

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

Derek Tam Anisha Mascarenhas Shiyue Zhang

Sarah Kwan Mohit Bansal Colin Raffel

University of North Carolina at Chapel Hill

{dtredsox, amascare, shiyue, mbansal, craffel}@cs.unc.edu

## 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

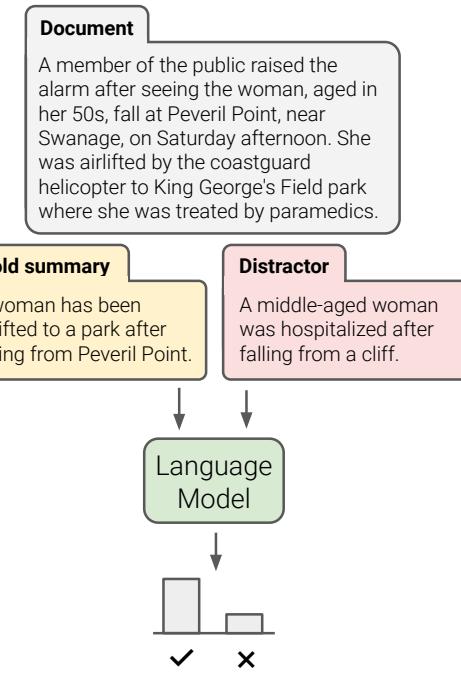


Figure 1: A schematic diagram of FIB, where we measure whether an LLM assigns a higher score to a factually consistent document summary than a factually inconsistent summary.

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

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

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 prefers 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). Relatively, 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

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

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:

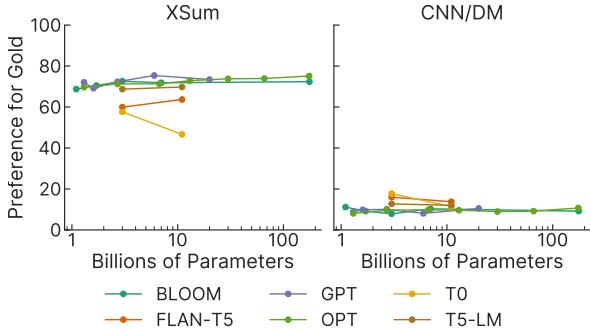


Figure 2: Performance of various models on FIB.

- **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

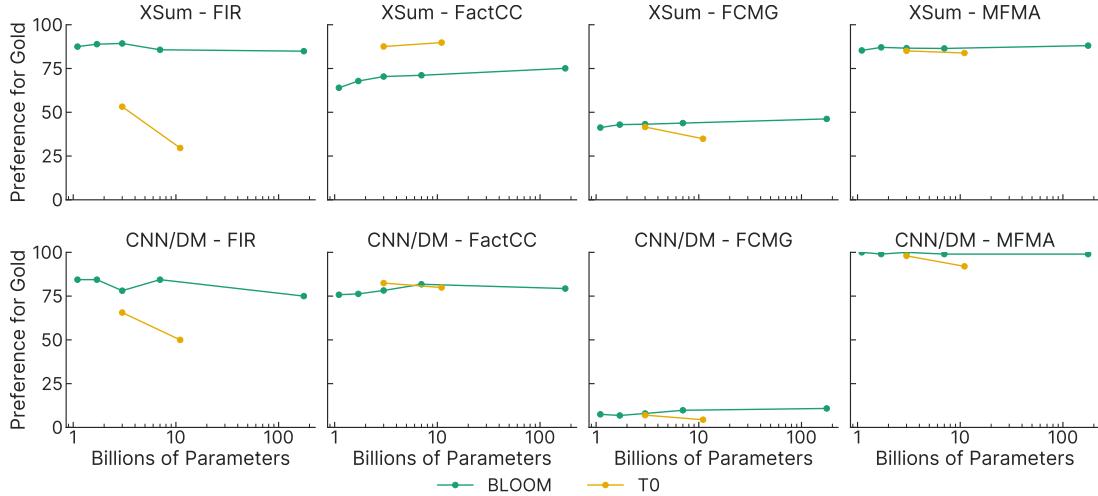


Figure 3: Preference for the Gold summary exhibited by BLOOM and T0 when using different methods for generating alternative choices.

*Peveril 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 Peveril 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 (**F**actually-**C**onsistent **M**odel-**G**enerated 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.

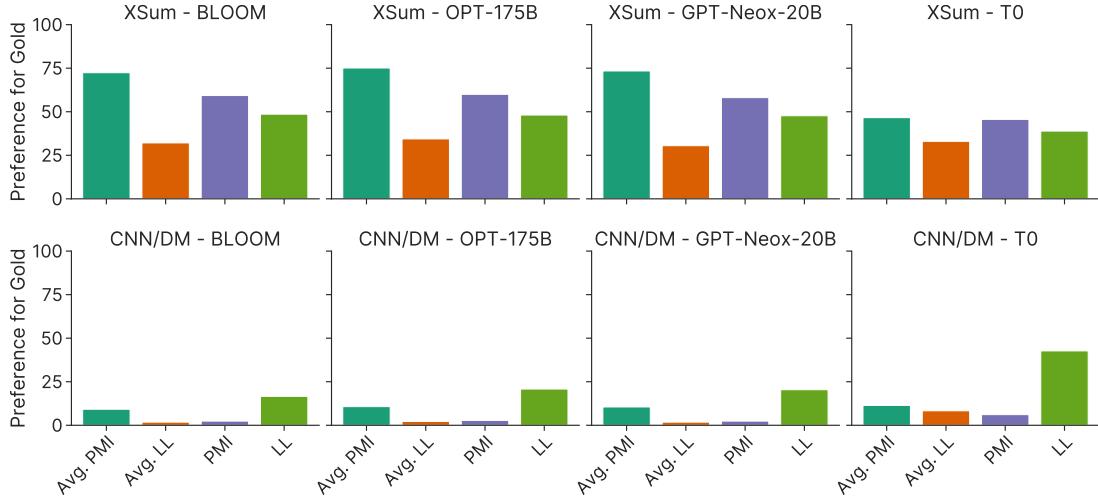


Figure 4: Performance of various models on FIB when using different scoring functions.

- *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.

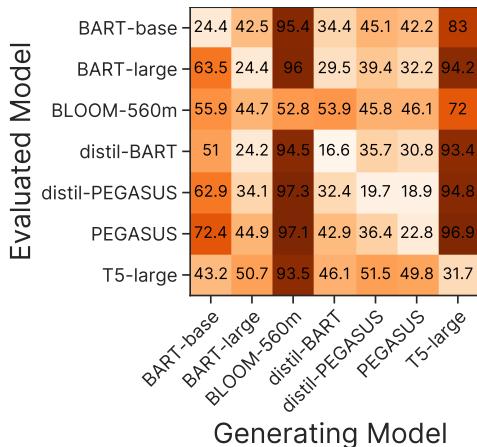


Figure 5: Heatmap showing the rate at which an “evaluated model” assigns a Gold summary on XSum a higher score than a factually inconsistent summary generated by the “generating model”.

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.

## Acknowledgements

This work was supported by NSF-AI Engage Institute DRL-2112635.

## References

- Isabelle Augenstein, Christina Lioma, Dongsheng Wang, Lucas Chaves Lima, Casper Hansen, Christian Hansen, and Jakob Grue Simonsen. 2019. **MultifC: A real-world multi-domain dataset for evidence-based fact checking of claims**. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 4685–4697, Hong Kong, China. Association for Computational Linguistics.
- Sidney Black, Stella Biderman, Eric Hallahan, Quentin Anthony, Leo Gao, Laurence Golding, Horace He, Connor Leahy, Kyle McDonell, Jason Phang, Michael Pieler, Usvsn Sai Prashanth, Shivanshu Purohit, Laria Reynolds, Jonathan Tow, Ben Wang, and Samuel Weinbach. 2022. **GPT-NeoX-20B: An open-source autoregressive language model**. In *Proceedings of BigScience Episode #5 – Workshop on Challenges & Perspectives in Creating Large Language Models*, pages 95–136, virtual+Dublin. Association for Computational Linguistics.
- Rishi Bommasani and Claire Cardie. 2020. **Intrinsic evaluation of summarization datasets**. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 8075–8096, Online. Association for Computational Linguistics.
- Ziqiang Cao, Furu Wei, Wenjie Li, and Sujian Li. 2018. **Faithful to the original: Fact aware neural abstractive summarization**. *Proceedings of the AAAI Conference on Artificial Intelligence*, 32(1).
- Yen-Chun Chen and Mohit Bansal. 2018. **Fast abstractive summarization with reinforce-selected sentence rewriting**. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 675–686, Melbourne, Australia. Association for Computational Linguistics.
- Hyung Won Chung, Le Hou, Shayne Longpre, Barret Zoph, Yi Tay, William Fedus, Eric Li, Xuezhi Wang, Mostafa Dehghani, Siddhartha Brahma, et al. 2022. Scaling instruction-finetuned language models. *arXiv preprint arXiv:2210.11416*.
- Tim Dettmers, Mike Lewis, Younes Belkada, and Luke Zettlemoyer. 2022. **Llm.int8(): 8-bit matrix multiplication for transformers at scale**. *arXiv preprint arXiv:2208.07339*.
- Ashwin Devaraj, William Sheffield, Byron Wallace, and Junyi Jessy Li. 2022. **Evaluating factuality in text simplification**. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 7331–7345, Dublin, Ireland. Association for Computational Linguistics.
- Yue Dong, Yikang Shen, Eric Crawford, Herke van Hoof, and Jackie Chi Kit Cheung. 2018. **Bandit-Sum: Extractive summarization as a contextual bandit**. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 3739–3748, Brussels, Belgium. Association for Computational Linguistics.
- Esin Durmus, He He, and Mona Diab. 2020. **FEQA: A question answering evaluation framework for faithfulness assessment in abstractive summarization**. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 5055–5070, Online. Association for Computational Linguistics.
- Tobias Falke, Leonardo F. R. Ribeiro, Prasetya Ajie Utama, Ido Dagan, and Iryna Gurevych. 2019. **Ranking generated summaries by correctness: An interesting but challenging application for natural language inference**. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 2214–2220, Florence, Italy. Association for Computational Linguistics.
- Saadie Gabriel, Asli Celikyilmaz, Rahul Jha, Yejin Choi, and Jianfeng Gao. 2021. **GO FIGURE: A meta evaluation of factuality in summarization**. In *Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021*, pages 478–487, Online. Association for Computational Linguistics.
- Ben Goodrich, Vinay Rao, Peter J. Liu, and Mohammad Saleh. 2019. Assessing the factual accuracy of generated text. In *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*.
- Tanya Goyal and Greg Durrett. 2020. **Evaluating factuality in generation with dependency-level entailment**. In *Findings of the Association for Computational Linguistics: EMNLP 2020*, pages 3592–3603, Online. Association for Computational Linguistics.
- Tanya Goyal and Greg Durrett. 2021. **Annotating and modeling fine-grained factuality in summarization**. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*,

- pages 1449–1462, Online. Association for Computational Linguistics.
- Karl Moritz Hermann, Tomas Kociský, Edward Grefenstette, Lasse Espeholt, Will Kay, Mustafa Suleyman, and Phil Blunsom. 2015. Teaching machines to read and comprehend. In *Advances in neural information processing systems*.
- Ari Holtzman, Peter West, Vered Shwartz, Yejin Choi, and Luke Zettlemoyer. 2021. Surface form competition: Why the highest probability answer isn’t always right. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 7038–7051, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.
- Wojciech Kryscinski, Bryan McCann, Caiming Xiong, and Richard Socher. 2020. Evaluating the factual consistency of abstractive text summarization. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 9332–9346, Online. Association for Computational Linguistics.
- Hwanhee Lee, Kang Min Yoo, Joonsuk Park, Hwaran Lee, and Kyomin Jung. 2022. Masked summarization to generate factually inconsistent summaries for improved factual consistency checking. In *Findings of the Association for Computational Linguistics: NAACL 2022*, pages 1019–1030, Seattle, United States. Association for Computational Linguistics.
- Brian Lester, Rami Al-Rfou, and Noah Constant. 2021. The power of scale for parameter-efficient prompt tuning. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 3045–3059, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.
- Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer. 2020a. Bart: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 7871–7880.
- Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer. 2020b. BART: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 7871–7880, Online. Association for Computational Linguistics.
- Chin-Yew Lin. 2004. ROUGE: A package for automatic evaluation of summaries. In *Text Summarization Branches Out*, pages 74–81, Barcelona, Spain. Association for Computational Linguistics.
- Klaus-Michael Lux, Maya Sappelli, and Martha Larson. 2020. Truth or error? towards systematic analysis of factual errors in abstractive summaries. In *Proceedings of the First Workshop on Evaluation and Comparison of NLP Systems*, pages 1–10, Online. Association for Computational Linguistics.
- Joshua Maynez, Shashi Narayan, Bernd Bohnet, and Ryan McDonald. 2020. On faithfulness and factuality in abstractive summarization. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 1906–1919, Online. Association for Computational Linguistics.
- Rada Mihalcea and Paul Tarau. 2004. TextRank: Bringing order into text. In *Proceedings of the 2004 Conference on Empirical Methods in Natural Language Processing*, pages 404–411, Barcelona, Spain. Association for Computational Linguistics.
- Shashi Narayan, Shay B. Cohen, and Mirella Lapata. 2018a. Don’t give me the details, just the summary! topic-aware convolutional neural networks for extreme summarization. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 1797–1807, Brussels, Belgium. Association for Computational Linguistics.
- Shashi Narayan, Shay B. Cohen, and Mirella Lapata. 2018b. Don’t give me the details, just the summary! topic-aware convolutional neural networks for extreme summarization. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 1797–1807.
- Shashi Narayan, Shay B. Cohen, and Mirella Lapata. 2018c. Ranking sentences for extractive summarization with reinforcement learning. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pages 1747–1759, New Orleans, Louisiana. Association for Computational Linguistics.
- Vishakh Padmakumar and He He. 2021. Unsupervised extractive summarization using pointwise mutual information. In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*, pages 2505–2512, Online. Association for Computational Linguistics.
- Artidoro Pagnoni, Vidhisha Balachandran, and Yulia Tsvetkov. 2021. Understanding factuality in abstractive summarization with FRANK: A benchmark for factuality metrics. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 4812–4829, Online. Association for Computational Linguistics.
- Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, et al. 2019. Pytorch: An imperative style, high-performance deep learning library. *Advances in neural information processing systems*, 32.

- Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. 2019. Teaching machines to read and comprehend. In *OpenAI Blog*.
- Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, Peter J Liu, et al. 2020. Exploring the limits of transfer learning with a unified text-to-text transformer. *J. Mach. Learn. Res.*, 21(140):1–67.
- Nils Reimers and Iryna Gurevych. 2019. Sentence-BERT: Sentence embeddings using Siamese BERT-networks. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 3982–3992, Hong Kong, China. Association for Computational Linguistics.
- Leonardo Ribeiro, Mengwen Liu, Iryna Gurevych, Markus Dreyer, and Mohit Bansal. 2022. FactGraph: Evaluating factuality in summarization with semantic graph representations. In *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 3238–3253, Seattle, United States. Association for Computational Linguistics.
- Victor Sanh, Albert Webson, Colin Raffel, Stephen H Bach, Lintang Sutawika, Zaid Alyafeai, Antoine Chaffin, Arnaud Stiegler, Teven Le Scao, Arun Raja, et al. 2022. Multitask prompted training enables zero-shot task generalization. *International Conference on Learning Representations (ICLR)*.
- Teven Le Scao, Angela Fan, Christopher Akiki, Elie Pavlick, Suzana Ilić, Daniel Hesslow, Roman Castagné, Alexandra Sasha Luccioni, François Yvon, Matthias Gallé, Jonathan Tow, Alexander M. Rush, Stella Biderman, Albert Webson, Pawan Sasanka Ammanamanchi, Thomas Wang, Benoît Sagot, Niklas Muennighoff, Albert Villanova del Moral, Olatunji Ruwase, Rachel Bawden, Stas Bekman, Angelina McMillan-Major, Iz Beltagy, Huu Nguyen, Lucile Saulnier, Samson Tan, Pedro Ortiz Suarez, Victor Sanh, Hugo Laurençon, Yacine Jernite, Julien Launay, Margaret Mitchell, Colin Raffel, Aaron Gokaslan, Adi Simhi, Aitor Soroa, Alham Fikri Aji, Amit Alfassy, Anna Rogers, Ariel Kreisberg Nitzav, Canwen Xu, Chenghao Mou, Chris Emezue, Christopher Klamm, Colin Leong, Daniel van Strien, David Ifeoluwa Adelani, Dragomir Radev, Eduardo González Ponferrada, Efrat Levkovich, Ethan Kim, Eyal Bar Natan, Francesco De Toni, Gérard Dupont, Germán Kruszewski, Giada Pistilli, Hady Elsahar, Hamza Benyamina, Hieu Tran, Ian Yu, Idris Abdulmumin, Isaac Johnson, Itziar Gonzalez-Dios, Javier de la Rosa, Jenny Chim, Jesse Dodge, Jian Zhu, Jonathan Chang, Jörg Frohberg, Joseph Tobing, Joydeep Bhattacharjee, Khalid Almubarak, Kimbo Chen, Kyle Lo, Leandro Von Werra, Leon Weber, Long Phan, Loubna Ben allal, Ludovic Tangy, Manan Dey, Manuel Romero Muñoz, Maraim Masoud, María Grandury, Mario Šaško, Max Huang, Maximin Coavoux, Mayank Singh, Mike Tian-Jian Jiang, Minh Chien Vu, Mohammad A. Jauhar, Mustafa Ghaleb, Nishant Subramani, Nora Kassner, Nurulaqilla Khamis, Olivier Nguyen, Omar Espejel, Ona de Gibert, Paulo Villegas, Peter Henderson, Pierre Colombo, Priscilla Amuok, Quentin Lhoest, Rheza Harliman, Rishi Bommasani, Roberto Luis López, Rui Ribeiro, Salomey Osei, Sampo Pyysalo, Sebastian Nagel, Shamik Bose, Shamsuddeen Hassan Muhammad, Shanya Sharma, Shayne Longpre, Somaieh Nikpoor, Stanislav Silberberg, Suhas Pai, Sydney Zink, Tiago Timponi Torrent, Timo Schick, Tristan Thrush, Valentin Danchev, Vassilina Nikoulina, Veronika Laippala, Violette Lepercq, Vrinda Prabhu, Zaid Alyafeai, Zeerak Talat, Arun Raja, Benjamin Heinzerling, Chenglei Si, Elizabeth Salesky, Sabrina J. Mielke, Wilson Y. Lee, Abheesht Sharma, Andrea Santilli, Antoine Chaffin, Arnaud Stiegler, Debjyoti Datta, Eliza Szczęsła, Gunjan Chhablani, Han Wang, Harshit Pandey, Hendrik Strobelt, Jason Alan Fries, Jos Rozen, Leo Gao, Lintang Sutawika, M Saiful Bari, Maged S. Al-shaibani, Matteo Manica, Nihal Nayak, Ryan Teehan, Samuel Albanie, Sheng Shen, Srulik Ben-David, Stephen H. Bach, Taewoon Kim, Tali Bers, Thibault Fevry, Trishala Neeraj, Urmi Thakker, Vikas Raunak, Xiangru Tang, Zheng-Xin Yong, Zhiqing Sun, Shaked Brody, Yallow Uri, Hadar Tojarieh, Adam Roberts, Hyung Won Chung, Jaesung Tae, Jason Phang, Ofir Press, Conglong Li, Deepak Narayanan, Hatim Bourfoune, Jared Casper, Jeff Rasley, Max Ryabinin, Mayank Mishra, Minjia Zhang, Mohammad Shoeybi, Myriam Peyrounette, Nicolas Patry, Nouamane Tazi, Omar Sanseviero, Patrick von Platen, Pierre Cornette, Pierre François Lavallée, Rémi Lacroix, Samyam Rajbhandari, Sanchit Gandhi, Shaden Smith, Stéphane Requena, Suraj Patil, Tim Dettmers, Ahmed Baruwa, Amanpreet Singh, Anastasia Chevleva, Anne-Laure Ligozat, Arjun Subramonian, Aurélie Névéol, Charles Lovering, Dan Garrette, Deepak Tunuguntla, Ehud Reiter, Ekaterina Taktasheva, Ekaterina Voloshina, Eli Bogdanov, Genta Indra Winata, Hailey Schoelkopf, Jan-Christoph Kalo, Jekaterina Novikova, Jessica Zosa Forde, Jordan Clive, Jungo Kasai, Ken Kawamura, Liam Hazan, Marine Carpuat, Miruna Clinciu, Na-joung Kim, Newton Cheng, Oleg Serikov, Omer Antverg, Oskar van der Wal, Rui Zhang, Ruochen Zhang, Sebastian Gehrmann, Shani Pais, Tatiana Shavrina, Thomas Scialom, Tian Yun, Tomasz Limisiewicz, Verena Rieser, Vitaly Protasov, Vladislav Mikhailov, Yada Pruksachatkun, Yonatan Belinkov, Zachary Bamberger, Zdeněk Kasner, Alice Rueda, Amanda Pestana, Amir Feizpour, Ammar Khan, Amy Faranak, Ana Santos, Anthony Hevia, Antigona Un-dreaj, Arash Aghagol, Arezoo Abdollahi, Aycha Tammour, Azadeh HajiHosseini, Bahareh Behroozi, Benjamin Ajibade, Bharat Saxena, Carlos Muñoz Ferrandis, Danish Contractor, David Lansky, Davis David, Douwe Kiela, Duong A. Nguyen, Edward Tan, Emi Baylor, Ezinwanne Ozoani, Fatima Mirza, Frankline Ononiwu, Habib Rezanejad, Hessie Jones, Indrani Bhattacharya, Irene Solaiman, Irina Sedenko, Isar

Nejadgholi, Jesse Passmore, Josh Seltzer, Julio Bonis Sanz, Karen Fort, Livia Dutra, Mairon Samagaio, Maraim Elbadri, Margot Mieskes, Marissa Gerchick, Martha Akinlolu, Michael McKenna, Mike Qiu, Muhammed Ghauri, Mykola Burynok, Nafis Abrar, Nazneen Rajani, Nour Elkott, Nour Fahmy, Olanrewaju Samuel, Ran An, Rasmus Kromann, Ryan Hao, Samira Alizadeh, Sarmad Shubber, Silas Wang, Sourav Roy, Sylvain Viguier, Thanh Le, Tobi Oyebade, Trieu Le, Yoyo Yang, Zach Nguyen, Abhinav Ramesh Kashyap, Alfredo Palasciano, Alison Callahan, Anima Shukla, Antonio Miranda-Escalada, Ayush Singh, Benjamin Beilharz, Bo Wang, Caio Brito, Chenxi Zhou, Chirag Jain, Chuxin Xu, Clémentine Fourrier, Daniel León Periñán, Daniel Molano, Dian Yu, Enrique Manjavacas, Fabio Barth, Florian Fuhrmann, Gabriel Altay, Giyaseddin Bayrak, Gully Burns, Helena U. Vrabec, Imane Bello, Ishani Dash, Jihyun Kang, John Giorgi, Jonas Golde, Jose David Posada, Karthik Rangasai Sivaraman, Lokesh Bulchandani, Lu Liu, Luisa Shinzato, Madeleine Hahn de Bykhovetz, Maiko Takeuchi, Marc Pàmies, Maria A Castillo, Marianna Nezhurina, Mario Sänger, Matthias Samwald, Michael Cullan, Michael Weinberg, Michiel De Wolf, Mina Mihaljevic, Minna Liu, Moritz Freidank, Myungsun Kang, Natasha Seelam, Nathan Dahlberg, Nicholas Michio Broad, Nikolaus Muellner, Pascale Fung, Patrick Haller, Ramya Chandrasekhar, Renata Eisenberg, Robert Martin, Rodrigo Canalli, Rosaline Su, Ruisi Su, Samuel Cahyawijaya, Samuele Garda, Shlok S Deshmukh, Shubhangshu Mishra, Sid Kiblawi, Simon Ott, Sinee Sang-aroonsiri, Srishti Kumar, Stefan Schweter, Sushil Bharati, Tanmay Laud, Théo Gigant, Tomoya Kainuma, Wojciech Kusa, Yanis Labrak, Yash Shailesh Bajaj, Yash Venkatraman, Yifan Xu, Yingxin Xu, Yu Xu, Zhe Tan, Zhongli Xie, Zifan Ye, Mathilde Bras, Younes Belkada, and Thomas Wolf. 2022. *Bloom: A 176b-parameter open-access multilingual language model*.

Thomas Scialom, Paul-Alexis Dray, Sylvain Lamprier, Benjamin Piwowarski, Jacopo Staiano, Alex Wang, and Patrick Gallinari. 2021. *QuestEval: Summarization asks for fact-based evaluation*. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 6594–6604, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Abigail See, Peter J. Liu, and Christopher D. Manning. 2017. *Get to the point: Summarization with pointer-generator networks*. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1073–1083, Vancouver, Canada. Association for Computational Linguistics.

Priyam Tejaswin, Dhruv Naik, and Pengfei Liu. 2021. *How well do you know your summarization datasets?* In *Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021*, pages 3436–3449, Online. Association for Computational Linguistics.

James Thorne, Andreas Vlachos, Christos

Christodoulopoulos, and Arpit Mittal. 2018. *FEVER: a large-scale dataset for fact extraction and VERification*. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pages 809–819, New Orleans, Louisiana. Association for Computational Linguistics.

Liam van der Poel, Ryan Cotterell, and Clara Meister. 2022. Mutual information alleviates hallucinations in abstractive summarization. *arXiv preprint arXiv:2210.13210*.

David Wan and Mohit Bansal. 2022. *FactPEGASUS: Factuality-aware pre-training and fine-tuning for abstractive summarization*. In *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 1010–1028, Seattle, United States. Association for Computational Linguistics.

Alex Wang, Kyunghyun Cho, and Mike Lewis. 2020a. *Asking and answering questions to evaluate the factual consistency of summaries*. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 5008–5020, Online. Association for Computational Linguistics.

Danqing Wang, Pengfei Liu, Yining Zheng, Xipeng Qiu, and Xuanjing Huang. 2020b. *Heterogeneous graph neural networks for extractive document summarization*. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 6209–6219, Online. Association for Computational Linguistics.

Rongxiang Weng, Heng Yu, Xiangpeng Wei, and Weihua Luo. 2020. *Towards enhancing faithfulness for neural machine translation*. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 2675–2684, Online. Association for Computational Linguistics.

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierrette Cistac, Tim Rault, Remi Louf, Morgan Funtowicz, Joe Davison, Sam Shleifer, Patrick von Platen, Clara Ma, Yacine Jernite, Julien Plu, Canwen Xu, Teven Le Scao, Sylvain Gugger, Mariama Drame, Quentin Lhoest, and Alexander Rush. 2020. *Transformers: State-of-the-art natural language processing*. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 38–45, Online. Association for Computational Linguistics.

Jiacheng Xu, Zhe Gan, Yu Cheng, and Jingjing Liu. 2020. *Discourse-aware neural extractive text summarization*. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 5021–5031, Online. Association for Computational Linguistics.

Jingqing Zhang, Yao Zhao, Mohammad Saleh, and Peter Liu. 2020. Pegasus: Pre-training with extracted gap-sentences for abstractive summarization. In *International Conference on Machine Learning*, pages 11328–11339. PMLR.

Shiyue Zhang, David Wan, and Mohit Bansal. 2022a. Extractive is not faithful: An investigation of broad unfaithfulness problems in extractive summarization. *arXiv preprint arXiv:2209.03549*.

Susan Zhang, Stephen Roller, Naman Goyal, Mikel Artetxe, Moya Chen, Shuhui Chen, Christopher Dewan, Mona Diab, Xian Li, Xi Victoria Lin, et al. 2022b. Opt: Open pre-trained transformer language models. *arXiv preprint arXiv:2205.01068*.

Hao Zheng and Mirella Lapata. 2019. Sentence centrality revisited for unsupervised summarization. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 6236–6247, Florence, Italy. Association for Computational Linguistics.

Ming Zhong, Pengfei Liu, Yiran Chen, Danqing Wang, Xipeng Qiu, and Xuanjing Huang. 2020. Extractive summarization as text matching. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 6197–6208, Online. Association for Computational Linguistics.

Ming Zhong, Pengfei Liu, Danqing Wang, Xipeng Qiu, and Xuanjing Huang. 2019. Searching for effective neural extractive summarization: What works and what’s next. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 1049–1058, Florence, Italy. Association for Computational Linguistics.

Qingyu Zhou, Nan Yang, Furu Wei, Shaohan Huang, Ming Zhou, and Tiejun Zhao. 2018. Neural document summarization by jointly learning to score and select sentences. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 654–663, Melbourne, Australia. Association for Computational Linguistics.

## 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 41c6edece127c396d17e2e9115a4a89252cc52b 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	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-IB7	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-IB1	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	23.9	23.9
BLOOM-IB7	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-IB1	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.