Evaluating the Factual Consistency of Large Language Models
Through News Summarization

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Abstract

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

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 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

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1We 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 prefer factually consistent summaries over factually inconsistent summaries. To do so, we evaluate these models on factually inconsistent summaries from three additional sources: (1) unedited reference summaries that we annotated as factually inconsistent, (2) summaries edited via FactCC (Kryscinski et al., 2020), and (3) summaries produced by MFMA (Lee et al., 2022). In addition, we test 4 different scoring functions: conditional log-likelihood (LL), length-normalized LL, pointwise mutual information (PMI), and length-normalized PMI. Overall, we find that: (1) The LLMs we consider typically assign a higher score to factually consistent summaries than to factually inconsistent summaries (e.g., 72.4% of the time for BLOOM (Scao et al., 2022)), but (2) LLMs rarely prefer factually consistent summaries over factually inconsistent summaries copied verbatim from the document (e.g., 9.6% of the time for BLOOM), (3) LLMs generally become more factually consistent as they are scaled up, and (4) FactCC-generated factually inconsistent summaries can fool some LLMs at a similar rate to model-generated factually inconsistent summaries.

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

2 Related Work

2.1 Factuality Evaluation Datasets

In the literature on text summarization, many datasets with human-labeled factually consistent and inconsistent summaries have been introduced for meta-evaluation purposes (i.e., evaluating factuality evaluation metrics) or for training the metrics themselves. Pagnoni et al. (2021) introduced the FRANK benchmark that contains 2250 model-generated summaries with factuality labels for each summary sentence. Similarly, Gabriel et al. (2021) proposed the GO FIGURE meta-evaluation framework that has 1500 model-generated summaries that include factuality labels. Besides these two benchmarks, many other works collected their own small-scale factuality evaluation datasets for evaluating their proposed metrics or analyzing the factuality of summarization models (Falke et al., 2019; Maynez et al., 2020; Kryscinski et al., 2020; Wang et al., 2020a; Durmus et al., 2020; Lux et al., 2020). Ribeiro et al. (2022) combined labeled datasets from four works and formed the FactCollect dataset with more than 9000 summary sentences and their factuality labels. Additionally, a few other works proposed to automatically obtain factually inconsistent summaries by perturbing the reference summaries (Kryscinski et al., 2020; Lee et al., 2022), e.g., entity swapping. However, Goyal and Durrett (2021) showed that these automatic techniques target inherently different error distributions than those seen in actual model generations. Goyal and Durrett (2020) considered model outputs at the top of beam search as factual and bottom generations as non-factual. The aforementioned works mainly focus on abstractive summarization; in contrast, Zhang et al. (2022a) introduced a factuality evaluation dataset for extractive summarization which we use as part of FIB. Previous datasets do not annotate reference summaries and instead only annotate model generations as factually consistent or factually inconsistent. However, the ref-
ference 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 sub-sentence) is entailed by the source document (Falke et al., 2019; Kryscinski et al., 2020; Goyal and Durrett, 2020; Maynez et al., 2020). QA/QG-based metrics are designed based on the idea that a question should have the same answer whether it is based on the summary or the document (Wang et al., 2020a; Durmus et al., 2020; Scialom et al., 2021). Relatedly, Goodrich et al. (2019) evaluated factuality by checking factual tuples extracted by OpenIE and Ribeiro et al. (2022) used the AMR graphs of the summary and the document for assessing factual consistency. All these metrics were designed to evaluate models trained specifically for summarization. In this work, we focus more broadly on evaluating the factual consistency of LLMs.

3 FIB: Factual Inconsistency Benchmark

Each example in FIB consists of a document and two summaries: a factually consistent summary and a factually inconsistent summary. Models are evaluated based on the proportion of times they assign a higher score to a factually consistent summary than to a factually inconsistent summary. We define a factually consistent summary as a summary whose contents can be inferred solely from the document. This means that even if a summary contains true information, if the information is not found in the document, then the summary is factually inconsistent. For example, the Gold summary in fig. 1 is factually consistent as it is written, but if we swapped Peveril Point with a cliff, then it would no longer be factually consistent, even if Peveril Point is technically a cliff, since this fact cannot be inferred from the document.

We compare the factual consistency of models on both extractive and abstractive summaries. Extractive summaries occur verbatim in the document while abstractive summaries do not. We use two summarization datasets as our testbed: CNN/DM (See et al., 2017; Hermann et al., 2015) for extractive summaries and XSum (Narayan et al., 2018a) for abstractive summaries. CNN/DM consists of English documents about the news from CNN/Daily Mail and summaries that are several sentences long with 287K/13K/11K examples for train/val/test. XSum consists of English documents about the news from BBC and short summaries with 204K/11K/11K examples for train/val/test. 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.
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 \(\{s_1, s_2, ..., s_T\}\), the length-normalized PMI is defined as

\[
\frac{1}{T} \log \sum_{t=1}^{T} P(s_t | d, s_1, ..., s_{t-1}) - \frac{1}{T} \log \sum_{t=1}^{T} P(s_t, s_1, ..., s_{t-1})
\]

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:
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 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
**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 (Factually-Consistent Model-Generated summaries).

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

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

| 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. |

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”.

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.

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7 Limitations

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

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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) - syreserch101/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)
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.

| 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 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 . | 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 41c66ecee127c396d17e2e9115a489252cc52b 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 |
| GPT-J-6B      | 88.0| 51.2 | 75.4| 74.0   | 87.3 |
| GPT-Neo-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-1B      | 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 |
| GPT-J-6B      | 28.3| 21.1 | 28.4| 96.8   | 68.9 |
| GPT-Neo-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-1B      | 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.
### 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            | 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 |
| GPT3-6B          | 55.7 | 54.9 | 57.8 | 66.7   | 84.3 |
| GPT-Neo-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 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            | 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 |
| GPT3-6B          | 55.7 | 54.9 | 57.8 | 66.7   | 84.3 |
| GPT-Neo-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 |

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### 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         | 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 |
| GPT-J-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| 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 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         | 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 |
| GPT-J-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 |
| 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 |
| GPT-6B       | 59.4 | 0.5  | 2.4  | 73.6   | 99.0 |
| GPT-Neo-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 |
| GPT-6B       | 78.1 | 21.0 | 18.6 | 97.9   | 99.0 |
| GPT-Neo-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    |
| GPT-1.6B             | 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    |
| GPT-1.6B             | 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               | 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    |
| GPT-J-6B            | 83.2      | 64.0    |
| GPT-Neo-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 14: The performance of the models on MFMA-generated alternative-choices using PMI 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    |
| GPT-J-6B            | 93.2      | 73.5    |
| GPT-Neo-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 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    |
| GPT-1.3B    | 60.0      | 70.6        | 85.1     | 54.4        | 63.4    |
| GPT-Neo-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-Neo-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.
### 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          | 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    |
| GPT-1.5B       | 69.1      | 66.9        | 69.4     | 52.9        | 63.4    |
| GPT-Neo-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 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          | 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-Neo-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 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            | 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 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            | 92.7      | 89.9        | 91.6     | 86.1        | 88.9    |
| T0               | 92.7      | 92.8        | 94.0     | 80.6        | 88.9    |
| 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    |
| 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-Neo-x20B     | 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       | 100.0    | 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 | 70.3     | 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    |
| GPT-6B         | 64.9     | 40.7      | 71.4      | 61.1        | 38.1          | 29.0   | 64.7    |
| GPT-Neo-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-7B       | 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-1B       | 70.3     | 33.7      | 52.4      | 45.6        | 22.2          | 29.0   | 70.6    |
| BLOOM-1B       | 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    |
| GPT-6B         | 51.4     | 9.3       | 52.4      | 17.8        | 9.5           | 8.1    | 47.1    |
| GPT-Neo-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-7B       | 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-1B       | 32.4     | 10.5      | 47.6      | 22.2        | 15.9          | 9.7    | 35.3    |
| BLOOM-1B       | 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   | 38.8    |
| OPT-2.7B       | 45.9     | 4.7       | 41.6      | 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.
### 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          | 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           | 48.4    | 58.8     |
| GPT-Neo-2.7B   | 64.9      | 37.2       | 9.5        | 56.7        | 46.0           | 43.5    | 58.8     |
| GPT-6B         | 70.3      | 40.7       | 9.5        | 62.2        | 55.6           | 48.4    | 58.8     |
| GPT-Neo-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        | 42.9           | 37.1    | 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    | 58.8     |
| 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 27: The performance of the models on XSum with factually consistent model-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          | 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     |
| GPT-6B         | 35.1      | 7.0        | 95.2       | 22.2        | 11.1           | 8.1     | 52.9     |
| GPT-Neo-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     |

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| 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-xl    | 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 | 6.7 | 4.7 |
| TS-LM-Adapt-xl| 5.4 | 5.2 | 0.0 | 0.0 | 0.0 | 0.0 | 18.4 | 35.7 | 0.0 | 0.0 | 1.3 | 15.9 | 3.1 | 3.1 | 1.9 |
| TS-LM-Adapt-xl| 5.4 | 5.2 | 0.0 | 1.1 | 5.1 | 6.1 | 14.5 | 28.6 | 0.0 | 2.3 | 1.4 | 17.4 | 5.3 | 6.3 | 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-Neo-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 | 5.7 | 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 | 6.7 | 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 | 7.1 | 8.7 | 3.7 |
| OPT-27B       | 8.1 | 7.6 | 0.0 | 4.7 | 6.7 | 6.6 | 25.0 | 17.9 | 6.5 | 6.7 | 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 | 2.3 | 2.7 | 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| 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| 1.3 | 47.4| 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| 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|
| T5-LM-Adapt-xl        | 0.0| 0.0| 0.0| 0.0| 0.0| 0.0| 1.3 | 21.4| 6.5| 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| 1.3 | 21.4| 6.5| 0.0| 0.0| 0.0 | 0.0| 4.7 | 1.9|
| GPT-Neo-1.3B          | 0.0| 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|
| GPT2-XL               | 0.0| 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|
| GPT-Neo-2.7B          | 0.0| 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|
| GPT-J-6B              | 0.0| 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|
| GPT-Neo-20B           | 0.0| 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|
| 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| 4.7 | 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| 4.7 | 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| 4.7 | 1.9|
| BLOOM-1B              | 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| 4.7 | 1.9|
| OPT-175B              | 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| 4.7 | 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| 4.7 | 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| 4.7 | 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| 4.7 | 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| 4.7 | 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| 4.7 | 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| 4.7 | 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          | 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    |
| GPT-6B        | 78.6      | 69.3      | 91.8       | 71.5        | 64.5           | 64.8    | 84.1    |
| GPT-Neo-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    |
| GPT-6B        | 35.2      | 7.0       | 43.2       | 18.5        | 9.8            | 10.5    | 66.7    |
| GPT-Neo-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.
### 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           | 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    |
| GPT-6B          | 70.0      | 49.0      | 28.9       | 66.6        | 54.7           | 54.1    | 80.7    |
| GPT-Neo-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 35: The performance of the models on XSum with FIB alternative-choices using LL 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    |
| GPT-6B          | 52.9      | 25.8      | 97.9       | 33.2        | 21.1           | 21.7    | 68.1    |
| GPT-Neo-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    |
| 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 | 1.0 |
| 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  | 1.0 |
| FLAN-T5-xl| 11.5 | 0.0 | 9.1 | 0.0 | 4.8 | 8.8 | 25.0 | 35.5 | 11.0 | 0.0 | 0.0 | 3.7  | 25.8 | 8.3  | 13.9 | 17.4 | 1.0 |
| FLAN-T5-xl | 11.5 | 0.0 | 9.1 | 0.0 | 4.8 | 8.8 | 16.7 | 35.5 | 7.4  | 0.0 | 0.0 | 19.4 | 8.3  | 8.3  | 17.4 | 1.0 |
| 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  | 1.0 |
| T5-LM-Adapt-xl | 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 | 1.0 |
| GPT2-XL   | 3.8  | 0.0 | 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  | 1.0 |
| GPT2-XL   | 3.8  | 0.0 | 0.0 | 0.0 | 0.0 | 4.8 | 2.9  | 29.2 | 23.6 | 3.7  | 0.0 | 0.0 | 16.1 | 4.2  | 2.8  | 4.3  | 1.0 |
| FLAN-T5-xl| 3.8  | 0.0 | 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  | 1.0 |
| FLAN-T5-xl | 3.8  | 0.0 | 0.0 | 0.0 | 0.0 | 4.8 | 2.9  | 29.2 | 23.6 | 3.7  | 0.0 | 0.0 | 16.1 | 4.2  | 2.8  | 4.3  | 1.0 |
| 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  | 1.0 |
| T5-LM-Adapt-xl | 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 | 1.0 |
| GPT2-XL   | 3.8  | 0.0 | 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  | 1.0 |
| GPT2-XL   | 3.8  | 0.0 | 0.0 | 0.0 | 0.0 | 4.8 | 2.9  | 29.2 | 23.6 | 3.7  | 0.0 | 0.0 | 16.1 | 4.2  | 2.8  | 4.3  | 1.0 |

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)
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 (tfdif) (PT), Refresh (R), RNN_Ext_RL (RE), Textrank (T), Textrank (st) (TS).

### Table 38: The performance of the models on CNN/DM with FIB alternative-choices using PMI as the scoring function.

| 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 | 8.3 | 0.0 | 13.0| 0.0 | 9.7 | 0.0 | 2.8 | 2.2 | 0.0 | 2.2 | 0.0 |
| T0          | 0.0 | 0.0 | 0.0 | 0.0 | 8.3 | 0.0 | 13.0| 0.0 | 3.2 | 0.0 | 2.8 | 4.3 | 0.0 | 2.2 | 0.0 |
| FLAN-T5-xl  | 0.0 | 0.0 | 0.0 | 0.0 | 8.3 | 0.0 | 13.0| 0.0 | 12.9| 0.0 | 2.2 | 0.0 | 0.0 | 2.2 | 0.0 |
| T5-LM-Adapt-xl | 0.0 | 0.0 | 0.0 | 0.0 | 4.8 | 0.0 | 2.2 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| GPT-Ne-1.3B | 0.0 | 0.0 | 0.0 | 0.0 | 4.8 | 0.0 | 13.0| 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| GPT2-XXL    | 0.0 | 0.0 | 0.0 | 0.0 | 4.8 | 0.0 | 13.0| 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| GPT-Ne-2.7B | 0.0 | 0.0 | 0.0 | 0.0 | 4.8 | 0.0 | 13.0| 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| GPT-3-7B    | 0.0 | 0.0 | 0.0 | 0.0 | 4.8 | 0.0 | 13.0| 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| BLOOM-7B1   | 0.0 | 0.0 | 0.0 | 0.0 | 4.8 | 0.0 | 13.0| 0.0 | 0.0 | 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 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| BLOOM-1B    | 0.0 | 0.0 | 0.0 | 0.0 | 4.8 | 0.0 | 13.0| 0.0 | 0.0 | 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 | 13.0| 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| GPT-175B    | 0.0 | 0.0 | 0.0 | 0.0 | 4.8 | 0.0 | 13.0| 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| OPT-6B      | 0.0 | 0.0 | 0.0 | 0.0 | 4.8 | 0.0 | 13.0| 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| OPT-3B      | 0.0 | 0.0 | 0.0 | 0.0 | 4.8 | 0.0 | 13.0| 0.0 | 0.0 | 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 | 13.0| 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| OPT-27B     | 0.0 | 0.0 | 0.0 | 0.0 | 4.8 | 0.0 | 13.0| 0.0 | 0.0 | 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 | 13.0| 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |

### 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 (tfdif) (PT), Refresh (R), RNN_Ext_RL (RE), Textrank (T), Textrank (st) (TS).
| Model          | Scoring Function | BART-base | BART-large | BLOOM-560m | distil-BART | 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.
The Responsible NLP Checklist used at ACL 2023 is adopted from NAACL 2022, with the addition of a question on AI writing assistance.
C2. Did you discuss the experimental setup, including hyperparameter search and best-found hyperparameter values?
   Section 4.1

C3. Did you report descriptive statistics about your results (e.g., error bars around results, summary statistics from sets of experiments), and is it transparent whether you are reporting the max, mean, etc. or just a single run?
   Section 4.1

C4. If you used existing packages (e.g., for preprocessing, for normalization, or for evaluation), did you report the implementation, model, and parameter settings used (e.g., NLTK, Spacy, ROUGE, etc.)?
   Section 4.1

D  ✓ Did you use human annotators (e.g., crowdworkers) or research with human participants?
   Section 3

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

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

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

D4. Was the data collection protocol approved (or determined exempt) by an ethics review board?
   Annotators were authors.

D5. Did you report the basic demographic and geographic characteristics of the annotator population that is the source of the data?
   Annotators were authors.