

# Evaluating the Factual Consistency of Large Language Models Through News Summarization

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## Abstract

While large language models (LLMs) have proven to be effective on a large variety of tasks, they are also known to hallucinate information. To measure whether an LLM prefers factually consistent continuations of its input, we propose a new benchmark called FIB (Factual Inconsistency Benchmark) that focuses on the task of summarization. Specifically, our benchmark involves comparing the scores an LLM assigns to a factually consistent versus a factually inconsistent summary for an input news article. For factually consistent summaries, we use human-written reference summaries that we manually verify as factually consistent. To generate summaries that are factually inconsistent, we generate summaries from a suite of summarization models that we have manually annotated as factually inconsistent. A model's factual consistency is then measured according to its accuracy, i.e. the proportion of documents where it assigns a higher score to the factually consistent summary. To validate the usefulness of FIB, we evaluate 23 large language models ranging from 1B to 176B parameters from six different model families including BLOOM and OPT. We find that existing LLMs generally assign a higher score to factually consistent summaries than to factually inconsistent summaries. However, if the factually inconsistent summaries occur verbatim in the document, then LLMs assign a higher score to these factually inconsistent summaries than factually consistent summaries. We validate design choices in our benchmark including the scoring method and source of distractor summaries.<sup>1</sup>

## 1 Introduction

Factual inconsistency is a widespread problem in natural language generation tasks (Maynez et al., 2020; Weng et al., 2020; Devaraj et al., 2022). For text summarization in particular, it has been shown that models often hallucinate new information or

<sup>1</sup>We include our code in the supplementary

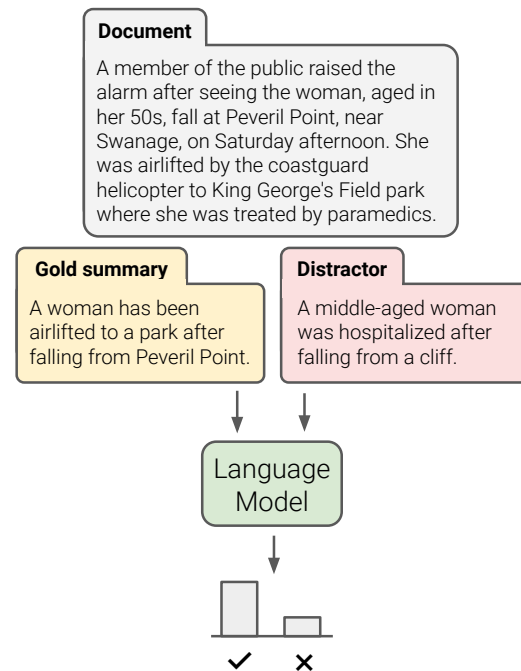


Figure 1: A schematic diagram of FIB, where we measure whether an LLM assigns a higher score to a factually consistent document summary than a factually inconsistent summary.

generate content that contradicts the source document (Cao et al., 2018; Maynez et al., 2020). These works usually study supervised summarization models that are either trained from scratch or fine-tuned from a pre-trained language model (Wan and Bansal, 2022). Recently, however, NLP has experienced a paradigm shift towards using large language models (LLMs) rather than supervised models. LLMs are generally pre-trained on a large corpus of unstructured text and then applied to a task through instructive prompts. In light of this new paradigm, our goal is to evaluate the factual consistency of large language models using text summarization as a testbed.

To achieve this goal, we propose FIB (the Factual Inconsistency Benchmark) to measure how often models prefer factually consistent summaries

over factually inconsistent summaries. In FIB, models are given a document and are evaluated on whether they assign a higher score to a factually consistent summary than a factually inconsistent summary. Scores are assigned based on a model’s assigned probability to the summary. We use accuracy on this binary classification task as a proxy for how factually consistent a model is. FIB consists of over 3,500 pairs of summaries that were *all* manually annotated as either factually consistent or factually inconsistent. The benchmark is based on documents and summaries from the XSum (Narayan et al., 2018b) and CNN/DM (Hermann et al., 2015) datasets to test behavior on abstractive and extractive summarization, respectively. For factually consistent summaries, we use reference summaries from the datasets that we verify are factually consistent or manually edit to make them factually consistent. The factually inconsistent summaries were generated from 22 models trained for summarization and then annotated as factually inconsistent.

To explore the behavior of existing models on FIB, we evaluate 23 LLMs from 6 different model families including BLOOM, OPT, GPT, and T0 (Radford et al., 2019; Zhang et al., 2022b; Sanh et al., 2022; Chung et al., 2022; Lester et al., 2021; Scao et al., 2022) ranging from 1B to 176B parameters. Next, we analyze whether the method used to generate the factually inconsistent summaries affects how often models prefer factually consistent summaries over factually inconsistent summaries. To do so, we evaluate these models on factually inconsistent summaries from three additional sources: (1) unedited reference summaries that we annotated as factually inconsistent, (2) summaries edited via FactCC (Kryscinski et al., 2020), and (3) summaries produced by MFMA (Lee et al., 2022). In addition, we test 4 different scoring functions: conditional log-likelihood (LL), length-normalized LL, pointwise mutual information (PMI), and length-normalized PMI. Overall, we find that: (1) The LLMs we consider typically assign a higher score to factually consistent summaries than to factually inconsistent summaries (e.g. 72.4% of the time for BLOOM (Scao et al., 2022)), but (2) LLMs rarely prefer factually consistent summaries over factually inconsistent summaries copied verbatim from the document (e.g. 9.6% of the time for BLOOM), (3) LLMs generally become more factually consistent as they are scaled up, and (4) FactCC-generated factually inconsistent summaries can fool some LLMs

at a similar rate to model-generated factually inconsistent summaries.

In summary, our contributions are: (1) a benchmarking procedure and collection of annotated summaries for probing the factual consistency of LLMs and (2) a thorough evaluation of 23 LLMs from 6 different model families of up to 176B parameters. We hope FIB and our results help shed light on the factuality of LLMs.

## 2 Related Work

### 2.1 Factuality Evaluation Datasets

In the literature on text summarization, many datasets with human-labeled factually consistent and inconsistent summaries have been introduced for meta-evaluation purposes (i.e., evaluating factuality evaluation metrics) or for training the metrics themselves. Pagnoni et al. (2021) introduced the FRANK benchmark that contains 2250 model-generated summaries with factuality labels for each summary sentence. Similarly, Gabriel et al. (2021) proposed the GO FIGURE meta-evaluation framework that has 1500 model-generated summaries that include factuality labels. Besides these two benchmarks, many other works collected their own small-scale factuality evaluation datasets for evaluating their proposed metrics or analyzing the factuality of summarization models (Falke et al., 2019; Maynez et al., 2020; Kryscinski et al., 2020; Wang et al., 2020a; Durmus et al., 2020; Lux et al., 2020). Ribeiro et al. (2022) combined labeled datasets from four works and formed the FactCollect dataset with more than 9000 summary sentences and their factuality labels. Additionally, a few other works proposed to automatically obtain factually inconsistent summaries by perturbing the reference summaries (Kryscinski et al., 2020; Lee et al., 2022), e.g., entity swapping. However, Goyal and Durrett (2021) showed that these automatic techniques target inherently different error distributions than those seen in actual model generations. Goyal and Durrett (2020) considered model outputs at the top of beam search as factual and bottom generations as non-factual. The aforementioned works mainly focus on abstractive summarization; in contrast, Zhang et al. (2022a) introduced a factuality evaluation dataset for extractive summarization which we use as part of FIB. Previous datasets do not annotate reference summaries and instead only annotate model generations as factually consistent or factually inconsistent. However, the ref-

erence summaries are not always factually consistent (Maynez et al., 2020; Bommasani and Cardie, 2020; Tejaswin et al., 2021) which means that some of the factually inconsistent summaries might not have any factually consistent summary to pair with. Hence, we perform a manual verification of reference summaries as factually consistent for FIB. Additionally, FIB aims to evaluate the factual consistency of LLMs themselves instead of meta-evaluating evaluation metrics.

Besides summarization, Devaraj et al. (2022) proposed a factuality evaluation dataset for text simplification. In addition, some datasets have been introduced for checking a fact or claim against a large knowledge base (Thorne et al., 2018; Augenstein et al., 2019); here, we instead focus on factual consistency of conditional model continuations.

## 2.2 Factuality Evaluation Metrics

Many metrics have been proposed to evaluate the factual consistency of model-generated summaries. These metrics can be roughly categorized into entailment-based metrics and question-generation/answering (QA/QG)-based metrics. Entailment-based metrics check whether each summary sentence (or a more fine-grained subsentence) is entailed by the source document (Falke et al., 2019; Kryscinski et al., 2020; Goyal and Durrett, 2020; Maynez et al., 2020). QA/QG-based metrics are designed based on the idea that a question should have the same answer whether it is based on the summary or the document (Wang et al., 2020a; Durmus et al., 2020; Scialom et al., 2021). Relatedly, Goodrich et al. (2019) evaluated factuality by checking factual tuples extracted by OpenIE and Ribeiro et al. (2022) used the AMR graphs of the summary and the document for assessing factual consistency. All these metrics were designed to evaluate models trained specifically for summarization. In this work, we focus more broadly on evaluating the factual consistency of LLMs.

## 3 FIB: Factual Inconsistency Benchmark

Each example in FIB consists of a document and two summaries: a factually consistent summary and a factually inconsistent summary. Models are evaluated based on the proportion of times they assign a higher score to a factually consistent summary than to a factually inconsistent summary. We define a factually consistent summary as a summary whose contents can be inferred solely from

the document. This means that even if a summary contains true information, if the information is not found in the document, then the summary is factually inconsistent. For example, the Gold summary in fig. 1 is factually consistent as it is written, but if we swapped *Peveril Point* with *a cliff*, then it would no longer be factually consistent, even if *Peveril Point* is technically *a cliff*, since this fact cannot be inferred from the document.

We compare the factual consistency of models on both extractive and abstractive summaries. Extractive summaries occur verbatim in the document while abstractive summaries do not. We use two summarization datasets as our testbed: CNN/DM (See et al., 2017; Hermann et al., 2015) for extractive summaries and XSum (Narayan et al., 2018a) for abstractive summaries. CNN/DM consists of English documents about the news from CNN/Daily Mail and summaries that are several sentences long with 287K/13K/11K examples for train/val/test.<sup>2</sup> XSum consists of English documents about the news from BBC and short summaries with 204K/11K/11K examples for train/val/test.<sup>3</sup> The CNN/DM dataset is distributed under an Apache 2.0 license and XSum is under a Creative Commons Attribution 4.0 International license. Our use is consistent with the intended use and we release our code under an Apache 2.0 license and the data for FIB under a Creative Commons Attribution 4.0 International license.

### 3.1 Dataset Construction

We describe how we construct the factually consistent and factually inconsistent summaries for FIB. When performing annotations, each summary was annotated by two annotators. Four of the authors performed the annotations. Our inter-annotator agreement was 91.3%. Whenever there was a disagreement on a given summary, the two annotators would discuss and resolve the disagreement. See appendix A for annotator instructions.

**Factually Consistent Summaries.** Though the summarization datasets we consider include reference summaries, the reference summaries are not necessarily factually consistent with the document (Maynez et al., 2020). To account for this, we annotate reference summaries for 500 and 100 documents from XSum and CNN/DM respectively

<sup>2</sup>[https://huggingface.co/datasets/cnn\\_dailymail](https://huggingface.co/datasets/cnn_dailymail)

<sup>3</sup><https://huggingface.co/datasets/xsum>

as either factually consistent or factually inconsistent. Then, we edit the factually inconsistent reference summaries to be factually consistent using minimal edits. Factually inconsistent reference summaries usually contain information that is true but not found in the document. Thus, most edits involve removing or changing certain keywords or phrases not present in the document. Two annotators then verified the edited summary was factually consistent. The percentage of factually consistent summaries that were edited from the original reference summary was roughly 90% for XSum and 30% for CNN/DM. We denote these annotated factually consistent reference summaries as *Gold* summaries. See appendix B for some examples of edited summaries.

**Factually Inconsistent Summaries.** To obtain factually inconsistent summaries, we generate summaries from models trained on a given summarization dataset and annotate the generated summaries as factually consistent or factually inconsistent. We then retain the model-generated summaries that were annotated as factually inconsistent. We use 15 extractive models to generate summaries for CNN/DM and 7 generative models to generate summaries for XSum. See appendix D for the list of models used to generate the summaries. For XSum, we annotate the model-generated summaries ourselves and for CNN/DM we source the factual-consistency annotations from Zhang et al. (2022a). See appendix C for some examples of factually inconsistent model-extracted summaries.

For the dataset underlying our benchmark, we create a paired example for every possible factually inconsistent summary with the Gold summary for a given document. In the end, we have 3,124 factually consistent/inconsistent summary pairs across 500 unique documents for XSum and 457 pairs across 96 unique documents for CNN/DM (4 CNN/DM documents were dropped since all the models generated factually consistent summaries for them). A model’s accuracy on FIB is then simply the proportion of summary pairs where the model assigns a higher score to the Gold summary than to the factually inconsistent summary.

### 3.2 Scoring Function

For FIB, we are primarily interested in a scoring function to measure the consistency of the summary and the document. A natural scoring function is the model’s assigned log-likelihood (LL)

of the summary given the document, but LL has two major issues. First, the log-likelihood has a bias towards shorter summaries since the probability of each token in a summary is multiplied together to obtain the log-likelihood of the entire summary, and thus shorter summaries tend to produce higher log-likelihoods. Second, if the summary alone has a high likelihood, then the model might assign a high likelihood to the summary, even if the summary and the document are not that related. To address the first issue, we normalize by the length of the summary. To address the second issue, we use the pointwise mutual information (PMI), which accounts for the likelihood of the summary by subtracting the log-likelihood of the summary alone from the log-likelihood of the summary conditioned on the document. Several recent works have used the pointwise mutual information (PMI) as a way of scoring a language model’s generations: Holtzman et al. (2021) used PMI to solve multiple-choice tasks that probe for knowledge using GPT3 and Padmakumar and He (2021) used PMI for unsupervised extractive summarization. Concurrently, van der Poel et al. (2022) show that optimizing for PMI during decoding can decrease hallucinations in language models.

To address both these issues, we use the length-normalized PMI as our default scoring function, where the length normalization is performed by averaging over tokens. Specifically, given document  $d$  and summary  $s$  which consists of  $T$  tokens  $\{s_1, s_2, \dots, s_T\}$ , the length-normalized PMI is defined as

$$\frac{1}{T} \log \sum_{t=1}^T P(s_t | d, s_1, \dots, s_{t-1}) - \frac{1}{T} \log \sum_{t=1}^T P(s_t | s_1, \dots, s_{t-1}) \quad (1)$$

We ablate the impact of using different scoring functions in section 4.4.

## 4 Experiments

Having defined our benchmark, we now evaluate the factual consistency of various LLMs and compare with several other methods for generating alternative summaries and assigning scores to LM generations.

### 4.1 Models

We evaluate 23 large language models (1B to 176B parameters) from 6 different model families:



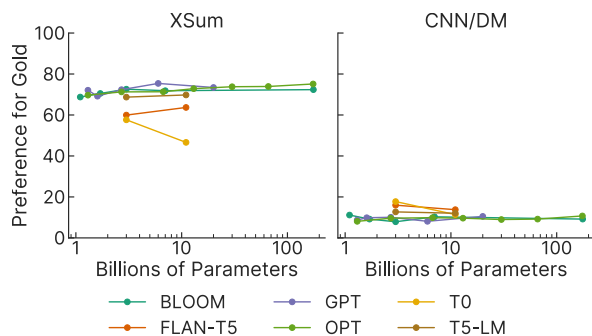


Figure 2: Performance of various models on FIB.

- **GPT:** GPT2-XL (Radford et al., 2019), GPT-Neo-1.3B, GPT-Neo-2.7B, GPT-NeoX-20B (Black et al., 2022)
- **OPT:** OPT-1.3B, OPT-2.7B, OPT-6.7B, OPT-13B, OPT-30B, OPT-66B, OPT-175B (Zhang et al., 2022b)
- **BLOOM:** BLOOM-1.1B, BLOOM-1.7B, BLOOM-3B, BLOOM-7B, BLOOM (Scao et al., 2022)
- **T0:** T0-3B, T0 (Sanh et al., 2022)
- **FLAN-T5:** FLAN-T5-XL, FLAN-T5-XXL (Chung et al., 2022)
- **T5-LM-Adapt:** T5-LM-Adapt-XL, T5-LM-Adapt-XXL (Lester et al., 2021)

Our chosen models consist of both zero-shot models that were not trained on XSum or CNN/DM (GPT, OPT, BLOOM, T5-LM-Adapt) and models that were trained on XSum and CNN/DM in a multi-task fashion (T0, FLAN-T5). For each model, we use the same 3 prompts and report the median performance across prompts, following Sanh et al. (2022). See appendix E for the prompt templates used. We use a maximum sequence length of 512, which was also applied when sampling 500 documents from XSUM for annotating factual consistency. We use Pytorch (Paszke et al., 2019) and HuggingFace (Wolf et al., 2020) to run the models, and use bitsandbytes (Dettmers et al., 2022) to do 8-bit inference for the larger models. All experiments were run on NVIDIA A6000s or 80GB NVIDIA A100s (depending on the model) and took about two days.

## 4.2 Main Results

We show the performance of all the models on XSum and CNN/DM in fig. 2. On XSum, we high-

light the following:

- *Factual Consistency:* Models generally prefer Gold summaries over factually inconsistent model-generated summaries, but the average accuracy of any model is still far from 100%.
- *Effect of Scale:* Performance generally increases slightly with scale within a given model family with the exception of T0, where the 11-billion-parameter model underperforms T0-3B. For zero-shot LLMs, the performance is remarkably similar across model families.
- *Effect of Training:* Both FLAN-T5 and T0 underperform the zero-shot models, which could be because they were trained on the XSum dataset, which had many reference summaries that were factually inconsistent.

In contrast to our results on XSum, we find that models rarely assign a higher score to factually consistent reference summaries than to factually inconsistent model-extracted summaries on the CNN/DM dataset. However, if the factually consistent summary is also model-extracted, then models also assign higher scores to the factually consistent model-extracted summary. This suggests that all models have a strong preference for text copied from the input regardless of its factual-consistency.

## 4.3 Generating Alternative Summaries

We also analyze the impact of the the method used to generate factually inconsistent summaries. To do so, we compare the model’s performance when using different methods for generating the factually inconsistent summary. We note that Goyal and Durrett (2021) showed that these automatic techniques target inherently different error distributions than those seen in actual model generations. We experiment with the following alternative methods for obtaining factually inconsistent summaries:

- MFMA, proposed by Lee et al. (2022), uses pre-trained masked language models to generate factually inconsistent summaries. Specifically, summaries are generated by reconstructing the reference summary conditioned on the document and reference summary with  $\alpha$  and  $\beta$  percent of the entities masked out respectively. The MFMA procedure first fine-tunes a pre-trained masked LM to reconstruct summaries in this setup and then uses the fine-tuned model to generate new summaries. For example, in fig. 1, if we masked out

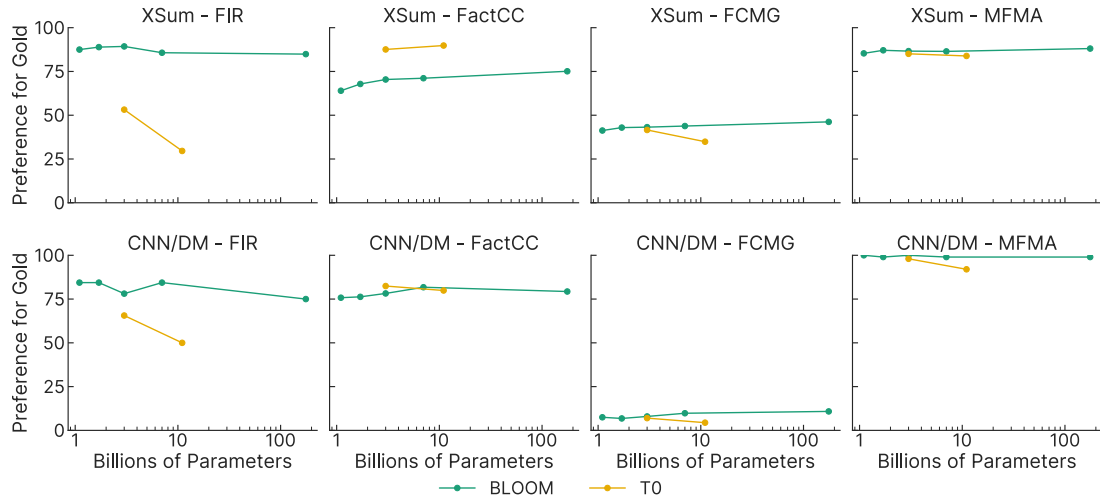


Figure 3: Preference for the Gold summary exhibited by BLOOM and T0 when using different methods for generating alternative choices.

*Peveiril Point* in the reference summary and the model generated *the grand canyon* instead, then the factually-inconsistent MFMA-generated summary would be *A middle-aged woman has been driven by ambulance to a park after falling from the grand canyon*. We follow the setup in MFMA and use T5-base (Raffel et al., 2020) and BART-base (Lewis et al., 2020a) to generate the summaries with  $\alpha = 0.8$  and  $\beta = 0.6$ . Since there is no guarantee that the model-reconstructed summaries are factually inconsistent, we annotate their factual-consistency and only keep the ones that are factually inconsistent. We construct factually inconsistent summaries from MFMA by combining all factually inconsistent summaries generated by T5-base and BART-base.

- FactCC, proposed by Kryscinski et al. (2020), generates factually inconsistent summaries via heuristic perturbations to reference summaries. FactCC uses two ways to perturb the reference summary: entity swapping and sentence negation. Entity swapping replaces an entity (i.e. pronouns, dates, numbers and named entities) in the reference summary with a different entity from the document and sentence negation refers to negating a verb. For example, in fig. 1, if we negated *has* to *hasn't*, then the factually-inconsistent FactCC-generated summary would be *A middle-aged woman hasn't been airlifted to a park after falling from Peveiril Point*.
- FIR (factually inconsistent reference) summaries. Since some of the original reference summaries were factually inconsistent and had to be edited

to become factually consistent, we use these original reference summaries as an alternative source of factually inconsistent summaries.

As an additional baseline, we consider using factually consistent model-generated summaries rather than a factually inconsistent summary as the alternative summary. This allows us to test whether models prefer model-generated summaries over Gold summaries. We call this setup of where the alternative choice is a factually consistent model-generated summaries FCMG (Factually-Consistent Model-Generated summaries).

A comparison of different methods for generating alternative summaries is shown in fig. 3. We only plot results for BLOOM and T0 since the results for other decoder-only zero-shot LLMs are similar to those for BLOOM and the results for FLAN-T5 are similar to T0. We highlight the following trends:

- *Preference for factually consistent model-generated summaries depends on whether summaries are extractive:* On XSum, models are almost at chance when distinguishing between factually consistent model-generated summaries and Gold summaries. This is evident from the accuracy on FCMG being around 50%. However, on CNN/DM, models consistently prefer factually consistent model-extracted summaries to Gold summaries. We conclude that models prefer model-extracted summaries that occur verbatim in the document, regardless of their factual consistency.

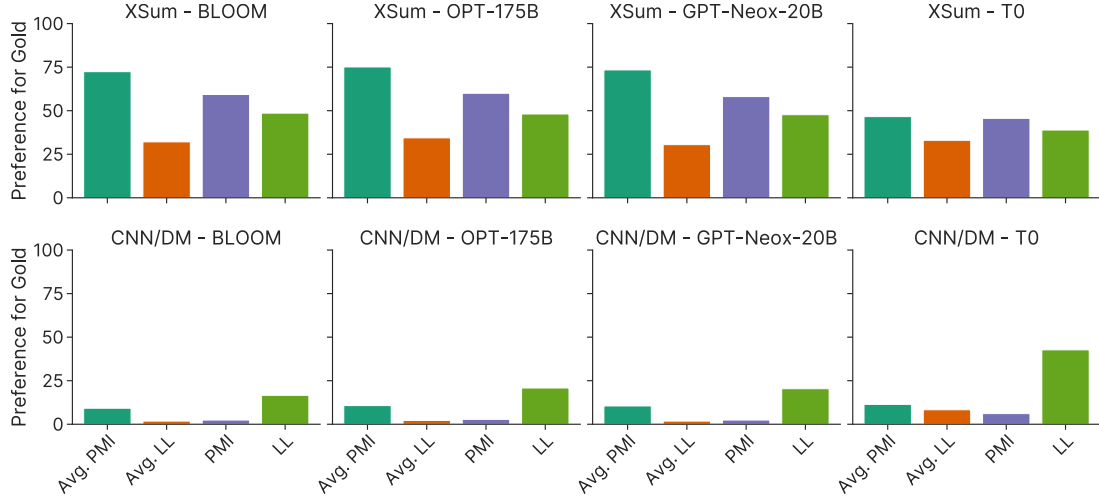


Figure 4: Performance of various models on FIB when using different scoring functions.

- *MFMA’s Ineffectiveness:* On both XSum and CNN/DM, models rarely assign MFMA-generated summaries a higher score than Gold summaries – the accuracy on MFMA is between 85% to 100% across all models.
- *FactCC’s Effectiveness for zero-shot LLMs:* On XSum, BLOOM’s performance is similar when either FactCC or model-generated factually inconsistent summaries are used as an alternative, and on CNN/DM, performance is similar for FactCC and factually inconsistent reference summaries. This suggests that FactCC generates somewhat plausible factually inconsistent summaries for zero-shot decoder-only LLMs.
- *FactCC’s Effectiveness for other models:* However, T0, FLAN-T5, and T5-LM-Adapt (see appendix H for FLAN-T5 and T5-LM-Adapt accuracies) all perform better when using FactCC-generated factually inconsistent summaries than when using model-generated factually inconsistent summaries. This indicates FactCC might not be effective in generating plausible factually inconsistent summaries across all model architectures and training schemes.
- *Preference for Edited Summaries:* On XSum and CNN/DM, models tend to prefer factually consistent reference summaries over factually inconsistent reference summaries. This is evident from the accuracy on FIR being around 80% and indicates that models tend to prefer factually consistent summaries over factually inconsistent summaries.

#### 4.4 Scoring Function

In FIB, we use the length-normalized PMI as the scoring function. To validate this choice, we compare various alternative scoring functions: standard log-likelihood, length-normalized log-likelihood, and the non-length-normalized PMI. We show results for BLOOM, OPT-175B and T0 on XSum and CNN/DM using different scoring methods in fig. 4. In general we see that the average PMI enables models to best distinguish between factually consistent and factually inconsistent summaries. We also compare each scoring function on the alternate sources of factually inconsistent summaries; see appendix F for detailed results. We find that log-likelihood works best when the factually inconsistent summary was produced by FactCC or is a model generation on CNN/DM. We hypothesize that log-likelihood works better than length-normalized PMI on FactCC because the generated summaries are often non-fluent and therefore are assigned a low likelihood regardless of their factual consistency. For model-extracted summaries on CNN/DM, we hypothesize that log-likelihood works better than length-normalized PMI because log-likelihood is not as biased towards summaries extracted from the document as PMI is.

## 5 Analysis

To get a better sense of what kind of factually inconsistent model-generated summaries tend to fool models into assigning a higher score than the Gold summary, we show some examples for BLOOM in table 1. These factually inconsistent summaries consist of extrinsic hallucinations that

Document	Factually Consistent Summary	Factually Inconsistent Summary
The \$5m (3.2m) prize is supposed to be awarded each year to an elected leader who governed well, raised living standards and then left office. This is the fourth time in five years there has been no winner ... Sudan-born telecoms entrepreneur Mr Ibrahim launched the prize in an attempt to encourage African leaders to leave power peacefully. ...	The prize from Ibrahim for good governance in Africa has gone unclaimed yet again.	The winner of the prestigious Africa Leadership Prize has been announced by the African Union’s executive committee.
The character with a huge papier mache head ... Hundreds of people attended an unveiling ceremony earlier, many in fancy dress for the occasion. Neil Taylor, who helped raise the donations for the statue, said its installation would mean that Frank will gaze on the Timperley sunset forever... Frank Sidebottom created a whole ...	A statue of the character Frank Sidebottom has been unveiled in Timperley.	A statue of Timperley’s character Frank Sidebottom has been unveiled at a Manchester museum.

Table 1: Two examples where BLOOM assigns a higher score to the factually inconsistent model-generated summaries than the Gold summary. These examples have id 24521870 and id 24601038 respectively.

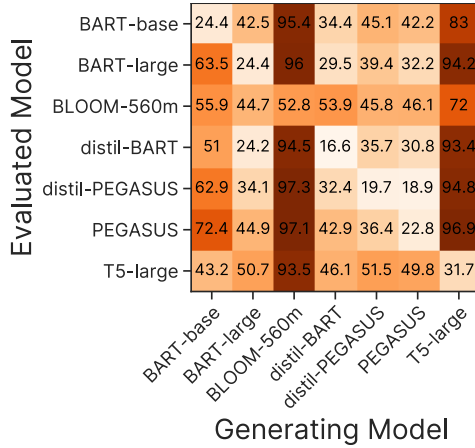


Figure 5: Heatmap showing the rate at which an “evaluated model” assigns a Gold summary on XSum a higher score than a factually inconsistent summary generated by the “generating model”.

add new information rather than intrinsic hallucinations that manipulate the information in the document (Maynez et al., 2020). In addition, these factually inconsistent summaries contain information that is actually false, not just information absent from the document.

### 5.1 Factual Consistency of Models Used to Generate Summaries

We take the models used to generate the factually inconsistent summaries for XSum and evaluate them against each other using the same procedure as in FIB. Specifically, we use factually inconsistent summaries produced by a “generating model” and measure how often an “evaluated model” assigns a higher score to the Gold summary than it

does to the factually inconsistent model-generated summaries. The result is summarized in fig. 5, with full results in appendix K. The accuracies down the diagonal are the lowest, which means models perform poorly when scoring their own factually inconsistent summary. This is expected since models should give high scores to factually inconsistent summaries they generate. In most cases, Gold summaries are preferred less than 50% of the time, suggesting that summarization models tend to assign higher scores to model-generated factually inconsistent summaries. However, certain models (BLOOM and T5-large) almost always produce summaries that are assigned low scores by the other models. We leave exploration of this trend to future work.

## 6 Conclusion and Takeaways

We present FIB, a new benchmark for evaluating the factual consistency of language models, and evaluate 23 large language models on FIB. Our takeaways are: (1) LLMs tend to assign higher scores to factually consistent summaries than to factually inconsistent summaries, except that LLMs almost always assign higher scores to extracted summaries even if they are factually inconsistent and (2) length-normalized PMI enables models to most effectively detect factually inconsistent summaries. Our results open new avenues for future work, including a more fine-grained study on the type of factually inconsistent errors different LLMs make and investigating the effect training on summarization has on the factual consistency of LLMs.



## 7 Limitations

One limitation with FIB is that it only measures the factual consistency of language models for the task of summarization, and specifically news summarization. It is not clear how well the results will generalize, for example, to other domains such as scientific article or other tasks such as question answering.

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## A Annotation Instructions

The annotators were instructed to mark a summary as factually inconsistent if any information in the summary was not implied in the document. We assume no access to external knowledge so the summary has to be implied solely from the document. External knowledge is broadly defined as any knowledge that cannot be inferred from common sense alone. For example, the capital of a country or the rules of a sport would be external knowledge.

## B Sample Edited Summaries

We show some examples of documents with the original factually inconsistent reference summary and the edited factually consistent summary on XSum in table 2.

## C Sample Model-Extracted factually inconsistent

We show some examples of documents with model-extracted factually inconsistent summaries on CNN/DM in table 3.

## D Models Used to Generate Summaries

We use the following models to generate summaries for XSum and include the respective HuggingFace model name:

- BLOOM-560m (Scao et al., 2022) - mrm8488/bloom-560m-finetuned-news-summarization-xsum
- BART-base (Lewis et al., 2020b) - VictorSanh/bart-base-finetuned-xsum
- distil-PEGASUS (Zhang et al., 2020) - sshleifer/distill-pegasus-xsum-16-8
- BART-large (Lewis et al., 2020b) - facebook/bart-large-xsum
- PEGASUS (Zhang et al., 2020) - google/pegasus-xsum
- distil-BART (Lewis et al., 2020b) - sshleifer/distilbart-xsum-12-6
- T5-large (Raffel et al., 2020) - sysresearch101/t5-large-finetuned-xsum

We use greedy decoding for all models with a maximum generation length of 50 tokens.

We use the following models to generate summaries for CNN/DM. See Zhang et al. (2022a) for more description of the models.

- Oracle (Lin, 2004)
- Oracle (discourse) (Xu et al., 2020)
- RNN Ext RL (Chen and Bansal, 2018)
- BanditSumm (Dong et al., 2018)
- NeuSumm (Zhou et al., 2018)
- Refresh (Narayan et al., 2018c)

Document	Original Ref. Summary	Edited Ref. Summary
West Midlands Ambulance Service said the car was discovered on Sunday at 09:35 GMT by two cyclists in Crakemarsh near Uttoxeter, Staffordshire. A spokesman said the black Ford Fiesta appeared to have hit a tree in very foggy conditions on the B5030. The girl, in the back of the car, was treated at hospital for minor injuries. The man, who was 25 and from the local area, has not yet been named ...	A five-year-old girl has been found with her dead father in a crashed car which had been in a ditch "for some time".	A girl has been found in a crashed car.
Aiden Webb, 22, from Norwich, was climbing Fansipan mountain alone on Friday when he fell down a ravine and lost his way ... in the fall on the 3,100m (10,300ft) high Fansipan mountain in the north of Vietnam ... A Foreign and Commonwealth Office spokeswoman said: "We are supporting the family of Aiden Webb, a British man reported missing in Vietnam. We are working closely with the local authorities leading the search."	A British man is missing in Vietnam after falling while attempting to climb the country's highest mountain.	A British man is missing in Vietnam after falling while attempting to climb a mountain.

Table 2: These examples have id 34696511 and id 36459564 respectively.

Document	Model-Extracted Factually Inconsistent Summary
the california public utilities commission on thursday said it is ordering pacific gas & electric co. to pay a record 1.6 billion penalty ... 850 million will go to " gas transmission pipeline safety infrastructure improvements , " the commission said ... pg & e failed to uphold the public 's trust , " commission president michael picker said ... the company 's chief executive officer said ... " since the 2010 explosion of our natural gas transmission pipeline in san bruno , we have worked hard to do the right thing for the victims , their families and the community of san bruno , " tony earley said ...	... 850 million will go to " gas transmission pipeline safety infrastructure improvements , " the commission said . " since the 2010 explosion of our natural gas transmission pipeline in san bruno , we have worked hard to do the right thing for the victims , their families and the community of san bruno ...
a passenger on an atlanta-bound air canada flight told a cnn reporter on the plane friday that a stranger sitting behind him tried to choke him . oliver minatel , 22 , said he was sleeping on air canada flight 8623 from toronto when he felt something around his neck ... " i forced it ( the cord ) down and then other people came to help , and then i got out and he started saying that we were here to kill him , " minatel said . the man was not restrained for the rest of the trip , but the flight crew told him to stay seated with his seat belt on . the man kept trying to get out of his seat but other passengers yelled at him whenever he tried to stand up .	oliver minatel , 22 , said he was sleeping on air canada flight 8623 from toronto when he felt something around his neck . the man kept trying to get out of his seat but other passengers yelled at him whenever he tried to stand up . the suspect was escorted off the plane .

Table 3: Two examples of model-extracted factually inconsistent summaries. The annotations were sourced from [Zhang et al. \(2022a\)](#). These examples have id 41c6edecee127c396d17e2e9115a4a89252cc52b and id 32655a04c9e4733a1ae4b210a045bc6e0d443d85 respectively. The first example uses Textrank ([Mihalcea and Tarau, 2004](#)) to extract the summary. It is factually incorrect since 'we' refers to pg & e and not the commission. The second example uses MatchSumm ([Zhong et al., 2020](#)) to extract the summary. It is factually inconsistent since the man refers to the stranger and not Oliver Minatel.

- BERT+LSTM+PN+RL (Zhong et al., 2019)
- MatchSumm (Zhong et al., 2020)
- HeterGraph (Wang et al., 2020b)
- Lead3
- Textrank (Mihalcea and Tarau, 2004)
- Textrank (ST) (Reimers and Gurevych, 2019)
- PacSum (tfidf) (Zheng and Lapata, 2019)
- PacSum (bert)
- MI-unsup (Padmakumar and He, 2021)

## E Prompt Templates

We use the following 3 prompt templates for all models, where [input] is replaced with the document:

- "[input]"
- "The summary of "[input]" is "
- "Summarize: [input]"

## F Accuracies Across All Scoring Functions

We show the performance of all the models across different scoring functions for XSum in table 4, table 5, table 6, and table 7 and for CNN/DM in table 8, table 9, table 10, and table 11.

## G Accuracies from MFMA-Generated Summaries

We show the performance of different models on MFMA-generated summaries broken down by the model used to generate the summary for XSum using different scoring functions in table 12, table 13, table 14, and table 15.

## H Accuracies from FactCC-Generated Summaries

We show the performance of different models on FactCC-generated summaries broken down by the method used to generate the summary using different scoring functions for XSum in table 16, table 17, table 18, table 19 and for CNN/DM in table 20, table 21, table 22, table 23.

## I Accuracies from Factual Model-Generated Summaries

We show the performance of different models on factually consistent model-generated summaries broken down by the model used to generate the summary using different scoring functions on XSum in table 24, table 25, table 26, and table 27 and on CNN/DM in table 28, table 29, table 30, and table 31.

## J Accuracies from FIB Summaries

We show the performance of different models on FIB broken down by the model used to generate the summary using different scoring functions for XSum in table 32, table 33, table 34, and table 35 and for CNN/DM in table 36, table 37, table 38, and table 39.

## K Accuracies from Models Used to Generate Summaries

We show the performance of different models using the same models to generate the alternative summaries for XSum using different scoring functions in table 40.

Model	FIR	FCMG	FIB	FactCC	MFMA
T0-3B	53.2	41.6	57.6	87.6	85.1
T0	29.6	34.9	46.6	89.8	83.9
FLAN-T5-xl	58.1	47.8	59.9	87.3	85.6
FLAN-T5-xxl	59.0	51.3	63.7	87.1	87.3
T5-LM-Adapt-xl	81.3	49.5	68.7	78.7	87.5
T5-LM-Adapt-xxl	81.7	50.7	69.8	84.2	88.7
GPT-Neo-1.3B	88.0	45.7	72.1	68.9	87.1
GPT2-XL	84.9	46.3	69.2	71.5	83.2
GPT-Neo-2.7B	87.8	47.7	72.3	72.2	85.1
GPTJ-6B	88.0	51.2	75.4	74.0	87.3
GPT-Neox-20B	82.9	49.6	73.4	74.1	86.4
BLOOM	84.9	46.2	72.4	75.1	88.1
BLOOM-7B1	85.7	43.8	71.8	71.1	86.5
BLOOM-3B	89.3	43.2	72.6	70.4	86.6
BLOOM-1B7	88.9	42.9	70.5	67.8	87.1
BLOOM-1B1	87.5	41.3	68.8	64.0	85.3
OPT-175B	84.4	48.3	75.1	71.2	87.0
OPT-66B	83.5	47.8	73.9	70.8	87.2
OPT-30B	84.4	48.3	73.8	72.0	87.2
OPT-13B	85.1	49.0	72.9	71.6	86.5
OPT-6.7B	83.3	47.4	71.3	70.5	86.3
OPT-2.7B	84.4	48.1	71.3	70.5	85.8
OPT-1.3B	85.7	46.3	69.7	70.5	86.0

Table 4: The performance of the models on XSum with various alternative-choices using avg. PMI as the scoring function.

Model	FIR	FCMG	FIB	FactCC	MFMA
T0-3B	20.0	15.5	29.1	97.7	68.2
T0	14.9	21.4	33.0	96.9	73.2
FLAN-T5-xl	23.6	16.2	29.4	97.7	68.9
FLAN-T5-xxl	21.6	17.6	32.1	98.1	72.0
T5-LM-Adapt-xl	34.1	17.7	23.9	93.1	62.3
T5-LM-Adapt-xxl	28.1	19.2	26.4	95.7	67.0
GPT-Neo-1.3B	37.4	18.1	24.7	94.7	59.1
GPT2-XL	33.6	19.3	26.0	95.3	60.7
GPT-Neo-2.7B	35.9	19.5	26.9	95.8	62.0
GPTJ-6B	28.3	21.1	28.4	96.8	68.9
GPT-Neox-20B	23.4	20.8	30.5	97.0	69.8
BLOOM	26.5	24.3	32.1	97.8	73.1
BLOOM-7B1	39.9	21.5	28.8	96.3	65.6
BLOOM-3B	44.3	20.5	28.2	95.7	63.9
BLOOM-1B7	49.0	20.8	27.1	94.7	61.2
BLOOM-1B1	51.4	20.4	27.4	93.0	59.7
OPT-175B	16.9	23.1	34.4	97.9	77.1
OPT-66B	18.7	22.8	32.3	97.5	75.1
OPT-30B	20.3	21.6	32.6	97.4	72.4
OPT-13B	22.5	21.4	31.0	96.6	73.2
OPT-6.7B	22.0	21.3	28.7	96.7	70.2
OPT-2.7B	29.0	20.1	28.4	96.7	68.7
OPT-1.3B	30.7	19.9	26.3	95.9	64.7

Table 5: The performance of the models on XSum with various alternative-choices using avg. LL as the scoring function.



Model	FIR	FCMG	FIB	FactCC	MFMA
T0-3B	18.3	46.0	49.1	83.2	83.7
T0	16.7	36.8	45.6	89.0	83.7
FLAN-T5-xl	16.7	52.0	49.0	82.0	82.9
FLAN-T5-xxl	16.7	51.2	53.6	81.3	85.6
T5-LM-Adapt-xl	39.0	52.6	54.7	69.9	83.8
T5-LM-Adapt-xxl	35.4	51.5	55.3	76.8	85.1
GPT-Neo-1.3B	58.4	46.5	57.2	60.5	83.9
GPT2-XL	56.1	51.6	54.9	64.5	80.2
GPT-Neo-2.7B	57.5	49.4	55.2	66.3	82.3
GPTJ-6B	55.7	54.9	57.8	66.7	84.3
GPT-Neox-20B	53.0	49.5	58.1	69.2	83.6
BLOOM	53.0	48.9	59.3	72.9	84.7
BLOOM-7B1	59.5	48.5	57.5	67.5	85.2
BLOOM-3B	59.5	49.3	59.9	65.7	85.3
BLOOM-1B7	63.3	46.2	56.6	63.9	83.4
BLOOM-1B1	60.8	44.7	54.9	58.6	82.3
OPT-175B	50.3	50.5	60.0	65.2	86.1
OPT-66B	53.5	50.9	57.5	65.1	84.5
OPT-30B	58.1	49.8	57.6	66.6	85.4
OPT-13B	54.6	51.3	56.6	65.3	83.7
OPT-6.7B	56.3	50.5	55.5	65.3	84.3
OPT-2.7B	56.6	52.1	55.4	66.2	84.2
OPT-1.3B	57.2	48.9	54.0	64.7	82.6

Table 6: The performance of the models on XSum with various alternative-choices using PMI as the scoring function.

Model	FIR	FCMG	FIB	FactCC	MFMA
T0-3B	45.2	15.9	34.4	98.5	73.5
T0	34.7	23.0	38.9	97.9	78.0
FLAN-T5-xl	52.8	18.5	35.6	98.3	74.9
FLAN-T5-xxl	49.4	18.5	39.2	98.3	78.1
T5-LM-Adapt-xl	82.6	23.8	44.6	98.1	71.4
T5-LM-Adapt-xxl	72.2	22.0	43.4	98.3	75.1
GPT-Neo-1.3B	83.3	22.2	46.9	97.0	66.1
GPT2-XL	78.6	22.1	45.6	97.3	67.9
GPT-Neo-2.7B	81.3	23.1	46.8	97.1	67.6
GPTJ-6B	72.2	22.9	47.2	98.0	74.6
GPT-Neox-20B	68.2	26.9	47.7	97.9	75.9
BLOOM	70.6	24.5	48.6	98.5	78.8
BLOOM-7B1	81.7	24.4	48.4	97.6	71.9
BLOOM-3B	85.1	24.4	48.6	97.3	68.5
BLOOM-1B7	87.3	25.4	48.5	96.2	65.1
BLOOM-1B1	90.4	24.7	49.3	96.2	64.2
OPT-175B	53.2	26.4	48.1	98.3	81.8
OPT-66B	61.0	25.5	47.4	98.3	80.2
OPT-30B	60.6	25.6	47.0	98.1	78.3
OPT-13B	66.8	24.6	46.3	98.1	78.8
OPT-6.7B	66.1	25.9	45.6	97.6	75.7
OPT-2.7B	72.6	24.6	45.7	98.1	73.2
OPT-1.3B	77.3	23.1	45.2	97.4	71.8

Table 7: The performance of the models on XSum with various alternative-choices using LL as the scoring function.

Model	FIR	FCMG	FIB	FactCC	MFMA
T0-3B	65.6	7.0	17.7	82.4	98.0
T0	50.0	4.4	11.4	79.9	92.0
FLAN-T5-xl	65.6	7.4	16.0	79.7	100.0
FLAN-T5-xxl	59.4	6.3	13.8	76.5	100.0
T5-LM-Adapt-xl	62.5	4.9	12.7	79.6	99.0
T5-LM-Adapt-xxl	59.4	6.0	12.0	76.8	99.0
GPT-Neo-1.3B	78.1	6.4	8.7	77.7	100.0
GPT2-XL	78.1	8.2	9.8	79.5	99.0
GPT-Neo-2.7B	78.1	7.9	10.1	78.2	99.0
GPTJ-6B	78.1	7.5	8.1	82.0	99.0
GPT-Neox-20B	71.9	8.6	10.5	76.2	97.0
BLOOM	75.0	10.8	9.2	79.3	99.0
BLOOM-7B1	84.4	9.8	10.3	81.8	99.0
BLOOM-3B	78.1	8.0	7.9	78.2	100.0
BLOOM-1B7	84.4	6.8	9.2	76.3	99.0
BLOOM-1B1	84.4	7.5	11.2	75.8	100.0
OPT-175B	71.9	11.9	10.7	75.2	98.0
OPT-66B	71.9	8.8	9.2	75.9	99.0
OPT-30B	71.9	11.1	9.0	77.3	100.0
OPT-13B	75.0	8.2	9.6	79.5	99.0
OPT-6.7B	81.2	10.2	9.9	79.8	99.0
OPT-2.7B	75.0	7.8	9.6	74.1	98.0
OPT-1.3B	78.1	6.8	8.1	75.3	100.0

Table 8: The performance of the models on CNN/DM with various alternative-choices using avg. PMI as the scoring function.

Model	FIR	FCMG	FIB	FactCC	MFMA
T0-3B	40.6	3.3	11.6	90.3	100.0
T0	37.5	2.2	8.3	90.8	100.0
FLAN-T5-xl	40.6	1.7	9.0	91.4	100.0
FLAN-T5-xxl	40.6	1.1	6.1	88.9	100.0
T5-LM-Adapt-xl	40.6	1.6	6.6	88.2	99.0
T5-LM-Adapt-xxl	31.2	1.2	5.3	89.8	100.0
GPT-Neo-1.3B	46.9	0.7	1.3	93.6	99.0
GPT2-XL	56.2	0.9	2.6	92.5	99.0
GPT-Neo-2.7B	50.0	0.8	1.8	92.9	97.0
GPTJ-6B	46.9	0.5	2.0	95.2	99.0
GPT-Neox-20B	40.6	0.2	1.8	94.2	98.0
BLOOM	40.6	0.3	1.8	93.8	99.0
BLOOM-7B1	50.0	1.0	2.8	95.9	100.0
BLOOM-3B	53.1	1.2	2.2	93.5	100.0
BLOOM-1B7	53.1	0.9	2.2	92.9	99.0
BLOOM-1B1	62.5	1.3	2.6	93.6	98.0
OPT-175B	40.6	0.6	2.2	91.4	99.0
OPT-66B	43.8	0.9	2.2	92.8	99.0
OPT-30B	43.8	0.8	2.0	94.1	99.0
OPT-13B	43.8	0.9	1.8	95.5	99.0
OPT-6.7B	56.2	0.9	2.6	94.6	98.0
OPT-2.7B	43.8	1.2	2.6	92.9	98.0
OPT-1.3B	46.9	1.2	2.0	92.5	98.0

Table 9: The performance of the models on CNN/DM with various alternative-choices using avg. LL as the scoring function.

Model	FIR	FCMG	FIB	FactCC	MFMA
T0-3B	46.9	1.6	8.5	76.6	100.0
T0	28.1	1.2	6.1	75.9	96.0
FLAN-T5-xl	40.6	1.6	7.2	74.6	100.0
FLAN-T5-xxl	34.4	1.7	5.9	69.9	100.0
T5-LM-Adapt-xl	34.4	1.1	6.1	69.4	98.0
T5-LM-Adapt-xxl	34.4	0.9	5.3	68.4	99.0
GPT-Neo-1.3B	50.0	0.5	3.7	69.8	99.0
GPT2-XL	43.8	0.4	3.5	69.8	99.0
GPT-Neo-2.7B	46.9	0.4	2.6	66.9	99.0
GPTJ-6B	59.4	0.5	2.4	73.6	99.0
GPT-Neox-20B	56.2	0.4	2.4	69.0	99.0
BLOOM	40.6	0.5	2.4	69.7	99.0
BLOOM-7B1	56.2	0.5	2.9	73.9	100.0
BLOOM-3B	56.2	0.5	2.9	71.1	100.0
BLOOM-1B7	53.1	0.5	3.3	64.8	98.0
BLOOM-1B1	59.4	0.5	3.5	68.4	99.0
OPT-175B	53.1	0.7	2.8	70.4	98.0
OPT-66B	59.4	0.5	2.4	68.1	99.0
OPT-30B	53.1	0.6	3.1	71.9	99.0
OPT-13B	43.8	0.6	3.1	71.3	98.0
OPT-6.7B	53.1	0.5	2.4	72.6	99.0
OPT-2.7B	56.2	0.5	3.1	66.0	98.0
OPT-1.3B	53.1	0.5	3.7	69.3	99.0

Table 10: The performance of the models on CNN/DM with various alternative-choices using PMI as the scoring function.

Model	FIR	FCMG	FIB	FactCC	MFMA
T0-3B	71.9	45.1	52.7	98.7	97.0
T0	62.5	37.4	42.7	97.4	97.0
FLAN-T5-xl	75.0	42.8	48.6	98.4	98.0
FLAN-T5-xxl	68.8	26.9	35.5	97.0	99.0
T5-LM-Adapt-xl	90.6	39.7	45.1	97.0	89.0
T5-LM-Adapt-xxl	68.8	31.4	32.6	98.7	94.0
GPT-Neo-1.3B	78.1	24.3	20.1	97.4	99.0
GPT2-XL	81.2	26.9	26.5	96.6	97.0
GPT-Neo-2.7B	75.0	24.1	19.9	97.0	98.0
GPTJ-6B	78.1	21.0	18.6	97.9	99.0
GPT-Neox-20B	75.0	22.5	20.4	98.0	99.0
BLOOM	59.4	16.7	16.6	98.3	100.0
BLOOM-7B1	78.1	22.1	21.0	97.6	100.0
BLOOM-3B	78.1	25.2	20.6	98.0	98.0
BLOOM-1B7	81.2	23.4	20.1	97.0	98.0
BLOOM-1B1	84.4	26.2	23.2	97.4	98.0
OPT-175B	65.6	25.9	20.8	97.3	99.0
OPT-66B	68.8	26.7	23.6	97.9	99.0
OPT-30B	75.0	25.3	21.0	97.9	100.0
OPT-13B	68.8	28.1	24.3	97.9	100.0
OPT-6.7B	78.1	29.4	26.7	98.7	100.0
OPT-2.7B	71.9	29.5	25.8	98.3	100.0
OPT-1.3B	75.0	27.8	23.8	98.3	100.0

Table 11: The performance of the models on CNN/DM with various alternative-choices using LL as the scoring function.

Model	BART-base	T5-base
T0-3B	93.4	74.9
T0	94.2	71.2
FLAN-T5-xl	94.8	74.3
FLAN-T5-xxl	95.0	77.9
T5-LM-Adapt-xl	94.2	79.3
T5-LM-Adapt-xxl	95.0	81.0
GPT-Neo-1.3B	93.6	79.1
GPT2-XL	91.7	72.9
GPT-Neo-2.7B	94.4	73.7
GPTJ-6B	94.2	78.8
GPT-Neox-20B	95.2	75.7
BLOOM	95.0	79.6
BLOOM-7B1	94.6	76.5
BLOOM-3B	94.4	77.1
BLOOM-1B7	95.0	77.4
BLOOM-1B1	93.2	75.7
OPT-175B	94.6	77.7
OPT-66B	95.2	77.4
OPT-30B	94.8	77.9
OPT-13B	95.0	76.0
OPT-6.7B	95.0	75.7
OPT-2.7B	94.0	75.7
OPT-1.3B	93.8	76.5

Table 12: The performance of the models on XSum with MFMA-generated alternative-choices using avg. PMI as the scoring function.

Model	BART-base	T5-base
T0-3B	79.7	54.2
T0	83.0	61.2
FLAN-T5-xl	81.0	54.2
FLAN-T5-xxl	82.8	58.7
T5-LM-Adapt-xl	71.2	51.4
T5-LM-Adapt-xxl	74.9	57.3
GPT-Neo-1.3B	65.6	51.1
GPT2-XL	66.5	53.6
GPT-Neo-2.7B	69.6	52.8
GPTJ-6B	76.8	59.2
GPT-Neox-20B	76.0	62.3
BLOOM	80.1	64.5
BLOOM-7B1	72.3	57.5
BLOOM-3B	71.4	54.7
BLOOM-1B7	69.4	51.1
BLOOM-1B1	67.9	49.7
OPT-175B	83.0	69.9
OPT-66B	81.8	67.0
OPT-30B	78.7	64.8
OPT-13B	79.5	65.6
OPT-6.7B	76.0	63.1
OPT-2.7B	74.1	62.0
OPT-1.3B	70.8	57.3

Table 13: The performance of the models on XSum with MFMA-generated alternative-choices using avg. LL as the scoring function.



Model	BART-base	T5-base
T0-3B	93.6	71.5
T0	94.2	70.9
FLAN-T5-xl	93.2	70.4
FLAN-T5-xxl	94.4	74.9
T5-LM-Adapt-xl	91.9	74.0
T5-LM-Adapt-xxl	93.6	74.6
GPT-Neo-1.3B	92.3	73.7
GPT2-XL	91.1	66.8
GPT-Neo-2.7B	92.3	70.1
GPTJ-6B	93.2	73.5
GPT-Neox-20B	93.4	71.5
BLOOM	93.2	74.3
BLOOM-7B1	93.8	74.6
BLOOM-3B	94.0	74.6
BLOOM-1B7	93.4	71.2
BLOOM-1B1	91.7	70.7
OPT-175B	94.0	76.5
OPT-66B	93.4	73.7
OPT-30B	94.4	74.3
OPT-13B	94.2	70.9
OPT-6.7B	93.0	73.7
OPT-2.7B	93.6	72.6
OPT-1.3B	92.1	70.9

Table 14: The performance of the models on MFMA-generated alternative-choices using PMI as the scoring function.

Model	BART-base	T5-base
T0-3B	85.9	58.4
T0	88.2	65.6
FLAN-T5-xl	87.4	59.5
FLAN-T5-xxl	89.6	64.0
T5-LM-Adapt-xl	80.3	60.6
T5-LM-Adapt-xxl	84.7	63.4
GPT-Neo-1.3B	73.3	57.3
GPT2-XL	75.4	58.7
GPT-Neo-2.7B	75.8	57.5
GPTJ-6B	83.2	64.0
GPT-Neox-20B	83.2	67.0
BLOOM	86.3	69.6
BLOOM-7B1	78.3	64.0
BLOOM-3B	76.4	58.9
BLOOM-1B7	72.0	56.7
BLOOM-1B1	72.3	54.2
OPT-175B	88.6	73.5
OPT-66B	86.1	72.9
OPT-30B	86.1	68.7
OPT-13B	86.1	69.8
OPT-6.7B	84.3	65.1
OPT-2.7B	81.2	63.4
OPT-1.3B	78.5	63.7

Table 15: The performance of the models on XSum with MFMA-generated alternative-choices using LL as the scoring function.

Model	Date Swap	Entity Swap	Negation	Number Swap	Pronoun
T0-3B	76.4	86.6	94.5	76.5	78.7
T0	85.5	86.9	93.9	92.6	84.8
FLAN-T5-xl	72.7	86.0	96.1	82.4	72.6
FLAN-T5-xxl	76.4	85.5	97.2	85.3	67.1
T5-LM-Adapt-xl	67.3	75.9	89.9	60.3	65.2
T5-LM-Adapt-xxl	69.1	81.4	94.5	70.6	72.0
GPT-Neo-1.3B	52.7	66.3	75.5	42.6	72.0
GPT2-XL	60.0	69.2	82.1	41.2	63.4
GPT-Neo-2.7B	65.5	65.7	81.2	54.4	70.7
GPTJ-6B	60.0	70.6	85.1	54.4	63.4
GPT-Neox-20B	61.8	68.9	86.2	55.9	62.8
BLOOM	60.0	72.1	83.4	67.6	66.5
BLOOM-7B1	60.0	71.5	76.8	52.9	65.9
BLOOM-3B	50.9	69.5	75.7	57.4	69.5
BLOOM-1B7	54.5	65.1	70.5	60.3	73.8
BLOOM-1B1	58.2	63.1	65.9	54.4	66.5
OPT-175B	56.4	64.8	83.2	61.8	59.8
OPT-66B	58.2	63.7	84.0	60.3	57.3
OPT-30B	61.8	65.1	84.5	63.2	59.1
OPT-13B	65.5	68.6	81.6	63.2	55.5
OPT-6.7B	63.6	66.9	80.1	60.3	57.9
OPT-2.7B	60.0	65.1	82.7	51.5	59.1
OPT-1.3B	63.6	63.1	83.2	57.4	58.5

Table 16: The performance of the models on XSum with FactCC-generated alternative-choices using avg. PMI as the scoring function.

Model	Date Swap	Entity Swap	Negation	Number Swap	Pronoun
T0-3B	96.4	96.5	98.7	94.1	99.4
T0	100.0	95.3	96.7	97.1	99.4
FLAN-T5-xl	100.0	96.2	98.7	92.6	99.4
FLAN-T5-xxl	98.2	95.9	99.1	98.5	99.4
T5-LM-Adapt-xl	92.7	91.0	92.8	89.7	100.0
T5-LM-Adapt-xxl	94.5	93.3	96.9	89.7	100.0
GPT-Neo-1.3B	96.4	89.5	97.6	88.2	99.4
GPT2-XL	96.4	91.3	97.8	86.8	100.0
GPT-Neo-2.7B	96.4	92.4	98.2	86.8	100.0
GPTJ-6B	98.2	93.9	98.9	88.2	100.0
GPT-Neox-20B	98.2	93.6	99.3	89.7	100.0
BLOOM	98.2	95.3	99.6	92.6	100.0
BLOOM-7B1	98.2	92.7	99.1	85.3	100.0
BLOOM-3B	92.7	91.6	99.1	85.3	100.0
BLOOM-1B7	92.7	89.8	98.5	83.8	99.4
BLOOM-1B1	90.9	86.9	96.7	85.3	99.4
OPT-175B	100.0	95.6	99.3	92.6	100.0
OPT-66B	98.2	94.8	99.6	89.7	100.0
OPT-30B	98.2	95.1	98.9	91.2	100.0
OPT-13B	98.2	94.8	97.8	88.2	100.0
OPT-6.7B	98.2	95.1	98.5	83.8	100.0
OPT-2.7B	98.2	93.9	98.9	86.8	100.0
OPT-1.3B	96.4	91.9	98.5	89.7	99.4

Table 17: The performance of the models on XSum with FactCC-generated alternative-choices using avg. LL as the scoring function.

Model	Date Swap	Entity Swap	Negation	Number Swap	Pronoun
T0-3B	83.6	83.7	84.2	80.9	80.5
T0	87.3	86.0	92.3	91.2	86.0
FLAN-T5-xl	80.0	78.8	87.1	83.8	74.4
FLAN-T5-xxl	78.2	79.9	86.2	86.8	69.5
T5-LM-Adapt-xl	70.9	70.9	69.8	64.7	70.1
T5-LM-Adapt-xxl	74.5	75.0	79.9	72.1	75.0
GPT-Neo-1.3B	63.6	63.4	57.1	38.2	72.0
GPT2-XL	65.5	64.0	68.5	42.6	63.4
GPT-Neo-2.7B	65.5	64.8	67.8	54.4	70.7
GPTJ-6B	69.1	66.9	69.4	52.9	63.4
GPT-Neox-20B	65.5	66.0	76.4	55.9	62.8
BLOOM	65.5	69.5	79.9	64.7	66.5
BLOOM-7B1	63.6	67.4	71.3	50.0	65.9
BLOOM-3B	58.2	65.4	67.4	52.9	69.5
BLOOM-1B7	54.5	63.7	63.2	52.9	73.8
BLOOM-1B1	58.2	59.9	56.2	50.0	66.5
OPT-175B	54.5	61.9	71.1	64.7	59.8
OPT-66B	67.3	58.7	73.3	60.3	57.3
OPT-30B	61.8	62.5	73.3	64.7	59.1
OPT-13B	67.3	64.5	69.4	63.2	55.5
OPT-6.7B	67.3	62.8	70.7	57.4	57.9
OPT-2.7B	63.6	65.4	72.2	50.0	59.1
OPT-1.3B	67.3	60.5	71.1	55.9	58.5

Table 18: The performance of the models on XSum with FactCC-generated alternative-choices using PMI as the scoring function.

Model	Date Swap	Entity Swap	Negation	Number Swap	Pronoun
T0-3B	98.2	96.8	100.0	95.6	99.4
T0	98.2	95.6	99.1	98.5	98.8
FLAN-T5-xl	100.0	96.2	100.0	94.1	99.4
FLAN-T5-xxl	98.2	95.6	100.0	98.5	99.4
T5-LM-Adapt-xl	98.2	95.9	100.0	91.2	100.0
T5-LM-Adapt-xxl	98.2	96.8	100.0	89.7	100.0
GPT-Neo-1.3B	96.4	93.9	99.8	88.2	99.4
GPT2-XL	96.4	95.1	99.6	86.8	100.0
GPT-Neo-2.7B	96.4	94.8	99.1	88.2	100.0
GPTJ-6B	98.2	96.2	100.0	88.2	100.0
GPT-Neox-20B	98.2	95.9	99.8	89.7	100.0
BLOOM	100.0	97.1	99.8	91.2	100.0
BLOOM-7B1	98.2	95.3	100.0	86.8	100.0
BLOOM-3B	92.7	94.8	100.0	88.2	100.0
BLOOM-1B7	90.9	93.0	99.3	88.2	99.4
BLOOM-1B1	94.5	92.2	99.6	86.8	99.4
OPT-175B	100.0	96.2	99.8	92.6	100.0
OPT-66B	98.2	97.1	100.0	89.7	100.0
OPT-30B	98.2	96.5	99.6	91.2	100.0
OPT-13B	100.0	96.8	99.8	86.8	100.0
OPT-6.7B	100.0	96.2	99.6	83.8	100.0
OPT-2.7B	100.0	96.5	100.0	86.8	100.0
OPT-1.3B	98.2	94.8	100.0	88.2	99.4

Table 19: The performance of the models on XSum with FactCC-generated alternative-choices using LL as the scoring function.

Model	Date Swap	Entity Swap	Negation	Number Swap	Pronoun
T0-3B	81.8	78.3	91.6	75.0	80.0
T0	81.8	73.9	94.0	66.7	73.3
flan-t5-xl	78.2	75.4	92.8	77.8	66.7
flan-t5-xxl	76.4	71.0	90.4	69.4	66.7
t5-lm-adapt-xl	80.0	81.2	84.3	75.0	71.1
t5-lm-adapt-xxl	80.0	71.0	86.7	75.0	66.7
GPT-Neo-1.3B	72.7	75.4	85.5	75.0	75.6
GPT2-XL	78.2	79.7	86.7	75.0	71.1
GPT-Neo-2.7B	74.5	73.9	85.5	80.6	75.6
GPTJ-6B	80.0	76.8	91.6	83.3	75.6
GPT-Neox-20B	67.3	72.5	88.0	77.8	71.1
BLOOM	80.0	75.4	85.5	77.8	75.6
BLOOM-7B1	81.8	78.3	84.3	80.6	84.4
BLOOM-3B	80.0	79.7	75.9	80.6	75.6
BLOOM-1B7	78.2	73.9	77.1	77.8	75.6
BLOOM-1B1	80.0	71.0	78.3	77.8	73.3
OPT-175B	70.9	72.5	84.3	75.0	68.9
OPT-66B	69.1	72.5	83.1	75.0	77.8
OPT-30B	74.5	68.1	88.0	77.8	77.8
OPT-13B	80.0	78.3	84.3	72.2	77.8
OPT-6.7B	76.4	84.1	88.0	66.7	71.1
OPT-2.7B	65.5	76.8	81.9	69.4	68.9
OPT-1.3B	72.7	75.4	79.5	72.2	73.3

Table 20: The performance of the models on CNN/DM with FactCC-generated alternative-choices using avg. PMI as the scoring function.

Model	Date Swap	Entity Swap	Negation	Number Swap	Pronoun
T0-3B	92.7	89.9	91.6	86.1	88.9
T0	92.7	92.8	94.0	80.6	86.7
flan-t5-xl	94.5	92.8	91.6	86.1	88.9
flan-t5-xxl	92.7	88.4	94.0	80.6	82.2
t5-lm-adapt-xl	89.1	88.4	89.2	86.1	86.7
t5-lm-adapt-xxl	90.9	92.8	88.0	88.9	86.7
GPT-Neo-1.3B	87.3	97.1	97.6	86.1	93.3
GPT2-XL	87.3	94.2	95.2	88.9	93.3
GPT-Neo-2.7B	89.1	95.7	94.0	91.7	91.1
GPTJ-6B	92.7	95.7	97.6	91.7	95.6
GPT-Neox-20B	90.9	95.7	96.4	91.7	93.3
BLOOM	92.7	94.2	95.2	88.9	95.6
BLOOM-7B1	92.7	97.1	98.8	91.7	95.6
BLOOM-3B	94.5	95.7	95.2	83.3	93.3
BLOOM-1B7	92.7	95.7	94.0	86.1	91.1
BLOOM-1B1	90.9	97.1	95.2	86.1	93.3
OPT-175B	89.1	92.8	94.0	91.7	86.7
OPT-66B	87.3	94.2	95.2	91.7	93.3
OPT-30B	89.1	94.2	97.6	94.4	93.3
OPT-13B	94.5	95.7	96.4	94.4	95.6
OPT-6.7B	92.7	97.1	95.2	91.7	93.3
OPT-2.7B	89.1	95.7	95.2	88.9	91.1
OPT-1.3B	89.1	94.2	95.2	86.1	93.3

Table 21: The performance of the models on CNN/DM with FactCC-generated alternative-choices using avg. LL as the scoring function.

Model	Date Swap	Entity Swap	Negation	Number Swap	Pronoun
T0-3B	74.5	73.9	83.1	72.2	75.6
T0	78.2	72.5	88.0	63.9	66.7
flan-t5-xl	76.4	73.9	79.5	75.0	64.4
flan-t5-xxl	74.5	65.2	80.7	66.7	55.6
t5-lm-adapt-xl	69.1	75.4	67.5	66.7	64.4
t5-lm-adapt-xxl	72.7	68.1	72.3	69.4	55.6
GPT-Neo-1.3B	63.6	76.8	68.7	63.9	71.1
GPT2-XL	74.5	75.4	67.5	66.7	60.0
GPT-Neo-2.7B	63.6	71.0	65.1	63.9	68.9
GPTJ-6B	69.1	72.5	74.7	86.1	68.9
GPT-Neox-20B	61.8	68.1	74.7	77.8	62.2
BLOOM	69.1	68.1	74.7	75.0	60.0
BLOOM-7B1	74.5	73.9	74.7	69.4	75.6
BLOOM-3B	74.5	76.8	65.1	72.2	66.7
BLOOM-1B7	65.5	69.6	57.8	66.7	66.7
BLOOM-1B1	70.9	68.1	67.5	66.7	68.9
OPT-175B	65.5	68.1	75.9	77.8	64.4
OPT-66B	61.8	68.1	71.1	69.4	68.9
OPT-30B	72.7	66.7	78.3	72.2	68.9
OPT-13B	74.5	73.9	71.1	69.4	64.4
OPT-6.7B	69.1	79.7	78.3	63.9	60.0
OPT-2.7B	65.5	73.9	63.9	58.3	62.2
OPT-1.3B	65.5	72.5	69.9	69.4	66.7

Table 22: The performance of the models on CNN/DM with FactCC-generated alternative-choices using PMI as the scoring function.

Model	Date Swap	Entity Swap	Negation	Number Swap	Pronoun
T0-3B	96.4	100.0	100.0	94.4	100.0
T0	96.4	100.0	100.0	88.9	95.6
flan-t5-xl	98.2	100.0	100.0	91.7	97.8
flan-t5-xxl	96.4	98.6	98.8	88.9	97.8
t5-lm-adapt-xl	98.2	98.6	97.6	88.9	97.8
t5-lm-adapt-xxl	96.4	100.0	100.0	94.4	100.0
GPT-Neo-1.3B	90.9	100.0	100.0	91.7	100.0
GPT2-XL	92.7	97.1	98.8	94.4	97.8
GPT-Neo-2.7B	90.9	98.6	100.0	91.7	100.0
GPTJ-6B	94.5	98.6	100.0	94.4	100.0
GPT-Neox-20B	94.5	100.0	100.0	91.7	100.0
BLOOM	96.4	98.6	100.0	94.4	100.0
BLOOM-7B1	94.5	98.6	98.8	94.4	100.0
BLOOM-3B	96.4	100.0	100.0	88.9	100.0
BLOOM-1B7	94.5	98.6	98.8	94.4	95.6
BLOOM-1B1	94.5	100.0	98.8	91.7	97.8
OPT-175B	94.5	98.6	100.0	94.4	95.6
OPT-66B	94.5	98.6	100.0	94.4	100.0
OPT-30B	94.5	98.6	100.0	94.4	100.0
OPT-13B	94.5	98.6	100.0	94.4	100.0
OPT-6.7B	96.4	100.0	100.0	94.4	100.0
OPT-2.7B	94.5	100.0	100.0	94.4	100.0
OPT-1.3B	94.5	100.0	100.0	94.4	100.0

Table 23: The performance of the models on CNN/DM with FactCC-generated alternative-choices using LL as the scoring function.

Model	BART-base	BART-large	BLOOM-560m	distil-BART	distil-PEGASUS	PEGASUS	T5-large
T0-3B	62.2	33.7	90.5	32.2	17.5	25.8	94.1
T0	64.9	18.6	85.7	23.3	14.3	29.0	76.5
FLAN-T5-xl	64.9	38.4	90.5	38.9	25.4	38.7	82.4
FLAN-T5-xxl	70.3	46.5	90.5	42.2	28.6	35.5	82.4
T5-LM-Adapt-xl	56.8	45.3	76.2	44.4	31.7	35.5	82.4
T5-LM-Adapt-xxl	59.5	45.3	71.4	45.6	34.9	38.7	76.5
GPT-Neo-1.3B	59.5	38.4	66.7	53.3	28.6	22.6	76.5
GPT2-XL	62.2	40.7	61.9	50.0	27.0	33.9	52.9
GPT-Neo-2.7B	56.8	41.9	57.1	52.2	28.6	33.9	76.5
GPTJ-6B	64.9	40.7	71.4	61.1	38.1	29.0	64.7
GPT-Neox-20B	73.0	36.0	61.9	58.9	33.3	32.3	64.7
BLOOM	56.8	41.9	71.4	51.1	27.0	25.8	70.6
BLOOM-7B1	56.8	34.9	52.4	50.0	30.2	27.4	70.6
BLOOM-3B	64.9	30.2	57.1	50.0	23.8	32.3	64.7
BLOOM-1B7	70.3	33.7	52.4	45.6	22.2	29.0	70.6
BLOOM-1B1	62.2	32.6	57.1	43.3	22.2	30.6	58.8
OPT-175B	59.5	41.9	66.7	52.2	34.9	25.8	76.5
OPT-66B	75.7	38.4	52.4	57.8	31.7	22.6	70.6
OPT-30B	62.2	39.5	52.4	55.6	38.1	27.4	70.6
OPT-13B	64.9	44.2	57.1	54.4	38.1	22.6	70.6
OPT-6.7B	73.0	38.4	52.4	58.9	34.9	17.7	70.6
OPT-2.7B	64.9	37.2	52.4	54.4	38.1	29.0	70.6
OPT-1.3B	62.2	40.7	61.9	53.3	28.6	27.4	58.8

Table 24: The performance of the models on XSum with factually consistent model-generated alternative-choices using avg. PMI as the scoring function.

Model	BART-base	BART-large	BLOOM-560m	distil-BART	distil-PEGASUS	PEGASUS	T5-large
T0-3B	27.0	2.3	95.2	3.3	7.9	3.2	52.9
T0	51.4	9.3	95.2	6.7	4.8	8.1	58.8
FLAN-T5-xl	27.0	2.3	95.2	2.2	7.9	8.1	52.9
FLAN-T5-xxl	37.8	5.8	95.2	4.4	4.8	4.8	52.9
T5-LM-Adapt-xl	32.4	7.0	38.1	11.1	17.5	12.9	29.4
T5-LM-Adapt-xxl	40.5	5.8	47.6	7.8	15.9	16.1	41.2
GPT-Neo-1.3B	40.5	7.0	42.9	16.7	6.3	11.3	41.2
GPT2-XL	35.1	5.8	47.6	13.3	14.3	14.5	47.1
GPT-Neo-2.7B	35.1	10.5	38.1	18.9	9.5	12.9	41.2
GPTJ-6B	51.4	9.3	52.4	17.8	9.5	8.1	47.1
GPT-Neox-20B	51.4	5.8	52.4	21.1	9.5	8.1	47.1
BLOOM	51.4	10.5	66.7	20.0	9.5	12.9	58.8
BLOOM-7B1	43.2	5.8	57.1	20.0	15.9	9.7	47.1
BLOOM-3B	35.1	9.3	52.4	21.1	9.5	14.5	35.3
BLOOM-1B7	32.4	10.5	47.6	22.2	15.9	9.7	35.3
BLOOM-1B1	27.0	11.6	47.6	22.2	12.7	16.1	23.5
OPT-175B	56.8	7.0	66.7	20.0	11.1	9.7	47.1
OPT-66B	54.1	5.8	66.7	20.0	12.7	9.7	47.1
OPT-30B	48.6	7.0	61.9	18.9	9.5	9.7	52.9
OPT-13B	51.4	5.8	61.9	17.8	7.9	9.7	58.8
OPT-6.7B	51.4	4.7	47.6	15.6	12.7	12.9	58.8
OPT-2.7B	45.9	4.7	47.6	18.9	12.7	11.3	41.2
OPT-1.3B	43.2	5.8	52.4	17.8	12.7	9.7	41.2

Table 25: The performance of the models on XSum with factually consistent model-generated alternative-choices using avg. LL as the scoring function.



Model	BART-base	BART-large	BLOOM-560m	distil-BART	distil-PEGASUS	PEGASUS	T5-large
T0-3B	64.9	27.9	66.7	34.4	38.1	45.2	76.5
T0	64.9	18.6	81.0	22.2	22.2	32.3	82.4
FLAN-T5-xl	59.5	39.5	66.7	44.4	47.6	48.4	58.8
FLAN-T5-xxl	59.5	40.7	57.1	40.0	49.2	46.8	64.7
T5-LM-Adapt-xl	56.8	40.7	38.1	48.9	50.8	51.6	64.7
T5-LM-Adapt-xxl	59.5	41.9	42.9	43.3	47.6	51.6	58.8
GPT-Neo-1.3B	67.6	36.0	4.8	54.4	42.9	35.5	58.8
GPT2-XL	67.6	38.4	28.6	53.3	49.2	46.8	52.9
GPT-Neo-2.7B	64.9	37.2	9.5	56.7	46.0	43.5	58.8
GPTJ-6B	70.3	40.7	9.5	62.2	55.6	48.4	58.8
GPT-Neox-20B	73.0	31.4	19.0	55.6	46.0	45.2	58.8
BLOOM	67.6	45.3	14.3	44.4	41.3	40.3	70.6
BLOOM-7B1	62.2	40.7	9.5	53.3	42.9	40.3	64.7
BLOOM-3B	73.0	34.9	19.0	54.4	36.5	48.4	64.7
BLOOM-1B7	62.2	37.2	14.3	43.3	39.7	48.4	52.9
BLOOM-1B1	62.2	32.6	9.5	46.7	38.1	46.8	52.9
OPT-175B	67.6	40.7	9.5	54.4	49.2	38.7	70.6
OPT-66B	75.7	38.4	4.8	54.4	52.4	37.1	70.6
OPT-30B	67.6	43.0	14.3	52.2	46.0	38.7	58.8
OPT-13B	64.9	43.0	9.5	53.3	50.8	41.9	64.7
OPT-6.7B	73.0	38.4	4.8	58.9	52.4	37.1	52.9
OPT-2.7B	73.0	40.7	9.5	57.8	52.4	40.3	58.8
OPT-1.3B	64.9	43.0	4.8	52.2	44.4	43.5	47.1

Table 26: The performance of the models on XSum with factually consistent model-generated alternative-choices using PMI as the scoring function.

Model	BART-base	BART-large	BLOOM-560m	distil-BART	distil-PEGASUS	PEGASUS	T5-large
T0-3B	21.6	4.7	100.0	5.6	6.3	4.8	47.1
T0	48.6	9.3	100.0	10.0	6.3	9.7	64.7
FLAN-T5-xl	27.0	7.0	100.0	4.4	6.3	11.3	52.9
FLAN-T5-xxl	32.4	7.0	100.0	4.4	3.2	12.9	47.1
T5-LM-Adapt-xl	32.4	12.8	95.2	15.6	14.3	11.3	47.1
T5-LM-Adapt-xxl	32.4	10.5	90.5	11.1	11.1	11.3	58.8
GPT-Neo-1.3B	37.8	9.3	85.7	23.3	6.3	11.3	35.3
GPT2-XL	32.4	8.1	85.7	16.7	9.5	14.5	52.9
GPT-Neo-2.7B	37.8	9.3	85.7	23.3	7.9	11.3	47.1
GPTJ-6B	35.1	7.0	95.2	22.2	11.1	8.1	52.9
GPT-Neox-20B	51.4	10.5	95.2	26.7	9.5	9.7	58.8
BLOOM	40.5	12.8	95.2	17.8	7.9	9.7	64.7
BLOOM-7B1	40.5	9.3	90.5	23.3	9.5	11.3	52.9
BLOOM-3B	37.8	10.5	90.5	23.3	11.1	12.9	41.2
BLOOM-1B7	40.5	12.8	85.7	25.6	11.1	12.9	41.2
BLOOM-1B1	32.4	16.3	81.0	23.3	9.5	12.9	47.1
OPT-175B	51.4	9.3	95.2	24.4	6.3	12.9	64.7
OPT-66B	43.2	11.6	95.2	21.1	7.9	11.3	64.7
OPT-30B	45.9	10.5	95.2	23.3	4.8	12.9	64.7
OPT-13B	48.6	9.3	95.2	20.0	6.3	9.7	64.7
OPT-6.7B	45.9	9.3	95.2	23.3	9.5	11.3	64.7
OPT-2.7B	37.8	12.8	95.2	20.0	7.9	11.3	58.8
OPT-1.3B	37.8	12.8	95.2	20.0	4.8	9.7	47.1

Table 27: The performance of the models on XSum with factually consistent model-generated alternative-choices using LL as the scoring function.

Model	B	BL	HG	L	MS	MI	NS	OD	O	PB	PT	R	RE	T	TS
T0-3B	1.4	3.9	1.3	2.1	5.1	4.5	23.7	39.3	8.7	3.4	0.0	23.2	2.6	4.7	3.7
T0	2.7	3.9	0.0	1.1	2.5	6.1	10.5	21.4	4.3	1.1	1.4	8.7	3.9	4.7	7.4
FLAN-T5-xl	1.4	3.9	1.3	0.0	3.8	3.0	25.0	28.6	0.0	2.3	1.4	23.2	5.3	6.2	5.6
FLAN-T5-xxl	2.7	2.6	1.3	1.1	2.5	3.0	14.5	35.7	0.0	0.0	1.4	15.9	6.6	4.7	1.9
T5-LM-Adapt-xl	5.4	2.6	0.0	0.0	0.0	3.0	18.4	35.7	0.0	0.0	0.0	20.3	2.6	3.1	1.9
T5-LM-Adapt-xxl	5.4	5.2	2.6	1.1	5.1	6.1	14.5	28.6	0.0	2.3	1.4	17.4	5.3	6.2	1.9
GPT-Neo-1.3B	1.4	1.3	0.0	1.1	3.8	4.5	35.5	32.1	2.2	1.1	2.7	20.3	2.6	3.1	0.0
GPT2-XL	1.4	2.6	2.6	1.1	2.5	6.1	44.7	14.3	0.0	2.3	2.7	40.6	2.6	0.0	1.9
GPT-Neo-2.7B	4.1	3.9	3.8	1.1	6.3	3.0	31.6	28.6	2.2	2.3	2.7	24.6	6.6	6.2	3.7
GPTJ-6B	4.1	5.2	5.1	2.1	5.1	6.1	25.0	14.3	2.2	3.4	6.8	20.3	6.6	6.2	3.7
GPT-Neox-20B	5.4	6.5	6.4	2.1	8.9	7.6	23.7	14.3	4.3	5.7	6.8	23.2	7.9	6.2	3.7
BLOOM	5.4	5.2	7.7	5.3	11.4	9.1	28.9	17.9	4.3	6.8	8.2	26.1	14.5	10.9	3.7
BLOOM-7B1	4.1	5.2	6.4	5.3	5.1	9.1	27.6	25.0	6.5	5.7	8.2	24.6	7.9	10.9	5.6
BLOOM-3B	5.4	5.2	3.8	3.2	3.8	4.5	28.9	28.6	2.2	4.5	4.1	20.3	5.3	7.8	3.7
BLOOM-1B7	2.7	2.6	2.6	1.1	3.8	3.0	27.6	32.1	2.2	2.3	2.7	23.2	5.3	4.7	1.9
BLOOM-1B1	2.7	2.6	1.3	0.0	5.1	4.5	31.6	32.1	2.2	1.1	4.1	27.5	7.9	4.7	0.0
OPT-175B	10.8	11.7	11.5	5.3	10.1	10.6	30.3	14.3	4.3	8.0	9.6	20.3	13.2	10.9	7.4
OPT-66B	9.5	9.1	9.0	3.2	8.9	6.1	19.7	10.7	4.3	5.7	8.2	15.9	9.2	7.8	5.6
OPT-30B	14.9	10.4	9.0	4.2	10.1	10.6	25.0	10.7	6.5	9.1	9.6	17.4	11.8	9.4	7.4
OPT-13B	6.8	6.5	5.1	2.1	6.3	7.6	23.7	14.3	2.2	4.5	8.2	20.3	7.9	7.8	3.7
OPT-6.7B	8.1	7.8	9.0	4.2	7.6	9.1	25.0	17.9	6.5	6.8	8.2	21.7	10.5	9.4	5.6
OPT-2.7B	6.8	5.2	5.1	1.1	3.8	6.1	26.3	17.9	4.3	4.5	5.5	20.3	6.6	7.8	1.9
OPT-1.3B	9.5	5.2	3.8	1.1	3.8	6.1	23.7	17.9	2.2	2.3	4.1	15.9	5.3	6.2	1.9

Table 28: The performance of the models on CNN/DM with factually consistent model-generated alternative-choices using avg. PMI as the scoring function. The models are BanditSumm (B), BERT\_LSTM\_PN\_RL (BL), Heter-Graph (HG), Lead3 (L), MatchSumm (MS), MI-unsup (MI), NeuSumm (NS), Oracle (discourse) (OD), Oracle (O), Pacsum (bert) (PB), Pacsum (tfidf) (PT), Refresh (R), RNN\_Ext\_RL (RE), Textrank (T), Textrank (st) (TS)

Model	B	BL	HG	L	MS	MI	NS	OD	O	PB	PT	R	RE	T	TS
T0-3B	1.4	0.0	0.0	1.1	1.3	1.5	13.2	14.3	2.2	0.0	1.4	8.7	5.3	3.1	3.7
T0	1.4	0.0	0.0	1.1	0.0	3.0	3.9	10.7	4.3	0.0	1.4	1.4	6.6	3.1	3.7
FLAN-T5-xl	1.4	0.0	0.0	0.0	0.0	0.0	5.3	0.0	4.3	0.0	0.0	5.8	0.0	4.7	3.7
FLAN-T5-xxl	0.0	0.0	0.0	0.0	0.0	1.5	1.3	3.6	2.2	0.0	0.0	1.4	0.0	3.1	3.7
T5-LM-Adapt-xl	0.0	0.0	0.0	0.0	0.0	0.0	5.3	7.1	2.2	0.0	1.4	5.8	2.6	3.1	1.9
T5-LM-Adapt-xxl	1.4	0.0	0.0	0.0	0.0	1.5	1.3	3.6	2.2	0.0	1.4	1.4	5.3	3.1	0.0
GPT-Neo-1.3B	0.0	0.0	0.0	0.0	0.0	0.0	2.6	0.0	2.2	0.0	0.0	4.3	0.0	1.6	0.0
GPT2-XL	0.0	0.0	0.0	0.0	0.0	1.5	3.9	0.0	2.2	0.0	0.0	4.3	0.0	1.6	0.0
GPT-Neo-2.7B	0.0	0.0	0.0	0.0	0.0	0.0	3.9	0.0	2.2	0.0	0.0	4.3	0.0	1.6	0.0
GPTJ-6B	0.0	0.0	0.0	0.0	0.0	0.0	2.6	0.0	2.2	0.0	0.0	1.4	0.0	1.6	0.0
GPT-Neox-20B	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.2	0.0	0.0	0.0	0.0	1.6	0.0
BLOOM	0.0	0.0	0.0	0.0	0.0	0.0	1.3	0.0	2.2	0.0	0.0	0.0	0.0	1.6	0.0
BLOOM-7B1	0.0	0.0	0.0	0.0	0.0	1.5	3.9	0.0	2.2	0.0	0.0	4.3	0.0	1.6	1.9
BLOOM-3B	0.0	0.0	0.0	0.0	0.0	1.5	5.3	0.0	2.2	0.0	0.0	5.8	0.0	1.6	1.9
BLOOM-1B7	1.4	0.0	0.0	0.0	0.0	1.5	2.6	3.6	2.2	0.0	0.0	4.3	0.0	0.0	0.0
BLOOM-1B1	2.7	1.3	0.0	1.1	0.0	1.5	2.6	0.0	2.2	0.0	0.0	5.8	0.0	1.6	1.9
OPT-175B	1.4	0.0	0.0	0.0	0.0	1.5	1.3	0.0	2.2	0.0	0.0	1.4	0.0	1.6	0.0
OPT-66B	1.4	0.0	0.0	0.0	0.0	1.5	3.9	0.0	2.2	0.0	0.0	2.9	0.0	1.6	0.0
OPT-30B	0.0	0.0	0.0	0.0	0.0	1.5	3.9	0.0	2.2	0.0	0.0	2.9	0.0	1.6	0.0
OPT-13B	0.0	0.0	0.0	0.0	0.0	1.5	5.3	0.0	2.2	0.0	0.0	2.9	0.0	1.6	0.0
OPT-6.7B	0.0	0.0	0.0	0.0	0.0	1.5	6.6	0.0	2.2	0.0	0.0	1.4	0.0	1.6	0.0
OPT-2.7B	1.4	0.0	0.0	0.0	0.0	1.5	6.6	0.0	2.2	0.0	0.0	4.3	0.0	1.6	0.0
OPT-1.3B	1.4	0.0	0.0	0.0	0.0	1.5	6.6	0.0	2.2	0.0	0.0	4.3	0.0	1.6	0.0

Table 29: The performance of the models on CNN/DM with factually consistent model-generated alternative-choices using avg. LL as the scoring function. The models are BanditSumm (B), BERT\_LSTM\_PN\_RL (BL), Heter-Graph (HG), Lead3 (L), MatchSumm (MS), MI-unsup (MI), NeuSumm (NS), Oracle (discourse) (OD), Oracle (O), Pacsum (bert) (PB), Pacsum (tfidf) (PT), Refresh (R), RNN\_Ext\_RL (RE), Textrank (T), Textrank (st) (TS)

Model	B	BL	HG	L	MS	MI	NS	OD	O	PB	PT	R	RE	T	TS
T0-3B	1.4	1.3	0.0	0.0	0.0	0.0	1.3	21.4	6.5	0.0	0.0	1.4	0.0	4.7	1.9
T0	1.4	0.0	0.0	0.0	0.0	0.0	0.0	14.3	6.5	0.0	0.0	0.0	0.0	4.7	1.9
FLAN-T5-xl	0.0	1.3	0.0	0.0	0.0	0.0	1.3	10.7	4.3	0.0	0.0	0.0	0.0	4.7	1.9
FLAN-T5-xxl	1.4	0.0	0.0	0.0	0.0	0.0	0.0	14.3	4.3	0.0	0.0	0.0	0.0	3.1	1.9
T5-LM-Adapt-xl	0.0	0.0	0.0	0.0	0.0	0.0	0.0	17.9	4.3	0.0	0.0	0.0	0.0	4.7	1.9
T5-LM-Adapt-xxl	0.0	0.0	0.0	0.0	0.0	0.0	0.0	14.3	4.3	0.0	0.0	0.0	0.0	3.1	1.9
GPT-Neo-1.3B	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3.6	4.3	0.0	0.0	0.0	0.0	1.6	1.9
GPT2-XL	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3.6	2.2	0.0	0.0	0.0	0.0	1.6	1.9
GPT-Neo-2.7B	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3.6	4.3	0.0	0.0	0.0	0.0	0.0	1.9
GPTJ-6B	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3.6	4.3	0.0	0.0	0.0	0.0	1.6	1.9
GPT-Neox-20B	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3.6	4.3	0.0	0.0	0.0	0.0	0.0	1.9
BLOOM	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3.6	4.3	0.0	0.0	0.0	0.0	1.6	1.9
BLOOM-7B1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3.6	4.3	0.0	0.0	0.0	0.0	1.6	1.9
BLOOM-3B	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3.6	4.3	0.0	0.0	0.0	0.0	1.6	1.9
BLOOM-1B7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3.6	4.3	0.0	0.0	0.0	0.0	1.6	1.9
BLOOM-1B1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3.6	4.3	0.0	0.0	0.0	0.0	1.6	1.9
OPT-175B	1.4	0.0	0.0	0.0	0.0	0.0	0.0	3.6	4.3	0.0	0.0	0.0	0.0	3.1	1.9
OPT-66B	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3.6	4.3	0.0	0.0	0.0	0.0	1.6	1.9
OPT-30B	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3.6	4.3	0.0	0.0	0.0	0.0	3.1	1.9
OPT-13B	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3.6	4.3	0.0	0.0	0.0	0.0	3.1	1.9
OPT-6.7B	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3.6	4.3	0.0	0.0	0.0	0.0	1.6	1.9
OPT-2.7B	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3.6	4.3	0.0	0.0	0.0	0.0	1.6	1.9
OPT-1.3B	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3.6	4.3	0.0	0.0	0.0	0.0	1.6	1.9

Table 30: The performance of the models on CNN/DM with factually consistent model-generated alternative-choices using PMI as the scoring function. The models are BanditSumm (B), BERT\_LSTM\_PN\_RL (BL), Heter-Graph (HG), Lead3 (L), MatchSumm (MS), MI-unsup (MI), NeuSumm (NS), Oracle (discourse) (OD), Oracle (O), Pacsum (bert) (PB), Pacsum (tfidf) (PT), Refresh (R), RNN\_Ext\_RL (RE), Textrank (T), Textrank (st) (TS)

Model	B	BL	HG	L	MS	MI	NS	OD	O	PB	PT	R	RE	T	TS
T0-3B	31.1	24.7	42.3	25.3	44.3	47.0	98.7	75.0	21.7	30.7	35.6	88.4	64.5	31.2	29.6
T0	35.1	20.8	26.9	13.7	26.6	45.5	85.5	57.1	23.9	23.9	28.8	76.8	47.4	32.8	35.2
FLAN-T5-xl	31.1	26.0	37.2	21.1	32.9	48.5	94.7	53.6	19.6	30.7	28.8	91.3	56.6	35.9	33.3
FLAN-T5-xxl	20.3	11.7	16.7	8.4	15.2	36.4	76.3	46.4	13.0	12.5	17.8	55.1	38.2	15.6	20.4
T5-LM-Adapt-xl	52.7	41.6	28.2	12.6	22.8	60.6	94.7	57.1	17.4	21.6	23.3	82.6	48.7	20.3	22.2
T5-LM-Adapt-xxl	47.3	36.4	14.1	6.3	13.9	57.6	82.9	32.1	10.9	11.4	15.1	68.1	40.8	15.6	22.2
GPT-Neo-1.3B	31.1	24.7	9.0	2.1	8.9	36.4	85.5	25.0	2.2	9.1	17.8	63.8	19.7	14.1	16.7
GPT2-XL	35.1	27.3	7.7	7.4	6.3	50.0	89.5	25.0	0.0	11.4	16.4	69.6	27.6	12.5	16.7
GPT-Neo-2.7B	35.1	28.6	5.1	1.1	7.6	43.9	85.5	21.4	0.0	8.0	15.1	55.1	26.3	10.9	16.7
GPTJ-6B	27.0	23.4	9.0	1.1	8.9	39.4	73.7	17.9	2.2	6.8	12.3	44.9	21.1	12.5	14.8
GPT-Neox-20B	28.4	24.7	10.3	4.2	10.1	31.8	72.4	21.4	4.3	9.1	13.7	44.9	27.6	18.8	16.7
BLOOM	18.9	14.3	7.7	0.0	5.1	27.3	57.9	21.4	0.0	4.5	12.3	36.2	25.0	9.4	14.8
BLOOM-7B1	31.1	22.1	6.4	3.2	6.3	39.4	80.3	21.4	0.0	9.1	13.7	46.4	23.7	12.5	14.8
BLOOM-3B	41.9	31.2	9.0	3.2	10.1	45.5	80.3	25.0	0.0	8.0	13.7	60.9	23.7	10.9	14.8
BLOOM-1B7	36.5	28.6	7.7	2.1	7.6	43.9	82.9	28.6	2.2	4.5	15.1	58.0	21.1	6.2	9.3
BLOOM-1B1	36.5	28.6	7.7	5.3	10.1	47.0	84.2	25.0	2.2	9.1	16.4	65.2	26.3	14.1	14.8
OPT-175B	45.9	33.8	11.5	1.1	8.9	48.5	78.9	25.0	2.2	10.2	12.3	55.1	25.0	14.1	16.7
OPT-66B	44.6	33.8	10.3	4.2	6.3	48.5	82.9	21.4	4.3	12.5	16.4	49.3	28.9	17.2	16.7
OPT-30B	44.6	31.2	7.7	3.2	6.3	47.0	81.6	21.4	2.2	9.1	15.1	56.5	22.4	14.1	16.7
OPT-13B	47.3	33.8	10.3	2.1	8.9	48.5	86.8	25.0	8.7	11.4	16.4	59.4	28.9	17.2	18.5
OPT-6.7B	44.6	33.8	11.5	4.2	8.9	54.5	89.5	28.6	6.5	12.5	19.2	62.3	27.6	20.3	20.4
OPT-2.7B	45.9	36.4	14.1	3.2	8.9	50.0	86.8	21.4	6.5	14.8	19.2	63.8	31.6	17.2	20.4
OPT-1.3B	45.9	40.3	10.3	3.2	8.9	50.0	85.5	17.9	2.2	12.5	16.4	63.8	21.1	15.6	18.5

Table 31: The performance of the models on CNN/DM with factually consistent model-generated alternative-choices using LL as the scoring function. The models are BanditSumm (B), BERT\_LSTM\_PN\_RL (BL), Heter-Graph (HG), Lead3 (L), MatchSumm (MS), MI-unsup (MI), NeuSumm (NS), Oracle (discourse) (OD), Oracle (O), Pacsum (bert) (PB), Pacsum (tfidf) (PT), Refresh (R), RNN\_Ext\_RL (RE), Textrank (T), Textrank (st) (TS)

Model	BART-base	BART-large	BLOOM-560m	distil-BART	distil-PEGASUS	PEGASUS	T5-large
T0-3B	61.1	37.9	96.0	35.1	38.7	30.6	94.0
T0	55.7	19.6	91.0	20.2	19.7	15.1	92.5
FLAN-T5-xl	64.1	40.8	98.7	38.3	40.7	34.5	92.8
FLAN-T5-xxl	67.8	47.6	99.0	42.9	44.6	41.8	93.2
T5-LM-Adapt-xl	66.5	60.9	90.8	57.1	61.1	53.4	86.3
T5-LM-Adapt-xxl	70.6	61.6	95.4	56.3	59.0	53.0	87.0
GPT-Neo-1.3B	71.3	67.9	79.9	72.4	64.8	66.2	80.3
GPT2-XL	67.8	63.5	84.7	64.4	61.6	60.3	78.9
GPT-Neo-2.7B	71.9	65.9	87.0	67.3	65.4	64.8	81.2
GPTJ-6B	78.6	69.3	91.8	71.5	64.5	64.8	84.1
GPT-Neox-20B	76.5	64.7	89.3	70.5	64.1	61.9	83.6
BLOOM	72.1	65.0	92.7	65.1	62.9	59.6	85.1
BLOOM-7B1	71.5	64.7	86.4	66.8	63.6	63.7	83.0
BLOOM-3B	70.8	68.8	85.7	68.5	65.0	66.2	80.7
BLOOM-1B7	68.3	67.1	82.6	68.5	65.0	61.6	78.3
BLOOM-1B1	66.5	63.5	80.7	66.1	65.4	63.2	73.9
OPT-175B	78.8	66.4	91.0	67.8	65.2	63.2	89.4
OPT-66B	76.7	66.7	88.5	67.6	64.5	61.6	88.0
OPT-30B	78.4	65.0	89.3	68.5	63.2	61.0	87.2
OPT-13B	76.5	63.0	89.1	65.4	64.1	61.2	86.5
OPT-6.7B	73.9	60.6	86.2	65.1	63.6	60.0	85.9
OPT-2.7B	72.1	62.8	84.9	67.1	63.4	62.1	83.2
OPT-1.3B	71.3	63.3	81.6	62.7	61.6	62.8	81.2

Table 32: The performance of the models on XSum with FIB alternative-choices using avg. PMI as the scoring function.

Model	BART-base	BART-large	BLOOM-560m	distil-BART	distil-PEGASUS	PEGASUS	T5-large
T0-3B	19.7	1.2	87.4	1.2	2.1	3.0	76.2
T0	33.9	5.3	80.3	5.4	5.7	3.2	84.1
FLAN-T5-xl	19.2	2.4	85.7	4.9	3.4	3.4	74.5
FLAN-T5-xxl	26.3	5.3	86.8	5.6	5.5	3.7	78.5
T5-LM-Adapt-xl	19.7	9.7	40.9	12.4	11.7	15.8	51.1
T5-LM-Adapt-xxl	23.8	8.9	51.2	12.0	10.1	9.6	61.3
GPT-Neo-1.3B	26.3	10.9	31.4	21.2	14.2	13.7	50.5
GPT2-XL	28.3	9.7	39.6	16.1	13.3	11.2	57.8
GPT-Neo-2.7B	32.0	10.6	36.5	20.5	12.8	12.1	58.0
GPTJ-6B	35.2	7.0	43.2	18.5	9.8	10.5	66.7
GPT-Neox-20B	39.1	8.5	46.3	20.0	9.6	10.5	71.4
BLOOM	42.8	8.5	50.9	20.7	9.8	10.7	72.5
BLOOM-7B1	32.6	10.9	43.0	20.7	13.3	13.9	60.9
BLOOM-3B	30.5	13.8	39.8	19.8	18.3	18.7	51.3
BLOOM-1B7	27.0	14.7	36.9	22.9	19.2	21.5	44.1
BLOOM-1B1	24.8	17.1	35.2	24.9	21.7	24.7	40.6
OPT-175B	48.8	8.7	56.0	20.7	9.8	7.8	78.9
OPT-66B	44.3	8.2	50.7	19.8	9.2	7.3	77.6
OPT-30B	45.6	7.7	50.7	20.7	9.6	8.4	76.6
OPT-13B	41.0	8.7	47.8	18.8	9.4	8.7	73.7
OPT-6.7B	37.1	8.0	43.4	17.8	8.2	8.7	69.6
OPT-2.7B	33.7	8.7	39.6	21.0	10.3	10.5	67.7
OPT-1.3B	29.8	8.5	37.7	17.6	11.2	10.7	62.3

Table 33: The performance of the models on XSum with FIB alternative-choices using avg. LL as the scoring function.

Model	BART-base	BART-large	BLOOM-560m	distil-BART	distil-PEGASUS	PEGASUS	T5-large
T0-3B	48.8	26.1	83.2	27.3	29.7	27.4	91.1
T0	53.8	16.4	91.2	19.3	18.1	16.0	91.9
FLAN-T5-xl	46.2	25.8	82.6	30.2	31.1	29.0	88.6
FLAN-T5-xxl	54.6	30.9	85.7	34.4	36.6	33.6	89.9
T5-LM-Adapt-xl	59.2	45.2	42.6	48.3	52.6	48.9	82.8
T5-LM-Adapt-xxl	60.5	42.5	54.7	48.3	48.7	43.6	84.5
GPT-Neo-1.3B	64.8	56.8	21.0	65.9	59.5	58.4	75.4
GPT2-XL	61.8	49.0	33.3	57.1	53.8	54.1	74.9
GPT-Neo-2.7B	63.9	51.7	23.9	60.2	55.1	55.7	76.2
GPTJ-6B	70.0	49.0	28.9	66.6	54.7	54.1	80.7
GPT-Neox-20B	68.5	51.0	29.4	65.6	55.8	53.4	82.6
BLOOM	65.2	51.0	45.1	58.5	55.8	54.3	83.0
BLOOM-7B1	64.8	53.4	30.6	61.2	56.8	56.6	79.1
BLOOM-3B	67.6	56.0	34.0	66.1	58.1	60.0	78.1
BLOOM-1B7	62.9	53.6	25.2	62.9	59.3	59.1	74.5
BLOOM-1B1	59.2	50.2	29.4	61.7	55.8	57.3	71.2
OPT-175B	71.9	50.0	39.8	61.5	55.8	53.7	85.7
OPT-66B	68.0	53.6	28.5	58.8	54.0	54.3	84.3
OPT-30B	69.5	48.3	33.8	59.8	53.3	54.1	83.2
OPT-13B	66.7	48.8	31.2	58.0	54.5	53.4	82.2
OPT-6.7B	64.8	47.8	26.2	59.8	51.0	55.9	82.4
OPT-2.7B	63.5	50.7	24.5	59.3	53.1	55.3	81.0
OPT-1.3B	63.5	50.0	22.6	57.1	51.9	55.7	77.0

Table 34: The performance of the models on XSum with FIB alternative-choices using PMI as the scoring function.

Model	BART-base	BART-large	BLOOM-560m	distil-BART	distil-PEGASUS	PEGASUS	T5-large
T0-3B	28.5	4.8	98.5	4.9	6.2	5.9	78.3
T0	42.8	10.4	98.7	8.3	7.3	5.9	84.9
FLAN-T5-xl	30.5	8.9	98.7	6.8	7.8	8.7	74.5
FLAN-T5-xxl	40.0	12.1	99.2	10.2	11.2	9.1	79.1
T5-LM-Adapt-xl	39.1	29.7	97.3	26.3	26.1	27.6	58.2
T5-LM-Adapt-xxl	42.1	24.2	97.7	23.2	20.1	21.2	65.8
GPT-Neo-1.3B	44.3	31.2	96.2	36.3	28.6	27.6	56.7
GPT2-XL	45.1	28.0	96.2	31.5	24.7	24.0	61.7
GPT-Neo-2.7B	48.2	28.3	96.0	33.9	25.4	26.5	61.3
GPTJ-6B	52.9	25.8	97.9	33.2	21.1	21.7	68.1
GPT-Neox-20B	54.6	24.6	97.9	33.9	20.4	20.1	72.7
BLOOM	54.0	26.1	98.1	32.4	23.6	22.1	73.7
BLOOM-7B1	49.2	30.2	97.5	33.4	28.8	29.7	62.1
BLOOM-3B	44.3	33.8	96.4	34.6	31.6	34.7	57.8
BLOOM-1B7	45.1	34.8	96.0	37.8	32.7	34.7	52.2
BLOOM-1B1	44.1	37.7	94.8	39.5	34.6	37.4	51.3
OPT-175B	59.0	23.4	98.3	30.5	17.4	16.4	80.5
OPT-66B	57.0	24.2	98.3	30.2	19.2	14.4	77.6
OPT-30B	55.7	22.9	97.9	30.2	18.3	16.0	77.2
OPT-13B	51.8	23.2	98.1	28.8	18.5	17.8	75.4
OPT-6.7B	52.7	23.7	97.1	29.3	18.1	16.7	71.4
OPT-2.7B	49.9	26.1	97.3	30.2	19.7	19.9	67.3
OPT-1.3B	45.8	26.6	97.1	30.5	22.4	23.1	62.5

Table 35: The performance of the models on XSum with FIB alternative-choices using LL as the scoring function.

Model	B	BL	HG	L	MS	MI	NS	OD	O	PB	PT	R	RE	T	TS
T0-3B	11.5	0.0	9.1	20.0	4.8	11.8	20.8	51.4	13.0	0.0	0.0	25.8	4.2	13.9	15.2
T0	7.7	0.0	4.5	0.0	4.8	8.8	12.5	37.5	9.3	0.0	0.0	9.7	0.0	8.3	8.7
FLAN-T5-xl	11.5	0.0	9.1	0.0	4.8	8.8	25.0	37.5	13.0	0.0	3.7	25.8	8.3	13.9	17.4
FLAN-T5-xxl	11.5	0.0	9.1	0.0	4.8	8.8	16.7	37.5	7.4	0.0	0.0	19.4	8.3	8.3	17.4
T5-LM-Adapt-xl	7.7	0.0	4.5	0.0	4.8	8.8	20.8	37.5	9.3	0.0	0.0	25.8	0.0	5.6	8.7
T5-LM-Adapt-xxl	11.5	0.0	9.1	0.0	4.8	14.7	20.8	30.6	7.4	0.0	0.0	9.7	8.3	8.3	10.9
GPT-Neo-1.3B	0.0	4.3	4.5	0.0	4.8	2.9	29.2	25.0	3.7	0.0	0.0	16.1	4.2	2.8	4.3
GPT2-XL	3.8	0.0	0.0	0.0	4.8	2.9	33.3	27.8	3.7	0.0	0.0	25.8	4.2	2.8	4.3
GPT-Neo-2.7B	7.7	0.0	9.1	0.0	4.8	5.9	29.2	23.6	3.7	0.0	0.0	16.1	8.3	5.6	8.7
GPTJ-6B	0.0	4.3	0.0	0.0	4.8	2.9	29.2	22.2	3.7	0.0	0.0	9.7	4.2	5.6	6.5
GPT-Neox-20B	11.5	0.0	9.1	20.0	9.5	5.9	20.8	23.6	5.6	0.0	0.0	16.1	8.3	5.6	8.7
BLOOM	11.5	4.3	9.1	0.0	9.5	5.9	16.7	19.4	5.6	8.3	0.0	12.9	8.3	5.6	4.3
BLOOM-7B1	7.7	8.7	0.0	0.0	4.8	2.9	20.8	25.0	9.3	0.0	0.0	12.9	8.3	5.6	10.9
BLOOM-3B	3.8	4.3	0.0	0.0	4.8	2.9	16.7	20.8	5.6	0.0	0.0	9.7	4.2	5.6	8.7
BLOOM-1B7	3.8	4.3	4.5	0.0	4.8	2.9	20.8	25.0	7.4	0.0	0.0	12.9	8.3	2.8	6.5
BLOOM-1B1	3.8	4.3	9.1	20.0	4.8	5.9	25.0	23.6	7.4	8.3	3.7	16.1	12.5	5.6	8.7
OPT-175B	7.7	4.3	9.1	40.0	9.5	8.8	12.5	23.6	5.6	8.3	0.0	9.7	8.3	8.3	10.9
OPT-66B	7.7	4.3	9.1	0.0	9.5	5.9	12.5	20.8	7.4	0.0	0.0	6.5	8.3	8.3	8.7
OPT-30B	7.7	4.3	9.1	0.0	4.8	5.9	16.7	19.4	5.6	0.0	0.0	9.7	8.3	8.3	8.7
OPT-13B	7.7	0.0	9.1	0.0	9.5	5.9	16.7	26.4	3.7	0.0	0.0	12.9	8.3	5.6	6.5
OPT-6.7B	7.7	4.3	4.5	20.0	4.8	5.9	16.7	23.6	5.6	8.3	0.0	6.5	12.5	5.6	10.9
OPT-2.7B	7.7	4.3	4.5	0.0	4.8	8.8	16.7	25.0	3.7	0.0	0.0	12.9	8.3	5.6	8.7
OPT-1.3B	3.8	4.3	4.5	0.0	4.8	5.9	20.8	19.4	5.6	0.0	0.0	12.9	8.3	2.8	4.3

Table 36: The performance of the models on CNN/DM with FIB alternative-choices using avg. PMI as the scoring function. The models are BanditSumm (B), BERT\_LSTM\_PN\_RL (BL), Heter-Graph (HG), Lead3 (L), MatchSumm (MS), MI-unsup (MI), NeuSumm (NS), Oracle (discourse) (OD), Oracle (O), Pacsum (bert) (PB), Pacsum (tfidf) (PT), Refresh (R), RNN\_Ext\_RL (RE), Textrank (T), Textrank (st) (TS)

Model	B	BL	HG	L	MS	MI	NS	OD	O	PB	PT	R	RE	T	TS
T0-3B	0.0	0.0	0.0	0.0	0.0	5.9	12.5	33.3	7.4	0.0	3.7	25.8	0.0	8.3	17.4
T0	0.0	0.0	0.0	0.0	0.0	2.9	8.3	23.6	9.3	0.0	3.7	12.9	0.0	5.6	13.0
FLAN-T5-xl	0.0	0.0	0.0	0.0	0.0	8.8	12.5	25.0	5.6	0.0	0.0	12.9	0.0	8.3	15.2
FLAN-T5-xxl	0.0	0.0	0.0	0.0	0.0	2.9	4.2	18.1	3.7	0.0	0.0	6.5	0.0	5.6	15.2
T5-LM-Adapt-xl	0.0	0.0	0.0	0.0	0.0	2.9	4.2	18.1	7.4	0.0	3.7	9.7	0.0	2.8	13.0
T5-LM-Adapt-xxl	0.0	0.0	0.0	0.0	0.0	2.9	4.2	12.5	5.6	0.0	3.7	6.5	0.0	2.8	13.0
GPT-Neo-1.3B	0.0	0.0	0.0	0.0	0.0	0.0	4.2	4.2	0.0	0.0	0.0	0.0	0.0	2.8	2.2
GPT2-XL	0.0	0.0	0.0	0.0	0.0	0.0	4.2	5.6	3.7	0.0	0.0	6.5	0.0	2.8	4.3
GPT-Neo-2.7B	0.0	0.0	0.0	0.0	0.0	0.0	4.2	5.6	0.0	0.0	0.0	3.2	0.0	2.8	2.2
GPTJ-6B	0.0	0.0	0.0	0.0	0.0	0.0	4.2	5.6	1.9	0.0	0.0	0.0	0.0	2.8	4.3
GPT-Neox-20B	0.0	0.0	0.0	0.0	0.0	0.0	0.0	5.6	1.9	0.0	0.0	0.0	0.0	2.8	4.3
BLOOM	0.0	0.0	0.0	0.0	0.0	0.0	0.0	4.2	1.9	0.0	0.0	0.0	0.0	2.8	6.5
BLOOM-7B1	0.0	0.0	0.0	0.0	0.0	0.0	4.2	8.3	3.7	0.0	0.0	0.0	0.0	2.8	6.5
BLOOM-3B	0.0	0.0	0.0	0.0	0.0	2.9	4.2	4.2	1.9	0.0	0.0	0.0	0.0	2.8	6.5
BLOOM-1B7	0.0	0.0	0.0	0.0	0.0	0.0	4.2	6.9	0.0	0.0	0.0	0.0	0.0	2.8	6.5
BLOOM-1B1	0.0	0.0	0.0	0.0	0.0	2.9	4.2	5.6	1.9	0.0	0.0	3.2	0.0	2.8	6.5
OPT-175B	0.0	0.0	0.0	0.0	0.0	2.9	4.2	4.2	1.9	0.0	0.0	3.2	0.0	2.8	4.3
OPT-66B	0.0	0.0	0.0	0.0	0.0	2.9	4.2	5.6	1.9	0.0	0.0	3.2	0.0	2.8	2.2
OPT-30B	0.0	0.0	0.0	0.0	0.0	0.0	4.2	5.6	1.9	0.0	0.0	3.2	0.0	2.8	2.2
OPT-13B	0.0	0.0	0.0	0.0	0.0	0.0	4.2	4.2	1.9	0.0	0.0	3.2	0.0	2.8	2.2
OPT-6.7B	0.0	0.0	0.0	0.0	0.0	2.9	4.2	8.3	1.9	0.0	0.0	3.2	0.0	2.8	2.2
OPT-2.7B	0.0	0.0	0.0	0.0	0.0	2.9	4.2	6.9	1.9	0.0	0.0	3.2	0.0	2.8	4.3
OPT-1.3B	0.0	0.0	0.0	0.0	0.0	2.9	4.2	4.2	0.0	0.0	0.0	6.5	0.0	2.8	2.2

Table 37: The performance of the models on CNN/DM with FIB alternative-choices using avg. LL as the scoring function. The models are BanditSumm (B), BERT\_LSTM\_PN\_RL (BL), Heter-Graph (HG), Lead3 (L), MatchSumm (MS), MI-unsup (MI), NeuSumm (NS), Oracle (discourse) (OD), Oracle (O), Pacsum (bert) (PB), Pacsum (tfidf) (PT), Refresh (R), RNN\_Ext\_RL (RE), Textrank (T), Textrank (st) (TS)



Model	B	BL	HG	L	MS	MI	NS	OD	O	PB	PT	R	RE	T	TS
T0-3B	0.0	0.0	0.0	0.0	4.8	0.0	8.3	33.3	13.0	0.0	0.0	9.7	0.0	2.8	2.2
T0	0.0	0.0	0.0	0.0	4.8	0.0	0.0	22.2	13.0	0.0	0.0	3.2	0.0	2.8	4.3
FLAN-T5-xl	0.0	0.0	0.0	0.0	4.8	0.0	8.3	25.0	13.0	0.0	0.0	12.9	0.0	0.0	2.2
FLAN-T5-xxl	0.0	0.0	0.0	0.0	4.8	0.0	8.3	20.8	11.1	0.0	0.0	3.2	0.0	0.0	4.3
T5-LM-Adapt-xl	0.0	0.0	0.0	0.0	4.8	0.0	4.2	25.0	11.1	0.0	0.0	3.2	0.0	0.0	2.2
T5-LM-Adapt-xxl	0.0	0.0	0.0	0.0	4.8	0.0	0.0	22.2	9.3	0.0	0.0	3.2	0.0	0.0	2.2
GPT-Neo-1.3B	0.0	0.0	0.0	0.0	4.8	0.0	4.2	16.7	5.6	0.0	0.0	0.0	0.0	0.0	0.0
GPT2-XL	0.0	0.0	0.0	0.0	4.8	0.0	0.0	13.9	5.6	0.0	0.0	6.5	0.0	0.0	0.0
GPT-Neo-2.7B	0.0	0.0	0.0	0.0	4.8	0.0	0.0	11.1	5.6	0.0	0.0	0.0	0.0	0.0	0.0
GPTJ-6B	0.0	0.0	0.0	0.0	0.0	0.0	4.2	11.1	3.7	0.0	0.0	0.0	0.0	0.0	0.0
GPT-Neox-20B	0.0	0.0	0.0	0.0	4.8	0.0	0.0	8.3	5.6	0.0	0.0	3.2	0.0	0.0	0.0
BLOOM	0.0	0.0	0.0	0.0	4.8	0.0	0.0	9.7	3.7	0.0	0.0	3.2	0.0	0.0	0.0
BLOOM-7B1	0.0	0.0	0.0	0.0	4.8	0.0	4.2	11.1	5.6	0.0	0.0	0.0	0.0	0.0	0.0
BLOOM-3B	0.0	0.0	0.0	0.0	4.8	0.0	0.0	12.5	5.6	0.0	0.0	0.0	0.0	0.0	0.0
BLOOM-1B7	0.0	0.0	0.0	0.0	4.8	0.0	0.0	16.7	3.7	0.0	0.0	0.0	0.0	0.0	0.0
BLOOM-1B1	0.0	0.0	0.0	0.0	4.8	0.0	4.2	15.3	5.6	0.0	0.0	0.0	0.0	0.0	0.0
OPT-175B	0.0	0.0	0.0	0.0	4.8	0.0	0.0	11.1	5.6	0.0	0.0	3.2	0.0	0.0	0.0
OPT-66B	0.0	0.0	0.0	0.0	4.8	0.0	0.0	9.7	5.6	0.0	0.0	0.0	0.0	0.0	0.0
OPT-30B	0.0	0.0	0.0	0.0	4.8	0.0	0.0	12.5	7.4	0.0	0.0	0.0	0.0	0.0	0.0
OPT-13B	0.0	0.0	0.0	0.0	4.8	0.0	0.0	13.9	5.6	0.0	0.0	0.0	0.0	0.0	0.0
OPT-6.7B	0.0	0.0	0.0	0.0	4.8	0.0	0.0	9.7	5.6	0.0	0.0	0.0	0.0	0.0	0.0
OPT-2.7B	0.0	0.0	0.0	0.0	4.8	0.0	0.0	13.9	5.6	0.0	0.0	0.0	0.0	0.0	0.0
OPT-1.3B	0.0	0.0	0.0	0.0	4.8	0.0	0.0	16.7	7.4	0.0	0.0	0.0	0.0	0.0	0.0

Table 38: The performance of the models on CNN/DM with FIB alternative-choices using PMI as the scoring function. The models are BanditSumm (B), BERT\_LSTM\_PN\_RL (BL), Heter-Graph (HG), Lead3 (L), MatchSumm (MS), MI-unsup (MI), NeuSumm (NS), Oracle (discourse) (OD), Oracle (O), Pacsum (bert) (PB), Pacsum (tfidf) (PT), Refresh (R), RNN\_Ext\_RL (RE), Textrank (T), Textrank (st) (TS)

Model	B	BL	HG	L	MS	MI	NS	OD	O	PB	PT	R	RE	T	TS
T0-3B	26.9	21.7	45.5	40.0	42.9	61.8	75.0	81.9	29.6	33.3	48.1	74.2	54.2	44.4	54.3
T0	15.4	21.7	31.8	0.0	38.1	58.8	62.5	65.3	16.7	8.3	40.7	61.3	37.5	47.2	50.0
FLAN-T5-xl	23.1	30.4	31.8	20.0	47.6	61.8	75.0	68.1	18.5	16.7	40.7	74.2	58.3	47.2	56.5
FLAN-T5-xxl	7.7	17.4	18.2	0.0	23.8	47.1	50.0	68.1	13.0	0.0	18.5	45.2	29.2	41.7	47.8
T5-LM-Adapt-xl	38.5	47.8	36.4	0.0	38.1	64.7	70.8	65.3	14.8	16.7	29.6	61.3	37.5	41.7	47.8
T5-LM-Adapt-xxl	34.6	26.1	9.1	0.0	23.8	55.9	54.2	52.8	13.0	0.0	11.1	48.4	20.8	27.8	37.0
GPT-Neo-1.3B	11.5	13.0	9.1	0.0	14.3	41.2	62.5	19.4	3.7	0.0	7.4	45.2	12.5	16.7	23.9
GPT2-XL	23.1	17.4	9.1	0.0	19.0	47.1	66.7	25.0	9.3	0.0	18.5	54.8	29.2	22.2	28.3
GPT-Neo-2.7B	15.4	17.4	4.5	0.0	14.3	44.1	50.0	19.4	5.6	0.0	7.4	38.7	16.7	16.7	23.9
GPTJ-6B	7.7	21.7	4.5	0.0	14.3	41.2	41.7	25.0	3.7	0.0	7.4	35.5	4.2	13.9	23.9
GPT-Neox-20B	0.0	13.0	4.5	0.0	14.3	47.1	50.0	26.4	3.7	0.0	14.8	32.3	4.2	25.0	28.3
BLOOM	7.7	13.0	4.5	0.0	14.3	38.2	29.2	20.8	5.6	0.0	3.7	29.0	16.7	13.9	21.7
BLOOM-7B1	19.2	17.4	0.0	0.0	9.5	44.1	45.8	22.2	7.4	0.0	11.1	41.9	16.7	19.4	26.1
BLOOM-3B	23.1	13.0	4.5	0.0	19.0	44.1	50.0	22.2	3.7	0.0	3.7	41.9	16.7	16.7	23.9
BLOOM-1B7	19.2	17.4	9.1	0.0	9.5	44.1	41.7	26.4	3.7	0.0	3.7	41.9	12.5	16.7	21.7
BLOOM-1B1	23.1	26.1	4.5	0.0	19.0	44.1	54.2	22.2	5.6	0.0	11.1	41.9	25.0	25.0	23.9
OPT-175B	23.1	34.8	4.5	0.0	19.0	50.0	45.8	19.4	3.7	0.0	7.4	32.3	16.7	16.7	21.7
OPT-66B	30.8	30.4	4.5	0.0	19.0	47.1	54.2	22.2	7.4	0.0	11.1	38.7	12.5	19.4	30.4
OPT-30B	26.9	34.8	4.5	0.0	14.3	50.0	45.8	20.8	3.7	0.0	3.7	35.5	12.5	13.9	26.1
OPT-13B	30.8	30.4	4.5	0.0	19.0	47.1	54.2	29.2	5.6	0.0	11.1	38.7	25.0	16.7	23.9
OPT-6.7B	30.8	39.1	4.5	0.0	19.0	50.0	58.3	26.4	7.4	0.0	18.5	38.7	29.2	27.8	26.1
OPT-2.7B	23.1	26.1	4.5	0.0	28.6	50.0	58.3	33.3	7.4	0.0	11.1	45.2	16.7	19.4	26.1
OPT-1.3B	26.9	30.4	9.1	0.0	19.0	44.1	62.5	25.0	7.4	0.0	7.4	45.2	16.7	16.7	23.9

Table 39: The performance of the models on CNN/DM with FIB alternative-choices using LL as the scoring function. The models are BanditSumm (B), BERT\_LSTM\_PN\_RL (BL), Heter-Graph (HG), Lead3 (L), MatchSumm (MS), MI-unsup (MI), NeuSumm (NS), Oracle (discourse) (OD), Oracle (O), Pacsum (bert) (PB), Pacsum (tfidf) (PT), Refresh (R), RNN\_Ext\_RL (RE), Textrank (T), Textrank (st) (TS)

Model	Scoring Function	BART-base	BART-large	BLOOM-560m	distil-BART	distil-PEGASUS	PEGASUS	T5-large
BART-base	Avg. PMI	24.4	42.5	95.4	34.4	45.1	42.2	83.0
BART-base	Avg. LL	0.0	2.2	97.1	0.5	3.4	5.5	50.1
BART-base	PMI	17.7	26.6	64.8	27.1	35.0	34.7	77.4
BART-base	LL	0.6	8.9	99.6	2.0	8.9	13.5	54.5
BART-large	Avg. PMI	63.5	24.4	96.0	29.5	39.4	32.2	94.2
BART-large	Avg. LL	32.8	0.0	96.9	4.4	2.5	3.0	77.0
BART-large	PMI	52.9	17.9	62.3	26.8	32.3	29.2	91.1
BART-large	LL	42.8	1.0	99.6	7.3	4.8	5.7	77.6
BLOOM-560m	Avg. PMI	55.9	44.7	52.8	53.9	45.8	46.1	72.0
BLOOM-560m	Avg. LL	18.6	6.0	0.4	11.7	6.6	7.5	50.9
BLOOM-560m	PMI	49.5	36.5	10.7	48.3	40.7	42.2	68.9
BLOOM-560m	LL	32.2	16.7	37.3	21.5	12.8	14.8	57.8
distil-BART	Avg. PMI	51.0	24.2	94.5	16.6	35.7	30.8	93.4
distil-BART	Avg. LL	11.0	0.0	97.7	0.0	2.1	4.3	72.5
distil-BART	PMI	44.7	18.6	52.8	18.8	30.9	26.5	88.6
distil-BART	LL	20.7	1.7	99.6	0.0	4.6	7.3	73.1
distil-PEGASUS	Avg. PMI	62.9	34.1	97.3	32.4	19.7	18.9	94.8
distil-PEGASUS	Avg. LL	16.4	1.9	88.9	2.0	0.0	0.7	74.1
distil-PEGASUS	PMI	51.4	22.7	77.8	26.6	17.2	17.1	92.3
distil-PEGASUS	LL	27.0	5.6	98.5	3.9	0.2	1.8	76.2
PEGASUS	Avg. PMI	72.4	44.9	97.1	42.9	36.4	22.8	96.9
PEGASUS	Avg. LL	29.4	1.7	87.8	2.9	0.5	0.0	84.3
PEGASUS	PMI	65.4	29.7	79.9	37.3	26.8	19.2	94.2
PEGASUS	LL	38.9	5.8	99.0	7.8	2.3	0.2	85.3
T5-large	Avg. PMI	43.2	50.7	93.5	46.1	51.5	49.8	31.7
T5-large	Avg. LL	8.6	12.3	94.8	10.2	13.3	18.9	0.2
T5-large	PMI	34.1	34.5	59.3	36.3	42.1	42.0	27.7
T5-large	LL	28.5	31.9	99.2	26.1	28.4	34.2	4.1

Table 40: The performance of the models on XSum using the same models to generate the factually inconsistent summary.

## ACL 2023 Responsible NLP Checklist

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### A For every submission:

- ☒ A1. Did you describe the limitations of your work?  
*Section 7*
- ☐ A2. Did you discuss any potential risks of your work?  
*Not applicable. Left blank.*
- ☒ A3. Do the abstract and introduction summarize the paper’s main claims?  
*Abstract: Section 1*
- ☒ A4. Have you used AI writing assistants when working on this paper?  
*Left blank.*

### B ☒ Did you use or create scientific artifacts?

*Section 3*

- ☒ B1. Did you cite the creators of artifacts you used?  
*Section 3*
- ☒ B2. Did you discuss the license or terms for use and / or distribution of any artifacts?  
*Section 3*
- ☒ B3. Did you discuss if your use of existing artifact(s) was consistent with their intended use, provided that it was specified? For the artifacts you create, do you specify intended use and whether that is compatible with the original access conditions (in particular, derivatives of data accessed for research purposes should not be used outside of research contexts)?  
*Section 3*
- ☒ B4. Did you discuss the steps taken to check whether the data that was collected / used contains any information that names or uniquely identifies individual people or offensive content, and the steps taken to protect / anonymize it?  
*The articles were from another dataset, which we think was reasonably cleaned.*
- ☒ B5. Did you provide documentation of the artifacts, e.g., coverage of domains, languages, and linguistic phenomena, demographic groups represented, etc.?  
*Section 3*
- ☒ B6. Did you report relevant statistics like the number of examples, details of train / test / dev splits, etc. for the data that you used / created? Even for commonly-used benchmark datasets, include the number of examples in train / validation / test splits, as these provide necessary context for a reader to understand experimental results. For example, small differences in accuracy on large test sets may be significant, while on small test sets they may not be.  
*Section 3.1*

### C ☒ Did you run computational experiments?

*Section 4*

- ☒ C1. Did you report the number of parameters in the models used, the total computational budget (e.g., GPU hours), and computing infrastructure used?  
*Section 4.1*

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*The Responsible NLP Checklist used at ACL 2023 is adopted from NAACL 2022, with the addition of a question on AI writing assistance.*

- ☒ C2. Did you discuss the experimental setup, including hyperparameter search and best-found hyperparameter values?

*Section 4.1*

- ☒ C3. Did you report descriptive statistics about your results (e.g., error bars around results, summary statistics from sets of experiments), and is it transparent whether you are reporting the max, mean, etc. or just a single run?

*Section 4.1*

- ☒ C4. If you used existing packages (e.g., for preprocessing, for normalization, or for evaluation), did you report the implementation, model, and parameter settings used (e.g., NLTK, Spacy, ROUGE, etc.)?

*Section 4.1*

**D ☒ Did you use human annotators (e.g., crowdworkers) or research with human participants?**

*Section 3*

- ☒ D1. Did you report the full text of instructions given to participants, including e.g., screenshots, disclaimers of any risks to participants or annotators, etc.?

*Annotators were authors.*

- ☒ D2. Did you report information about how you recruited (e.g., crowdsourcing platform, students) and paid participants, and discuss if such payment is adequate given the participants' demographic (e.g., country of residence)?

*Annotators were authors.*

- ☒ D3. Did you discuss whether and how consent was obtained from people whose data you're using/curating? For example, if you collected data via crowdsourcing, did your instructions to crowdworkers explain how the data would be used?

*Annotators were authors.*

- ☒ D4. Was the data collection protocol approved (or determined exempt) by an ethics review board?

*Annotators were authors.*

- ☒ D5. Did you report the basic demographic and geographic characteristics of the annotator population that is the source of the data?

*Annotators were authors.*