Post-Editing Extractive Summaries by Definiteness Prediction

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Abstract

Extractive summarization has been the mainstay of automatic summarization for decades. Despite all the progress, extractive summarizers still suffer from shortcomings including coreference issues arising from extracting sentences away from their original context in the source document. This affects the coherence and readability of extractive summaries. In this work, we propose a lightweight post-editing step for extractive summaries that centers around a single linguistic decision: the definiteness of noun phrases. We conduct human evaluation studies that show that human expert judges substantially prefer the output of our proposed system over the original summaries. Moreover, based on an automatic evaluation study, we provide evidence for our system’s ability to generate linguistic decisions that lead to improved extractive summaries. We also draw insights about how the automatic system is exploiting some local cues related to the writing style of the main article texts or summary texts to make the decisions, rather than reasoning about the contexts pragmatically.

1 Introduction

More than half a century after Hans Peter Luhn’s seminal work (1958), automatic summarization remains a challenge, one that is increasingly pressing with the explosion of information online and elsewhere. One of the proposed approaches is extractive summarization: the task of selecting spans, typically sentences, from a source text such that they best convey the overall meaning. It is the most popular approach given its simplicity and scalability compared to more sophisticated abstractive approaches. The simplicity of this method, however, is not without its costs, as extractive summaries are known to suffer from a variety of issues. In addition to problems pertaining to verbosity (Barzilay et al., 1999), a system that centers around sentence extraction is inherently exposed to the risk of selecting a sentence that depends on a non-selected context, thereby affecting the summary’s overall coherence. Examples include coreference issues (Steinberger et al., 2016) (e.g., selecting a sentence with an anaphor that refers to an entity in a non-selected previous sentence) and breaks in the pragmatic context (Hutchins, 1987) (e.g., a presupposition triggered in a selected sentence and corresponding to an event/proposition that appeared in a non-selected sentence).

In this work, we ask the following question: Can a lightweight post-editing step following the generation of extractive summaries, for instance along one specific linguistic decision, lead to an improvement in the quality of those summaries?

We focus in this work on predicting the definiteness of noun phrase articles. We propose a lightweight method for post-editing extractive summaries, which consists of a definiteness prediction model that decides whether articles in the extractive summaries should be kept as is or modified (including the possibility of being removed altogether). The goal of this post-editor is to improve the overall quality of the summary in terms of coherence and readability. We believe definiteness

Source Text:
The school had to deal with a suspicious package received early in the morning. A student thought to be from another district addressed a mail that had a very strong smell. Police was called in. The student was eventually questioned by the police for 5 hours.

Original Extractive Summary:
The school had to deal with a suspicious package received early in the morning. Police was called in. The student was eventually questioned by the police for 5 hours.

Post-Edited Pseudo-Extractive Summary:
The school had to deal with a suspicious package received early in the morning. Police was called in. A student was eventually questioned by the police for 5 hours.

Figure 1: A simple change to an article choice (in bold) in the extractive summary can improve its readability and coherence.
is an attractive case study since it is an interesting test-bed for pragmatic reasoning as both contextual and local cues play a crucial role in deciding whether a given article is appropriate or not in a given context.

Consider the motivating example in Figure 1. Assuming an extractive summarizer selected the first, third and fourth sentences to be included in the summary, the final summary would be incoherent as the last sentence would refer to “the student” without it being introduced earlier in the context. A simple change to the article (the → a) would improve both the coherence and readability of the summary as seen in the last part of the figure.

In this work, we focus on post-editing extractive summaries to form pseudo-extractive outputs, rather than directly developing an abstractive summarizer, which we see as a separate (but worthy) use case. Compared to full-fledged abstractive summarization, limited post-editing is less likely to lead to problems of factual correctness and consistency, which are a known issue of existing abstractive systems (Cao et al., 2018; Goodrich et al., 2019; Kryściński et al., 2019).

We conduct two studies to understand different aspects of the problem using two English datasets, CNN/DailyMail and PubMed. First, we examine how often expert judges prefer summaries modified by such a system over the original version of generated extractive summaries. For the second study, we carry out an annotation study to obtain gold standard annotations on the definiteness of noun phrases in sampled subsets of extractive summaries that are generated by different summarizers for both CNN/DailyMail and PubMed. By comparing our model’s decisions to the collected annotations, we can evaluate its performance using standard classification accuracy.

Our contribution is three-fold. First, we provide evidence that human expert judges show substantial preference for the summaries modified by our proposed system over the original extractive summaries in terms of coherence and readability. Second, we collect gold standard annotations on the definiteness of noun phrases in sampled subsets of extractive summaries. This collected dataset of annotated extractive summaries can be useful for further development of similar systems. Third, using the collected annotations, we show that our system generates decisions that highly overlap with those of expert judges, further validating the efficacy of our proposed method. We also present insights into how the automatic system is exploiting some local cues related to the writing style of the main article texts or summary texts to make the decisions, rather than pragmatically reasoning about the contexts. Overall, we show that our findings generalize over multiple combinations of datasets and summarizers, thus demonstrating further the efficacy of our method.

2 Related Work

2.1 Extractive Summarization

There exists a long line of work on extractive summarization beginning as early as the mid-1950s. For a comprehensive review, the reader is referred to Nenkova and McKeown (2011). More recent approaches are based on neural networks including sequence-to-sequence models (Sutskever et al., 2014; Cho et al., 2014). These consist of MLE-based approaches (Cheng and Lapata, 2016; See et al., 2017; Nallapati et al., 2017) and RL-based approaches (Paulus et al., 2018; Dong et al., 2018). Recently, extractive summarization models that are based on fine-tuning pre-trained transformers have also shown strong performance (Liu and Lapata, 2019; Zhong et al., 2020).

Extractive summarizers are known to suffer from issues such as verbosity (Barzilay et al., 1999), coreference issues (Steinberger et al., 2016) (e.g., selecting a sentence with an anaphor that refers to an entity in a non-selected previous sentence) and breaks in the pragmatic context (Hutchins, 1987) (e.g., a selected sentence containing a presupposition that is linked to an event/proposition appearing in a non-selected sentence). Accordingly, we propose to exploit one linguistic phenomenon, namely, definiteness, in an attempt to provide a post-editing step that can improve the quality of extractive summaries.

While recent approaches have been pushing on the abstractive front, we note that, in various domains, extractive summarization is still the clear favorite due to domain restrictions and limitations in abstractive systems. Indeed, extractive models are still attractive in applications where faithfully preserving the original text is the priority. For example, guaranteeing the factual correctness of a summary can be integral in the health or scientific domains, which is a known weakness of current abstractive methods (Kryściński et al., 2019).
2.2 Definiteness Prediction

The question of definiteness has been extensively covered in the areas of linguistics and philosophy of language with early work that studies the nature and properties of definiteness dating back as early as (Russell, 1905) and (Strawson, 1950). In the computational linguistics literature, several models for definiteness prediction were proposed such as (Knight and Chander, 1994; Minnen et al., 2000; Han et al., 2006; Gamon et al., 2008). De Felice (2008) presented a logistic regression classifier extracting a number of linguistically motivated features from the context of each head noun. The most recent work (Kabbara et al., 2016) presents an attention-based RNN that achieves state of the art on definiteness prediction and investigates, among other factors, the effect of having a local or wider context. In our work, we adopt this model as the basis for the proposed post-editing step.

3 Proposed Post-Editor Method

The learning task can be stated as follows: Given a document $D = \{s_1, \ldots, s_n\}$ with $n$ sentences, a pre-trained extractive summarizer, $f$, generates a summary $S = f(D) \subset D$ with the length of $S$ being $m < n$. The generated summary is then passed to a post-editing step in which decisions are made regarding the definiteness of noun phrases (NPs). Thus, a definiteness prediction model $g$ generates a modified summary $S' = g(S)$ which we refer to as pseudo-extractive summary. The goal is thus to compare the final output to the original summary to understand whether such a post-editing step improves the coherence and readability of extractive summaries. Figure 2 depicts the proposed pipeline.

3.1 Extractive Summarization

In order to focus the investigation solely on the effect of leveraging the discussed pragmatic knowledge, the learning task is concerned with single document summarization—as opposed to multi-document summarization where there is an added layer of complication regarding generating a coherent output using sentences from multiple documents.

In our work, we experiment with three different summarizers: MatchSum (Zhong et al., 2020) casts the extractive summarization task as a semantic text matching problem and is currently state-of-the-art on both CNN/DailyMail and PubMed. HipoRank (Dong et al., 2021) is a recent unsupervised graph-based ranking model for extractive summarization of long scientific documents with competitive performance on PubMed. Since it’s tailored for long scientific documents, we use HipoRank for PubMed only. Finally, to have another set of results for CNNDM, we use BanditSum (Dong et al., 2018) an RL-based neural extractive summarizer with near-SOTA performance on CNNDM (better than HipoRank). To generate summaries, we use the source code made public by the authors.\footnote{https://github.com/marandrom/HipoRank} \footnote{https://github.com/yuedongP/BanditSum} \footnote{https://github.com/maszhongming/MatchSum}

3.2 Definiteness Prediction

For the second step of predicting the definiteness of NPs, we adopt the methodology of Kabbara et al. (2016) in which they present an LSTM-based (Hochreiter and Schmidhuber, 1997) learning model for definiteness prediction. The learning task is a three-way classification where the labels represent one of three classes: “the”, “a” (or “an”) and “none”. In order to explore the suitability and performance of different learning models on this task, we explore the use of a logistic regression classifier (De Felice, 2008), an LSTM model and a BERT-based (Devlin et al., 2019) neural model which has shown strong performance across a wide range of NLP tasks (Rogers et al., 2020).

3.2.1 Model Description

The first model is a logistic regression classifier which learns the probabilities describing the possible outcomes of an input using a logistic function. The LSTM model is first fed a sequence of (one-hot encoded) input tokens representing the sample. The tokens are then embedded using pre-trained word representations. The resulting embedded vectors are encoded by a number of stacked LSTM recurrent layers. We explore in Section 7 the effect of having a unidirectional or bidirectional recurrent layer. The last hidden state is then fed to a linear layer followed by a softmax unit. To reduce the effect of overfitting, we apply dropout (Srivastava et al., 2014) on the embedding layer and hidden layers. As a note, in preliminary experiments, we
tried the same model architecture but with GRU cells (Cho et al., 2014) instead of LSTM cells, however, the performance on the development set was worse in the case of GRU layers. Accordingly, we adopted the LSTM cell for our experiments.

In the BERT-based model, a sequence of input tokens is fed into a pre-trained BERT Model which produces representations that are passed to a number of stacked GRU layers (unidirectional or bidirectional). We use here GRU layers instead of LSTM because our preliminary experiments showed that a combination of BERT followed by GRU layers outperformed one with LSTM layers instead on the development set. The last hidden state is fed to a linear layer followed by a softmax unit. Similarly, we apply dropout on the hidden layers.

3.2.2 Input Representation

The input to the logistic regression classifier (De Felice, 2008) is a set of different types of manually-constructed linguistic features extracted from a fixed window surrounding the head noun of a noun phrase such as noun type, named entity or not, singular or plural, WordNet category and POS tags of the surrounding tokens. For more details, the reader is referred to (De Felice, 2008).

The two other models are trained on data samples that are constructed according to the configurations proposed in (Kabbara et al., 2016), namely the local context and the extended context. A sample in the local context configuration is defined to be the set of tokens from the previous head noun of a noun phrase up to and including the head noun of the current noun phrase. For example, take the following passage (head nouns indicated in bold):

Example 1 The newly elected mayor plans to actively fight corruption plaguing the city.

Noting that all instances of the articles in question (the, a/an) are removed from all the data (training/validation/testing), the following samples—relying on local context—are shown, with their labels: newly elected mayor — ‘the’, plans to actively fight corruption — ‘none’, plaguing city — ‘the’.

Since Kabbara et al. (2016) provide evidence that an extended context leads to a better performance on their task of definiteness prediction, we explore using the extended context which constructs the sample in the same way (as described above) and, in addition, tokens from the previous sample(s) are added sequentially (in reverse) until a pre-specified total number of tokens per sample is reached. Similar to (Kabbara et al., 2016), we set that number to be 50.

4 Experimental Setup

4.1 Datasets

In our work, we use two datasets: CNN/DailyMail (Hermann et al., 2015) and PubMed (Cohan et al., 2018). CNN/DailyMail contains news articles and associated highlights, i.e., a few bullet points giving a brief overview of the article. The dataset is a collection of 93K articles from CNN and 220K articles from Daily Mail. Approximately 90k documents and 197k documents are used for training, respectively, in the CNN and Daily Mail portions of the dataset. The PubMed dataset consists of long and structured scientific papers obtained from the PubMed repository of biomedical research papers. The abstracts are considered to be the summaries of the articles. The dataset consists of 133K articles of which 120K are used for training.

To obtain the data for the second step (definiteness prediction), we first parse each dataset using Stanford CoreNLP (Manning et al., 2014) and then extract all of the NPs present in the parsed dataset whose head noun’s POS tag is one of NN, NNS, NNP, or NNPS. We do not lemmatize and ignore case and punctuation. As mentioned before, we remove all instances of the relevant articles (the, a, an) from all of the datasets. The numbers of training samples are as follows: For CNNDM, 48M samples from the stories and 3.9M samples from the summaries. For PM, 69M samples from the articles and 6M from the summaries.

4.2 Training Details

The logistic regression classifier is implemented using the scikit-learn library (Pedregosa et al., 2011) with all the corresponding default parameters. For the LSTM model, we use a vocabulary of size 30,000 and we initialize the word embeddings with GloVe vectors (Pennington et al., 2014) having 300-dimensions and trained on the 840 billion token version of the Common-Crawl corpus. For the LSTM model, unknown words are randomly initialized according to a normal distribution to the same size as the GloVe embeddings. For BERT, we use the bert-base-uncased implementation by HuggingFace (Wolf et al., 2019) which implements a 12-layer 768-hidden 12-head 110M-parameter version of the model that was trained on lower-cased
English text. All model hyperparameters are kept as default. During training, we freeze the weights of the BERT part of the corresponding model. This is to ensure a fair comparison (in terms of trainable parameters) between the LSTM model and a BERT-based model that contains recurrent layers as well. In the appendix, we explore the effect of fine-tuning BERT on its performance on our task.

Both neural models are implemented in PyTorch (Paszke et al., 2019). They are trained to minimize the standard cross-entropy cost with Adam (Kingma and Ba, 2015) as the optimizer with all default parameters except for the learning rate. Following hyperparameter search, we found the following hyperparameters to work best: 0.0001 for the learning rate, 128 for the mini-batch size and 0.6 for the dropout probability. We train the models for a maximum number of 35 epochs and to reduce the effects of overfitting we stop the training if the accuracy on the dev. set does not improve for 10 epochs. All test set results are reported based on the best trained model as measured on the dev. set.

5 Study 1: Preference Judgments

5.1 Methodology

In this study, we attempt to understand the effect of the proposed post-editing step on the quality of generated extractive summaries. We randomly sample 100 summaries generated by the summarizers for CNN/DailyMail and PubMed, pre-process them (See Section 4.1 for details) and then pass them through a definiteness prediction model to generate decisions that inform us on whether the noun phrases in those summaries should have an article (the, a/an) or not. We use the LSTM model with the best performance on the development set (8 layers, 2048 units – See Section 7 for a full comparison of models and hyperparameter search details). The resulting modified summaries are then given along with their corresponding original summaries (generated by the summarizers) to three annotators that are native speakers of English and paid 15 CAD/hour for their work. We ask them to evaluate which passage is better by choosing the one that is more coherent, more readable and/or more fluent. We also give the option of specifying that both versions are equally good. To reduce any biasing, the passages are anonymized in the sense that the judges do not know which of the two passages is the modified summary. We also randomize the order of the two passages in a given pair (i.e. in some instances, the modified summary is given as Passage A and in the rest as Passage B).

5.2 Results

The results of the human evaluation are given in Figure 3. We notice that across all combinations, the judges significantly prefer the modified version (on average, approx. 3 times). Furthermore, on average across the 4 scenarios, in 46% of the (overall) cases, the judges demonstrated full agreement in terms of their preference of the modified version. An interesting observation is that, as expected, the scores were higher in the PubMed experiments. This is because PubMed summaries are longer on average than CNNDM summaries. Accordingly, on average, there are more NPs in PubMed summaries.
thus more possibilities for our system to lead to
to changes. Overall, the findings of this study consti-
tute strong evidence that a light-weight post-editing
step focusing on NP definiteness has the potential
to improve the quality of extractive summaries in
in terms of coherence, readability and overall flow.

6 Study 2: Automatic Evaluation of the
Post-Editor Method

In this study, we carry out a human annotation
study to obtain gold standard annotations on the
definiteness of noun phrases in sampled subsets of
extractive summaries that are generated by different
summarizers. By comparing our model’s decisions
to the collected annotations, we can evaluate its
performance using standard classification accuracy.
Also, the collected dataset of annotated extractive
summaries can be useful for further development
and evaluation of similar post-editing systems.

6.1 Methodology

We randomly sample 100 extractive summaries
generated by the different summarizers (Bandit-
Sum, MatchSum, HipoRank) for the two datasets
CNNDM and PubMed. We remove all instances of
articles (the, a/an) and replace them by a blank. We
also include a blank for the “none” cases. We ask
three graduate students that are native speakers of
English to fill the blanks with the appropriate arti-
cles or to keep them blank such that the summaries
are the most coherent and readable to them. The an-
notators are paid 15 CAD/hour for their work. We
also include a blank for the “none” cases. We ask
three graduate students that are native speakers of
English to fill the blanks with the appropriate arti-
cles or to keep them blank such that the summaries
are the most coherent and readable to them. The an-
notators are paid 15 CAD/hour for their work. The
resulting annotations show a high inter-annotator
agreement ranging from 0.66 to 0.72 (Fleiss Kappa
measure) across the 4 different combinations of
summarizers/datasets. To evaluate the models’ per-
formance, we compare the decisions made by the
models on the same 100 samples to those done by
the three annotators. We evaluate how the models
perform in terms of overlap with each of the anno-
tators and compute the average overlap score for
each model. In each case, the figures represent the
test set performance of the best model as measured
on the development set. In Section 7, we discuss
the different hyperparameters that were examined
and their effect on the models’ performance.

To better understand how the data size and the
linguistic variation between the writing of source
documents and summaries affect the model perfor-
mance, we investigate training on the following:

1. All source documents (CNNDM stories 48M
samples; PubMed articles 69M samples).
2. A subset of source documents (CNNDM 3.9M
samples; PubMed 6M samples).
3. Summaries (CNNDM 3.9M samples;
PubMed 6M samples).
4. A combination of the last two datasets.

The rationale behind these variations is to under-
stand how the difference in structure and style be-
tween source documents and summaries affects
the performance of the models. Indeed, since the
summarizer is extractive, the generated summaries
should in principle closer in style to the source
documents. Thus, we expect the model to perform
better when it is trained on source documents. How-
ever, since the source documents dataset is much
bigger than the summaries dataset, we also train on
a subset of source documents of comparable size
to that of the summaries dataset. This is to isolate
the effect of dataset size and focus the comparison
on the style difference between source documents
and summaries. Finally, we present the “source +
summaries” dataset in an attempt to understand
whether training on both types of data can lead to
some compound effect in terms of performance
improvement.

6.2 Results

Figure 4 shows the results across the different com-
binations of summarizers and datasets and for the
different training sets. First, we notice that the
performances of the BERT and LSTM models are
overall comparable with LogReg consistently per-
forming the worst. We notice a general difference
in trends between the CNNDM and PubMed sce-
narios. Isolating the training size effect, the BERT
and LSTM models trained on the summaries (SM)
score respectively approx. 6 and 3 points less than
those that trained on the subset of stories (sub_ST)
for the two CNNDM cases. This is due to the fact
that the test samples in question are summaries
generated by extractive summarizers. Accordingly,
the generated summaries are closer in distribution
to the stories compared to the golden summaries
which are essentially story highlights written by
the editors of the respective newspapers and which
could differ substantially in style and structure from
the stories. This shows the effect of the type (style)
of training data. Also, for CNNDM, when we
add more training data (ST), the performance goes
Figure 4: Performance of the learning models in terms of (average) overlap (in %) between the models’ decisions and those of the annotators on 100 randomly sampled summaries generated by the different summarizers. Abbreviations: ST: Stories, AR: Articles, SM: Summaries, sub: subset.

slightly up but not enough given that ST is almost 10 times larger than sub_ST. Moreover, the models trained on both stories and summaries perform worse than those trained solely on the subset of stories, suggesting again that the performance was hurt due to training on data that is now less similar to the test data. For PubMed, the trends are different and the performance across the 4 training sets is more homogeneous. This is explained by the fact that the summaries are abstracts of the articles and so one would not expect the writing style to be different between the abstract and the body of the article. This explains the negligible performance difference between the two cases SM and sub_ST. Moreover, for this dataset, the results show that additional training data does not lead to a higher performance as the performance difference between ST and sub_ST is also negligible.

On a separate note, we point out that we do not include ROUGE scores as part of our evaluation because it primarily measures semantic content, not coherence or referential clarity. Since we’re only changing articles, ROUGE is not expected to change much (or even not at all in case stopwords (including articles) are filtered out before computing ROUGE as is common practice).

Focusing on the CNNDM scenarios where there exists a difference in style between source and summary, the results seem to suggest that the current models pay attention to the source of the data rather than actually attempting to reason about the pragmatics of the decision. Indeed, a model seems to do well when the source of a test sentence matches the training data but otherwise does less well. This can be seen as evidence that the automatic system is exploiting some cues related to the style of how main article texts or summary texts are written to make the decisions.

In conclusion, Study 2 shows that our proposed system is robust and generalizes to various changes in dataset size, data type/style, problem domains and summarizers. The results show our system making decisions that highly overlap with those of expert judges (the highest being 82.41% for CNNDM and 84.62% for PubMed). This shows that our system has the ability to generate decisions (on definiteness) which may lead to improved extractive summaries. This is based on the belief that the decisions made by the judges actually reflect the best coherence and readability of the presented extractive summaries. This conclusion complements the results of Study 1 which showed that the judges substantially prefer our system’s summaries.

7 Analyzing the Hyperparameters Effect on Model Performance

In this section, we attempt to understand the effect of certain hyperparameters and modeling choices on the models’ performance on this task.

We focus on the CNNDM/BanditSum scenario...
and vary the size of the neural models in terms of depth (number of recurrent layers) and width (size of the recurrent layers) and whether the recurrent layer is bidirectional or not. We also investigate the effect of having a local context (i.e. within the current NP) versus an extended context. Figure 5 presents the results showing the performance of the models across these different dimensions. As a note, given the very large size of the stories dataset (~48M samples), we decided to train on it only the biggest models (8 or 5 layers).

**Effect of Network Size.** The trends in the results point to the fact that, as expected, bigger networks lead to a higher performance. While the trend in performance upwards is not 100% perfect, it shows that when we start with 2 layers in the LSTM case, the performance is lower in all three relevant datasets and goes up as we increase the number of layers. Similarly, if we look at increasing the width of layers, a similar trend holds.

**Effect of Bidirectionality.** In most cases, a bidirectional layer does lead to an improvement in performance. However, this is minimal.

**Effect of Context Length.** Given prior work (Kabbara et al., 2016), we expected to find some evidence that an extended context has a positive effect. Indeed, in Figure 5, if we look at the 4-layer and 5-layer models for both LSTM and BERT-based models, the expectation holds and in some cases in a substantial way. One interpretation is the fact that, as a transformer model, BERT processes words in relation to all the other words in a sentence, rather than one-by-one in order. Accordingly, the BERT-based models can consider the full context of a word by looking at the words that come before and after it, and when given a wider context (the extended case), BERT can capitulate even more on its ability to better extract contextual information.

**Effect of Dataset Size and Type.** Training on stories leads to a higher performance than training on summaries (as we explained in Section 6). Moreover, having a 10-time larger dataset does not lead to a noticeable improvement even when used to train a larger model (i.e. the 8-layer case).

8 Conclusion

In this work, we proposed a method to modify the output of an extractive summarizer via a post-editing step involving definiteness prediction. The goal is to generate decisions on modifying articles (or not) such that the quality of the extractive summary is improved in terms of coherence and readability. We presented evidence that human expert judges show substantial preference for the output of such a system. We collected annotations of generated extractive summaries on NP definiteness which we believe would be useful for further development and evaluation of similar post-editing systems. Based on automatic evaluation, we validated our system’s ability to generate linguistic decisions that highly overlap with the golden annotations, thus pointing at the system’s efficacy and potential for generating improved extractive summaries. Finally, we presented insights about how
the system could be exploiting some local cues related to the writing style of the main article texts or summary texts to make the decisions, rather than pragmatically reasoning about the contexts. Our work points to the importance of future research that centers around understanding the discourse context to make predictions that lead to pseudo-extractive summaries of even higher quality.

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