from the task of generating an appositive where it is due. As negative samples in the dataset have the special `<EMPTY>` token as target, the models are performing the classification task *implicitly* by choosing whether to predict the `<EMPTY>` token or not.

Preliminary experiments with the `base` architecture showed that the choice between providing the model with three sentences of preceding context, one or zero had little impact on its performance, so all results reported below use one sentence of preceding context, following Kang et al. (2019). Further details on the implementations and the hyperparameters we used can be found in Appendix A.3.

6.2 Evaluation

We follow Kang et al. (2019) in the choice of performance metrics for predictions over the positive instances in the data: we measure F1 score of the predicted bag-of-words excluding stopwords; BLEU (Papineni et al., 2002) over n-grams, where $n = 1, 2, 3$;[8] and METEOR (Denkowski and Lavie, 2014), which supports stemming and synonymy only in English, Spanish and German, so these features are not used for Polish. We use accuracy to measure the models' ability to determine when an appositive is due.

7 Results

We view the results of our experiments from two angles: one concerns the expansion of the task definition we achieve with `ApposCorpus`, from a constrained scenario to an end-to-end one; the other concerns the increased coverage of the dataset, which allows us to compare and contrast appositive generation across different languages and named entity types.

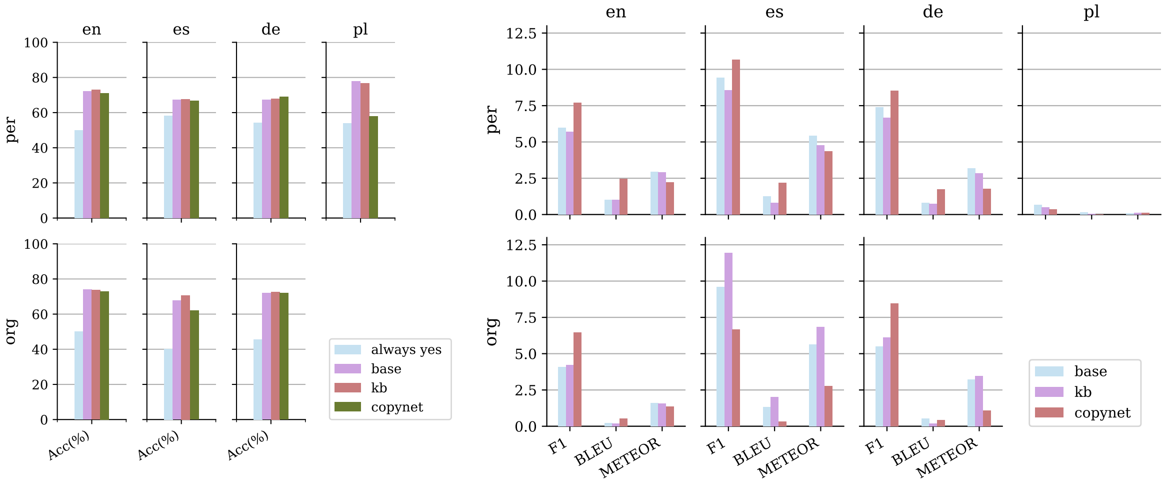
7.1 Constrained v. end-to-end scenario

To draw a direct comparison to the work of Kang et al. (2019), in this subsection we focus on English PERSON appositives, as this is the subset that was covered by their dataset, dubbed `PoMo`. We begin by replicating exactly their train and test settings, both constrained, using the model architecture they proposed, `base`. In the first two rows of Table 3, the performance of the model is reported on both the constrained subset of our News test data and on the `PoMo` test set, constrained by design. There is a considerable difference in performance as measured on the two test sets. Since they were both drawn from the same domain, this difference may largely be due to one test set being gold standard and the other silver standard, which highlights the importance of having gold standard evaluation data.

Using these results as a starting point, we consider two important factors in the shift from a constrained to an end-to-end setting: one concerns learning and the other, evaluation.

Learning complexity can be expected to increase in the end-to-end training setting, since the model has to learn not just what appositive to predict, but also whether or not to predict an appositive. Due to gaps in WikiData, the model also has to learn how to best handle instances of appositives based on unobserved facts. We demonstrate how these factors affect performance by comparing the `base` model trained in a constrained setting to one trained in an end-to-end setting. We measure the models' performance in a constrained test setting, to make the comparison fair to the former. Shifting from a

[8] Kang et al. (2019) also included four-grams, but seeing that the average length of an appositive across the different subsets of the data is 3.08 tokens, we exclude four-grams from consideration.



(a)

(b)

Figure 2: (a) Evaluation of (a) the models' ability to correctly decide when an appositive is due, (b) generated predictions for positive test instances. Measured on the News test set.

constrained train setting (rows 1 and 2 of Table 3) to an end-to-end setting (rows 3 and 4), we observe a drop in performance of around 50% on all generation metrics. The model trained end-to-end does very well on choosing whether or not to predict an appositive (accuracy is 95% for `ApposCorpus` and 91.7% for `PoMo`) , so we have to conclude that the lower generation scores are not a matter of predicting empty appositives, but rather of predicting worse appositives due to the increased learning complexity.

Evaluation is another aspect to consider when comparing the constrained and full data settings. The quality of evaluation is key to understanding how well a model would perform if deployed in the real world. Constrained evaluation, however, only tells us how a model would do in an idealistic scenario, where all the facts about all the entities were indeed covered by a knowledge base. As this is not the case with WikiData (Balaraman et al., 2018), and with any existing knowledge base for that matter, it is important to evaluate models in a manner that reflect gaps in external knowledge sources. We report the performance of a model trained and tested in an end-to-end setting in the last row of Table 3. Compared to the model's performance as measured on the constrained test set (row 3), these numbers are substantially lower. Yet, they are the numbers that most truly represent the performance of the base model, at least in terms of automatic evaluation. We return to this matter when analysing the model's performance in Section 8.

7.2 Languages and entity types

The full range of results on the News test set are shown in Figure 2. Results are averaged over three models trained from different random initializations. We evaluate how well the models can detect when an appositive is needed (implicit classification) and how well it can perform the end-to-end task of classifying and generating a good appositive.

Implicit classification of the positive and negative samples in the data appears to be roughly equally challenging across the two entity types and the four languages, as viewed across all three models (see Figure 2a. One exception is Polish PERSON appositives, where `base` and `kb` score higher than they do on the other subsets, while `copynet` barely beats the baseline. Since the models are not explicitly trained to perform this type of classification, it is encouraging to see that even in this setting, they can outperform the baseline (always predicting the positive class) by as much as 20% in several cases.

Generation is the more difficult aspect of the task, as shown in Figure 2b. We see that, somewhat surprisingly considering the amounts of training data (see Table 1a), performance is not highest on English, but rather on Spanish. In line with the small amount of training data, on the other hand, performance on

	true	system	neutral		true	system	neutral
PER	46.3%	47.3%	6.1%	ORG	66.0%	26.5%	7.4%

Table 4: Results from the ranking paradigm study comparing true appositives to system-generated ones.

Polish is virtually non-existent. There are no clear differences between overall performance on PERSON and ORGANIZATION appositives. Only in English, the latter seem to pose a greater challenge to all three models and according to all three metrics. Model comparison is not straightforward since the different metrics reveal different strengths and weaknesses in each approach. It does appear to be the case that injecting external knowledge through pretrained knowledge-base embeddings (kb) is beneficial to the prediction of ORGANIZATION appositives and somewhat harmful to the prediction of PERSON appositives. Since the differences between the three methods are not consistent across all languages, named entity types and metrics, we cannot conclusively say which method is best, but we do note that copynet scores high on the most metrics, languages and entity types. To better understand the performance of this model, we stepped away from automatic generation metrics, which are known to suffer from certain biases and can be difficult to interpret, and we carried out an additional manual evaluation.

8 Analysis

8.1 Manual evaluation

We used Amazon Mechanical Turk to carry out a ranking paradigm study on the predictions of copynet for English PERSON and ORGANIZATION appositives. The annotators were shown a true appositive and a predicted appositive side-by-side (in the context of the input sentence) and were asked to express their preference towards either of these two, or their lack of preference as a third option. One example prompt is shown in Appendix A.7. Five annotations were obtained per data instance, and we then took the majority vote as an indication of the overall preference. The results are shown in Table 4. For PERSON appositives, the writer's choice (true) and the system's prediction were preferred at almost equal rates—this observation challenges the numbers obtained with the automatic evaluation metrics, as it suggests that the predicted appositives were not necessarily of poor quality. A bigger gap was observed between true and system-generated ORGANIZATION appositives, where the crowdworkers preferred the original appositive 66.0% of the time. The lower preference for ORGANIZATION predictions is in line with the trend in the automatic results, where performance on English ORGANIZATION appositives was shown to be lower than that on English PERSON appositives. Notice, however, that even for organization appositives, annotators still showed preference for the predicted ones at a considerable rate. This suggests that the automatic metrics may have severely under-represented the abilities of the models.

8.2 Qualitative analysis

To better understand the source of error in the models' predictions, we manually inspected 50 data points from the PERSON subset and 50 data points from the ORGANIZATION subset, where a choice was made in favour of the true appositive over the predicted one. Half of the data points were instances where the true appositive was not empty, but the models predicted an empty appositive. The annotators seemed to strongly prefer non-empty appositives, possibly due to the fact that they where shown sentences without their original context, where the role of an entity might have been clarified at an earlier mention. Yet, that is not categorically so as seen in example 1 in Table 5, where the predicted appositive is redundant in the given context, so the annotators preferred the true empty appositive. Other types of errors the models made were to predict appositives that concern the right piece of information but are too general (examples 2 and 3), to predict appositives based on the wrong piece of information (examples 4 and 5), and, specifically for ORGANIZATION appositives, to just repeat the named entity (example 6). While the latter is the result of either suboptimal learning or noise in the data, the rest of the errors we saw point to the need for an approach with deeper understanding of the facts and their relevance to the context.

	Gold sentence	Prediction
1	In response to an April 9 court ruling declaring the military backed government of Frank Bainimarama <EMPTY> to power illegally when he dissolved Parliament and deposed the government of Laisenia Qarase , the country 's President nullified the Fiji 's constitution , fired the entire judiciary and appointment himself head of state and the armed forces.	the President of Fiji
2	Artyom Loskutov, creator of the popular counter - culture art movement " Monstration ", made waves on RuNet by signing a letter in support of Dmitry Kiselyov , a journalist who many consider to be Putin 's chief propagandist.	a Russian painter
3	In a fatal blow to our already lackluster sources of entertainment , the Sudanese government has blocked access to YouTube, the online video sharing Web site.	platform
3	Modi, a tech-savvy nationalist from the right-wing Bharata Janatiya Party, has traveled the world to sell the idea of India as an emerging digital economy, making deals with the likes of Google and (less successfully) Facebook.	the Prime minister of India
4	Some critics also highlighted the fact that Jabrailov is from Chechnya, a republic in the Northern Caucasus region of Russia where Muslim separatists fought two bloody wars against the Russian army.	Chechnya
5	He steers between Soukous , rhumba and RnB " , and links to an interview with the singer on Radio Okapi, the nationwide radio station sponsored by the UN and Fondation Hirondelle.	the Democratic Republic of the Congo
6	In particular , tweeps took note of Abed Rabbo 's attacks on Qatar, the home of Al Jazeera.	Qatar

Table 5: Examples where true appositives were preferred over predicted ones by human annotators.

9 Conclusion

ApposCorpus targets factual appositive generation, a phenomenon frequently occurring in a range of textual domains. It substantially extends the prior resources in the area by spanning four languages, two named entity types , and two domains. This resource also allows the burgeoning field to investigate end-to-end appositive generation. Our manual and automatic evaluations with ApposCorpus show that standard model architectures can approach the quality of human targets in specific cases but there is still room for improvement. With this dataset, appositive generation can be studied in much more depth than previously possible, ultimately paving the way for novel NLP applications in the generation and writing space. The focus in future research, we believe, should fall on explicit methods for cross-domain learning, on richer knowledge sources, and on the development of test sets for new domains.

10 Acknowledgements

We acknowledge the responsiveness and help of Jun Seok Kang and Robert L. Logan IV in discussions on the design choices and goals of their work on post-modifier generation and on how to accurately reproduce their experiments. We also thank researchers from Dataminr: Saran Krishnasamy, Lin Nie, and Isabel Zhang for their help in setting up experiments and annotation. Finally, we thank the three anonymous reviewers for their feedback and comments.

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	Fact type	News (%)	Wiki(%)
PER	position held	20.9	9.4
	occupation	15.9	10.6
	citizenship	10.1	4.3
	member of party	7.6	1.9
	award received	5.2	3.9
	nominated for	3.6	0.4
	educated at	3.1	3.1
ORG	instance of	23.1	10.9
	official website	6.3	6.2
	country	5.9	3.3
	member of	4.2	2.4
	subsidiary	3.5	2.1
	capital of	3.2	0.1
	has quality	3.0	0.0

(a) English

	Fact type	News (%)	Wiki(%)
PER	position held	27.1	4.9
	occupation	11.2	10.3
	citizenship	9.8	4.8
	participant of	8.7	1.1
	member of party	7.3	1.3
	award received	4.1	3.2
	employer	3.2	0.5
ORG	instance of	28.9	10.5
	country	7.8	3.5
	has quality	5.1	0.1
	capital of	4.4	0.5
	member of	4.3	2.9
	is located in	3.4	2.2

(b) Spanish

	Fact type	News (%)	Wiki(%)
PER	position held	35.2	6.7
	employer	5.9	2.9
	citizenship	5.9	1.3
	member of party	5.3	2.4
	award received	4.9	2.1
	occupation	4.8	3.6
	participant of	4.6	1.5
	member of	3.6	1.0
ORG	official website	15.6	12.4
	instance of	15.1	4.5
	owner of	7.5	2.4
	member of	5.8	0.9
	has quality	4.6	0.0
	Commons category	3.2	4.5

(c) German

	Fact type	News (%)	Wiki(%)
PER	position held	77.2	5.7
	participant of	3.2	0.7

(d) Polish

Table 6: Top fact types per language.

A Appendices

A.1 Manual validation

We hired annotators fluent in the languages of the data to manually validate it. They had to mark instances where an error had occurred in the appositive detection, the detected appositive was not factual, or the entity had been incorrectly linked to WikiData (all instances of *noise* in the data, resulting from errors in appositive detection and entity linking). Our ultimate goal was to build test sets of 1,000 instances per language per entity type, equally balanced between positive and negative instances, i.e. we needed 500 valid data instances per language per entity type. Based on a pilot study, we determined that noise levels for candidate appositives for PERSON entities were approximately 33% and for ORGANIZATION entities, 50% (averaged across languages). We therefore gave annotators 750 and 1,000 candidates to annotate for the PERSON and ORGANIZATION types, respectively. For most language-entity type combinations, the manual annotation successfully yielded close to 500 valid instances. That was not the case for Polish ORGANIZATION appositives, where only 80 valid candidates were retrieved, so we excluded this language-entity type combination from our work. It remains an open question whether ORGANIZATION appositives in Polish are rare or our automatic detection method failed at catching them.

A.2 Composition of cross-lingual data

Table 6 present findings on the composition of the Spanish, German and Polish positions of the data, respectively, as observed through cross-referencing with WikiData. The low number of facts for Polish is the result of one fact type dominating a large amount of the data (*position held*).

	Base/KB	Copynet
vocab size	50k	50k
embedding dim	300	300
hidden units	250	250
num layers	2	2
optimizer	Adam	Adam
learning rate	0.001	0.0001
batch size	16	6
dropout	0.3	0.3

Table 7: Hyperparameter configurations for Base/KB models and Copynet models.

A.3 Implementations and hyperparameters

[Base] and [KB] We use the implementation of (Kang et al., 2019) from `https://github.com/rloganiv/claimrank-allennlp`. We set the model hyperparameters to the ones reported in their paper, changing only the dimension of the embeddings from 500 to 300, to make the comparison between [Base] and [KB] fair in terms of model parameterization. Training hyperparameters were tweaked to achieve stable training that fits on one 16 GB GPU. See the full list of hyperparameters in Table 7.

A.4 Projection of NTEE embeddings

We obtained a bilingual dictionary with CSLS retrieval over the cross-lingual FastText embeddings. CSLS retrieval is similar to nearest neighbor retrieval, but has proven more accurate: (Joulin et al., 2018) report an accuracy of 83.7%, 77.6% and 73.5% for word translation, respectively, from Spanish, German and Polish to English, as measured on a sample of 1,500 medium frequency words. Any errors in the bilingual dictionaries would inevitably lead to noise in the NTEE embedding projection.

Copynet We use the AllenNLP (Gardner et al., 2017) implementation of Copynet with the hyperpameters shown in Table 7.

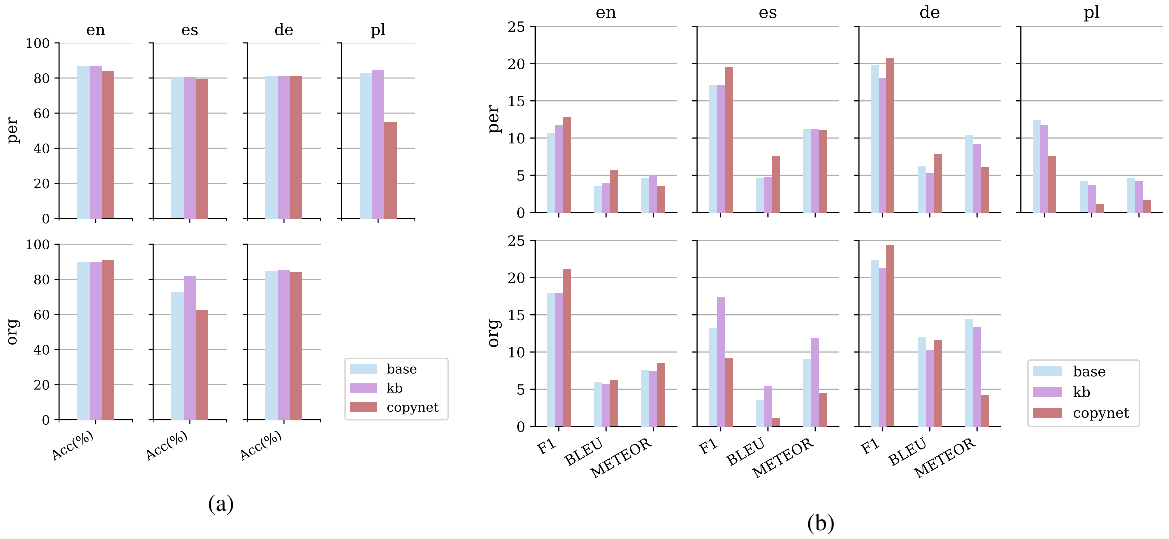
A.5 Transformer experiments

Transformer-based architectures are state-of-the-art for many NLP tasks, so it is only fair that we experiment with such an architecture as well. As BERT models (Devlin et al., 2019) have been made available for all four languages we work with, we chose to train BERT-to-BERT encoder-decoder models for appositive generation. DBLP:journals/corr/abs-1907-12461 found that architecture to give strong performance on tasks like sentence fusion and rephrasing. We used their training schedule but unfortunately, found that all models learned to predict the `<empty>` token exclusively. As it is not the goal of our work to explore the capabilities of the BERT-to-BERT architecture in particular, we did not use further resources to adjust the training schedule. Yet, we do believe this to be an optimization problem, and we would not discourage future research from attempting to solve the task of appositive generation with a transformer-based approach.

A.6 Results

The results as measured on the Wikipedia test set are shown in Figure 3. Compared to results on the News test set (see Figure 2, the numbers seen here are higher, which is to be expected considering that this test set is in-domain and any noise found in it (due to it being silver standard) likely resembles the noise found in the training data. It is worth noting though, that certain patterns repeat between the two test sets, as for example the fact that `copynet`, as measured on F1 score and BLEU, outperforms the other models on the majority of language-named entity type combinations, but not on Polish PERSON appositives and Spanish ORGANIZATION appositives. This suggests that, while evaluation on the silver-standard Wikipedia test set cannot be consider fully stable and representative, it can be taken as a proxy in model comparison for developmental purposes.

The numbers behind the results from Figures 2 and 3 are shown in Tables 8 and 9, respectively.



(a)

(b)

Figure 3: (a) Evaluation of (a) the models' ability to correctly decide when an appositive is due, (b) generated predictions for positive test instances. Measured on the News test set.

		Acc	F1	BLEU	METEOR
EN-PER	always yes	0.5	0.0	0.0	0.0
	base	71.91	0.72	1.03	2.96
	kb	71.73	0.73	1.03	2.9
	copynet	70.19	0.71	2.45	2.24
EN-ORG	always yes	0.5	0.0	0.0	0.0
	base	68.09	0.74	0.23	1.61
	kb	66.58	0.74	0.21	1.58
	copynet	65.98	0.73	0.52	1.37
ES-PER	always yes	0.58	0.0	0.0	0.0
	base	62.84	0.67	1.24	5.44
	kb	61.18	0.68	0.79	4.79
	copynet	64.08	0.67	2.2	4.36
ES-ORG	always yes	0.4	0.0	0.0	0.0
	base	47.39	0.68	1.32	5.64
	kb	60.91	0.71	2.02	6.83
	copynet	33.57	0.62	0.33	2.77
DE-PER	always yes	0.54	0.0	0.0	0.0
	base	62.94	0.67	0.8	3.19
	kb	63.47	0.68	0.75	2.84
	copynet	67.63	0.69	1.75	1.76
DE-ORG	always yes	0.46	0.0	0.0	0.0
	base	62.77	0.72	0.54	3.21
	kb	65.13	0.73	0.19	3.47
	copynet	62.22	0.72	0.43	1.08
PL-PER	always yes	0.54	0.0	0.0	0.0
	base	72.83	0.78	0.16	0.09
	kb	73.8	0.77	0.06	0.13
	copynet	2.75	0.58	0.0	0.12

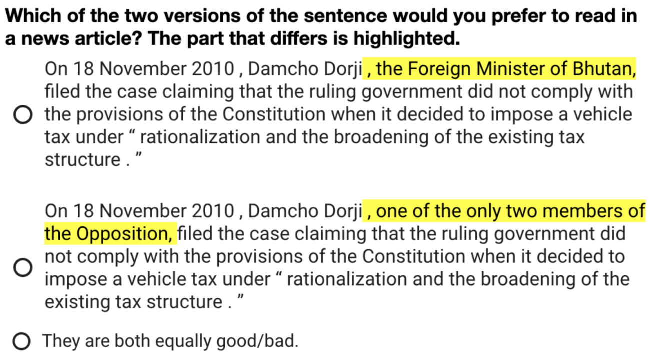
Table 8: Evaluation of the models' ability to correctly decide when an appositive is due and of generated predictions for positive test instances. Measured on the News test set.

EN-PER	base	85.42	0.87	3.59	4.7
	kb	85.32	0.87	3.94	5.07
	copynet	81.95	0.84	5.7	3.57
EN-ORG	base	89.47	0.9	5.99	7.54
	kb	89.43	0.9	5.65	7.49
	copynet	89.17	0.91	6.17	8.53
ES-PER	base	78.49	0.8	4.57	11.17
	kb	78.73	0.8	4.71	11.19
	copynet	79.1	0.8	7.54	11.04
ES-ORG	base	61.63	0.73	3.58	9.07
	kb	80.69	0.82	5.45	11.92
	copynet	46.91	0.62	1.14	4.46
DE-PER	base	79.28	0.81	6.19	10.35
	kb	80.09	0.81	5.24	9.19
	copynet	80.12	0.81	7.85	6.11
DE-ORG	base	84.09	0.85	12.04	14.45
	kb	84.58	0.85	10.28	13.31
	copynet	82.07	0.84	11.57	4.19
PL-PER	base	82.67	0.83	4.23	4.61
	kb	84.46	0.85	3.67	4.29
	copynet	24.49	0.55	1.1	1.71

Table 9: Evaluation of the models' ability to correctly decide when an appositive is due and of generated predictions for positive test instances. Measured on the Wiki test set.

A.7 Ranking paradigm study

Figure 4 shows an example prompt from the blind taste test. Instances where either the true appositive was empty or the predicted one was empty were included in the the study, but instances where both were empty were excluded, as the comparison would not have been meaningful in this case. The average time for completing a HIT was 53 seconds.



Which of the two versions of the sentence would you prefer to read in a news article? The part that differs is highlighted.

○ On 18 November 2010 , Damcho Dorji , the Foreign Minister of Bhutan, filed the case claiming that the ruling government did not comply with the provisions of the Constitution when it decided to impose a vehicle tax under " rationalization and the broadening of the existing tax structure . "

○ On 18 November 2010 , Damcho Dorji , one of the only two members of the Opposition, filed the case claiming that the ruling government did not comply with the provisions of the Constitution when it decided to impose a vehicle tax under " rationalization and the broadening of the existing tax structure . "

○ They are both equally good/bad.

Figure 4: Prompt for manual evaluation.