Analyzing the Abstractiveness-Factuality Tradeoff
With Nonlinear Abstractiveness Constraints

Markus Dreyer  Mengwen Liu  Feng Nan  Sandeep Atluri  Sujith Ravi
Amazon
{mddreyer, mengwliu, nanfen, satluri, sujithai}@amazon.com

Abstract

We analyze the tradeoff between factuality and abstractiveness of summaries. We introduce abstractiveness constraints to control the degree of abstractiveness at decoding time, and we apply this technique to characterize the abstractiveness-factuality tradeoff across multiple widely-studied datasets, using extensive human evaluations. We train a neural summarization model on each dataset and visualize the rates of change in factuality as we gradually increase abstractiveness using our abstractiveness constraints. We observe that, while factuality generally drops with increased abstractiveness, different datasets lead to different rates of factuality decay. We propose new measures to quantify the tradeoff between factuality and abstractiveness, incl. µQAGS, which balances factuality with abstractiveness. We also quantify this tradeoff in previous works, aiming to establish baselines for the abstractiveness-factuality tradeoff that future publications can compare against.

1 Introduction

Summarization is the task of generating a semantically faithful, wellformed and concise text representation of some input documents’ main information. Automatically generated summaries have traditionally been extractive (Neto et al., 2002; Erkan and Radev, 2004; Wong et al., 2008), leading to issues with readability and coherence, as different extracted fragments may not fit well when taken out of their original contexts (Poibeau and Saggon, 2012). More recently, researchers have invested in methods for abstractive summarization, aiming to paraphrase the input documents’ main points without borrowing their exact lexical expressions (Radford et al., 2019; Gehrmann et al., 2019; Lewis et al., 2019; Zhang et al., 2020). Abstractive summaries generated by state-of-the-art neural models tend to be fluent and wellformed, but lack semantic faithfulness (Cao et al., 2017; Kryscinski et al., 2019). Observed rates of factual errors in abstractive summaries have ranged from 30% to over 75% (Cao et al., 2017; Maynez et al., 2020). The research community has started to address this problem by developing automatic factuality metrics (Wang et al., 2020; Kryscinski et al., 2020; Goodrich et al., 2019) and methods that attempt to increase factuality (Fan et al., 2018; Scialom et al., 2019; Zhang et al., 2019; Falke et al., 2020).

However, we argue that the factuality problem of abstractive summaries cannot be well understood without considering the degree of abstractiveness of a given summary: Any summary is on a spectrum between extractive and abstractive (See et al., 2017), and a summary that is more abstractive typically has more problems with factual inconsistencies. Summaries that are extractive to a larger extent tend to be more factual since the copying of text from the input into the summary rarely introduces factual errors while the task of paraphrasing.
which results in summaries that are more abstractive, is harder and prone to semantic errors. As an example, Figure 1 shows part of a Washington Post article and three automatically generated summaries with increasing degrees of abstractiveness, which we have generated using our abstractiveness constraints (Section 2.1). The first two summaries are correct, but the third, most abstractive, summary has factual errors, misinterpreting the input.

Few authors have discussed this connection. Lebanoff et al. (2019) observe that abstractive summaries consisting of concatenated extracted fragments tend to be more factual than those created by more complex fusion. Durmus et al. (2020) observe that models trained on the more extractive CNN/DM dataset (Hermann et al., 2015) create more factual summaries than models trained on the more abstractive XSum dataset (Narayan et al., 2018). We show that such models differ in factuality even when we bias them to generate summaries that have similar levels of abstractiveness. Our analysis (Section 4) situates summarization models on the spectrum outlined in Figure 2, where factual summaries range from “trivially factual” (extractive) to truly “paraphrasing” (abstractive).

We make the following contributions:

1. We introduce nonlinear abstractiveness constraints (NAC), which control the degree of abstractiveness at decoding time using length-based penalties for extractive fragments;
2. Using this decoding technique, we systematically explore the relationship of abstractiveness and factuality, within a particular dataset as well as across datasets.
3. As part of this exploration, we conduct an extensive human factuality study and perform an evaluation of automatic factuality metrics.
4. We introduce measures to quantify the abstractiveness-factuality tradeoff and use them to compare multiple summarization models. Our automatic measure, $\mu_{QAGS}$, will enable future researchers to compare their own models and demonstrate progress.

## 2 Abstractiveness

### 2.1 Nonlinear Abstractiveness Constraints

We now introduce a technique to control the degree of abstractiveness of any summary $y$ obtained by decoding input $x$. With this technique – soft constraints applied during decoding, which we call nonlinear abstractiveness constraints (NAC) – we can use any previously trained model to generate summaries with varying degrees of abstractiveness (see Figure 1 for an example).

Let $F(x, y)$ be the set of the longest extractive fragments in $y$ with respect to $x$. In Figure 1, such fragments are marked in color for each summary. We define a function $\lambda_h(|f|)$ that assigns a discount probability to any extractive fragment $f \in F(x, y)$:

$$\lambda_h(|f|) = 2^{-|f|^2/h^2}$$

(1)

We configure this function with a parameter $h$, interpreted as the length of an extracted fragment for which $\lambda_h = 0.5$. Setting $h$ to smaller values results in summaries that are more abstractive since shorter extractive fragments will be discounted more strongly by $\lambda_h$, see Figure 3. Our discount penalty grows nonlinearly, affecting longer contiguous extractive fragments more strongly than multiple shorter ones with the same combined length – extracting a 10-gram makes a summary more extractive than using ten words from the article separately.

In decoding, we search for the summary $\hat{y}$ that maximizes the product of the summarization model probability, $p_M(y \mid x)$, and the discount probabilities of the extractive fragments $F(x, y)$:

$$\hat{y} = \arg \max_y p_M(y \mid x) \times \prod_{f \in F(x, y)} \lambda_h(|f|)$$

(2)

Additionally, the exponent used in $|f|^2$ and $h^2$ could be configured, but we keep it at 2 in our experiments. A larger exponent would result in a steeper descent around $h$. 

Figure 2: Four extremes at the abstractiveness-factuality spectrum.

Figure 3: $\lambda_h$ defines discounts for extractive fragments based on their lengths. Smaller $h$ values lead to more abstractive summaries.
**Beam Decoding.** The model probability $p_M(x, y)$ in neural text generation models (Section 5.2) decomposes for token-by-token decoding as $\prod_{i=1}^{[y]} p_M(y_i \mid x, y_1, \ldots, y_{i-1})$. Similarly, we decompose the application of the $\lambda_h$ function for any partial or completed extractive fragment $f$:

$$
\lambda_h(|f|) = \prod_{l=1}^{[f]} \lambda_h(l - 1)
$$

Therefore, to successively apply $\lambda_h$ at each output position $i$ in beam decoding, each candidate for token $y_i$ is evaluated to check whether choosing it would extend an extractive fragment to length $l$. If so, its model probability $p_M(y_i \mid \ldots)$ is multiplied with $\lambda_h(l)$ and the $\lambda_h(l - 1)$ that was applied to the previous token $y_{i-1}$ is divided out.

**Log Space.** In practice, we equivalently search for $\hat{y}$ in log space using log probabilities and the log of $\lambda_h$ defined in Equation 1. It can be shown that log $\lambda_h(|f|)$ = $-\frac{|f|^2}{(10.2011x^3)}$.

**Extraction Rewards.** We choose to apply an extraction reward, rather than a penalty, by using the inverse $1/\lambda_h$; smaller $h$ then result in summaries that are more extractive.

### 2.2 Measuring Abstractiveness

The abstractiveness constraints directly control the abstractiveness of the generated summaries and indirectly influence their factuality. We now discuss metrics for abstractiveness, before discussing metrics for factuality (Section 3).

To measure abstractiveness, most authors list the proportions of summary $n$-grams that are novel, i.e., do not occur in the corresponding input documents (See et al., 2017; Narayan et al., 2018; Gao et al., 2019). Grusky et al. (2018) proposed a new metric that is also based on contiguous overlapping text spans, called density (Grusky et al., 2018), meaning the average length of extracted fragments in a summary. Others have proposed metrics that take common non-contiguous subsequences into account, e.g., perfect fusion, (Durmus et al., 2020) measures the percentage of summary sentences that assemble substrings from $k$ source sentences in their original order.

Based on these previous works, we define a comprehensive abstractiveness metric that combines measures of contiguous as well as non-contiguous extractive summary fragments. We define this metric as a ratio, in order to facilitate combining it with a factuality metric of the same [0,1] range (Section 4). Let $\chi(x, y) = \ln\text{mean}(p_1, p_2, p_3, p_4, lcsr)$ be a measure of extractive overlap between input $x$ and summary $y$, using the harmonic mean of multiple component measures. Each $p_n$, short for $p_n(x, y)$, is the $n$-gram precision of the $n$-grams in $y$ with respect to $x$, i.e., the percentage of $n$-grams in $y$ that are extracted from $x$.\footnote{We smooth all $n$-gram counts (Chen and Cherry, 2014) to avoid undefined or zero harmonic mean values in highly abstractive summaries. See Appendix B for details.}

To measure abstractiveness, we define MINT (Metric for lexical independence of generated text) as $\text{MINT}(x, y) = 1 - \chi(x, y)$. For a set of inputs and their summaries, we report the average MINT score. See Figure 1 for the MINT scores of three sample summaries.

The described MINT score capitalizes on prior work to provide a comprehensive and unified metric for abstractiveness of conditionally generated text, combining measures of contiguous and non-contiguous overlap into a single percentage score. We will provide a reference implementation to facilitate a standardized comparison of abstractiveness across different works.

### 3 Factuality

We now describe metrics for factuality, before we can describe the relationship between abstractiveness and factuality (Section 4). By factuality of a summary $y$, we mean factual consistency with the input $x$, rather than objective factuality or universal truth. Measuring factuality automatically is an active area of research (Gabriel et al., 2020). Factuality is most naturally measured by human annotators; we describe our setup for human factuality annotation first, then move to automatic metrics. In Section 5.4, we measure the correlations of automatic factuality metrics to our human judgements.

### 3.1 Human-annotated Factuality

We use Amazon’s Mechanical Turk (AMT) to measure the factuality of automatically generated summaries with human annotators. Mechanical Turk...
annotators are untrained, so we use multiple mitigation strategies to obtain reliable judgements.

We simplify the task: To avoid overwhelming annotators with long text, we select a single sentence per summary and ask the annotators if it is factually consistent with the shown article (or, in the case of multi-document summarization, multiple articles). The other sentences of the summary are given as well for context, shown in gray, see Figure 4 for an example. The article(s) are shortened to show a total of 9 sentences that were determined to be semantically most similar to the selected summary sentence; the remaining article parts are replaced by “...”. The summary sentence is selected at random in proportion to its length. For each summary, we get judgements only for the randomly selected sentence. Aggregated over a set of summaries, we measure the average chance of any randomly selected summary sentence to be factual.

We also provide detailed task instructions, incl. examples for intrinsic and extrinsic factual errors (Maynez et al., 2020). We require that potential annotators pass our custom qualification test consisting of three of our example tasks of finding factual summary errors. Only workers who have previously completed 100 or more tasks on AMT with an acceptance rate of 95% or higher may take the test; 15% of those pass, enabling them to work on our evaluation tasks. We use three annotators per task and use MACE (Hovy et al., 2013) to aggregate these multiple annotations per summary and recover the most likely binary factuality judgement per summary. More details about our setup are in Appendix C.

For any set of automatically generated summaries, we create the AMT tasks, get an aggregate binary judgement per summary based on the multiple answers from annotators as described, and report the average of the human binary summary factuality judgements; we call this score \( \text{FactH} \) (Table 1). We collect human judgements on the first 150 samples of the test sets.

### 3.2 Automatically Measured Factuality

We use four metrics based on question answering (QA): SummaQA (Scialom et al., 2019), FEQA (Durmus et al., 2020), QAGS (Wang et al., 2020) and QUALS (Nan et al., 2021) and one entailment-based metric: FactCC (Kryscinski et al., 2020).

#### SummaQA

converts input sentences into Cloze-style questions by masking entities, applies BERT to recover them based on the summary and reports match \( F_1 \) score. Since SummaQA measures summaries based on how well they answer questions from the input, it measures both factuality and content selection. FEQA generates declarative questions from masked summary sentences whose masked entities are used as “gold” answers; these are compared to the answers obtained from a QA model on the input. In QAGS, a question generation (QG) model generates questions from the summary, a QA model answers these questions from both summary and input, and the similarity of the answer pairs is evaluated. QUALS is similar, but achieves runtime and memory reductions by replacing the QG and QA models with a single model, QAGen (Shakeri et al., 2020). It generates QA pairs from the summary, computes their average log probability given the input and given the summary and reports their difference \( \in [-\infty, \infty] \).

FactCC is a BERT-based binary classifier trained on weakly-supervised sentence pairs derived from rules. We took the pre-trained FactCC model and fine-tuned it using the ANLI dataset (Nie et al., 2020). FactCC is trained with sentence pairs, so we obtain scores at the sentence level and use their

---

3We measure cosine similarity of sentence encodings computed by the Universal Sentence Encoder (Cer et al., 2018).
mean as the factuality score of a summary.  

4 The Abstractiveness-Factuality Tradeoff

The metrics for factuality and abstractiveness, described above, along with the abstractiveness constraints presented in Section 2.1, provide us with tools to systematically explore the relationship between abstractiveness and factuality.

Factuality Trend Lines. To explore this relationship, we train summarization models on different datasets. For any trained summarization model, we decode the test set multiple times with different \( h \) values for \( \lambda_h \) (Equation 1), resulting in sets of summaries with different degrees of abstractiveness. For each of these test set decodings, we measure the average abstractiveness using MINT and the corresponding average factuality, using human annotations, unless otherwise noted. This results in a series of (abstractiveness, factuality) points for any trained summarization model, which can be plotted, along with a linear trend line. Figure 5 shows such a plot; Section 5.3 discusses its details.

F@50 Score. Given the multiple datapoints per model exhibiting different degrees of abstractiveness and associated factuality, we estimate the factuality at 50% abstractiveness, an intuitively interpretable metric, which we call F@50; it provides a comparison of the factuality of different models with a fixed degree of abstractiveness.

\( \mu_{\text{FactH}} \) and \( \mu_{\text{QAGS}} \). We characterize the tradeoff on any decoding output using a weighted average between factuality and abstractiveness, \((\phi F + A)/(\phi + 1)\). To measure abstractiveness \( A \), we use MINT; to measure factuality \( F \), we use either human-measured factuality or an automatic metric with [0,1] range like QAGS, resulting in abstractiveness-adjusted factuality metrics \( \mu_{\text{FactH}} \) and \( \mu_{\text{QAGS}} \). We give factuality twice as much weight, since low factuality can have large negative impact (Zellers et al., 2019), setting \( \phi \) to 2. By this definition, a system whose factuality decreases by \( x \) units, as compared to another system, must make up for the lost factuality by \( 2x \) units in abstractiveness to get the same score. When two systems have the same factuality, the score prefers the one with higher abstractiveness.

5 Experiments

5.1 Datasets

We use CNN/DM (Hermann et al., 2015), XSum (Narayan et al., 2018), and Multi-News (Fabbri et al., 2019). The former two are single-doc summarization datasets, and the latter one is a multi-doc summarization dataset. CNN/DM contains news articles from two news providers: CNN and DailyMail. The summaries are in the format of...
160GB of text and has been shown to give state-

We use a bilinear transformer model as encoder and a

Table 2: Impact of on ROUGE-L $F_1$ (RL) and abstrac-
tiveness metrics on the full test sets. $p_3$, $p_4$ and lcsr are
among MINT’s component scores (Sec. 2.2), density is the
average length of extracted fragments (Grusky et al.,
2018).

| $\lambda$       | RL     | MINT   | $p_3$ | $p_4$  | lcsr | density |
|-----------------|--------|--------|-------|-------|------|---------|
| $1/\lambda_2$   | 38.1   | 8.6    | 89.5  | 85.3  | 93.3 | 31.0    |
| none            | 40.8   | 14.7   | 82.1  | 75.5  | 89.7 | 20.3    |
| $\lambda_1$     | 41.7   | 38.4   | 55.4  | 41.8  | 78.6 | 6.4     |
| $\lambda_2$     | 40.0   | 61.8   | 32.2  | 19.7  | 68.7 | 3.4     |
| $1/\lambda_2$   | 44.7   | 35.7   | 61.6  | 54.2  | 60.4 | 15.9    |
| none            | 45.4   | 46.1   | 50.0  | 41.2  | 54.2 | 9.9     |
| $\lambda_1$     | 45.1   | 59.0   | 36.5  | 26.1  | 46.6 | 4.7     |
| $\lambda_2$     | 43.7   | 70.7   | 25.5  | 16.3  | 40.4 | 3.5     |
| $1/\lambda_2$   | 44.9   | 27.5   | 69.9  | 62.7  | 69.3 | 19.5    |
| none            | 45.8   | 37.3   | 58.7  | 49.9  | 63.4 | 12.9    |
| $\lambda_1$     | 45.7   | 52.6   | 42.4  | 31.2  | 53.8 | 5.8     |
| $\lambda_2$     | 44.2   | 66.4   | 29.0  | 19.0  | 46.1 | 4.0     |
| $1/\lambda_1$   | 30.6   | 57.6   | 37.7  | 28.2  | 63.5 | 4.6     |
| $1/\lambda_2$   | 36.0   | 74.7   | 22.3  | 13.4  | 57.4 | 2.2     |
| none            | 36.8   | 80.2   | 17.6  | 9.2   | 54.5 | 1.6     |
| $\lambda_1$     | 36.8   | 83.1   | 15.0  | 7.0   | 53.0 | 1.3     |
| $\lambda_2$     | 36.3   | 87.0   | 11.7  | 4.8   | 50.3 | 1.1     |

5.2 Setup

We use BART (Lewis et al., 2020) for our analyses of the relationship between factuality and abstrac-
tiveness. BART is a sequence-to-sequence model
with a bilinear transformer model as encoder and a
left-to-right transformer model as decoder. The encoder-decoder joint model was pretrained on
160GB of text and has been shown to give state-
of-the-art results on CNN/DM and XSum. Our models use the provided model checkpoints for
CNN/DM and the XSum datasets as well as the recommended decoding settings. For Multi-
News (MN), we train a model on the training set,
starting from the bart.large.cnn pretrained model with a learning rate of $2e-5$ for five epochs
and decode with a maximum length of 50 and a
maximum length of 300 tokens. For Multi-News,
we truncate the input documents per cluster so that
their combined length does not exceed $N$ words, follow-
ing Fabbi et al. (2019). We train models with
$N = 500$ and $N = 800$, called MN-500 and MN-
800, respectively. We measure the MINT scores for the reference summaries in these datasets; these
can be compared to the MINT scores obtained in
decoding (Section 5.3). The test set references for MN-500 have a MINT score of 78.2%, com-
pared to 72.8% for MN-800. MINT is naturally higher for MN-500 since the shorter truncation re-
moves content that could otherwise overlap with
the outputs. The MINT scores for the CNN/DM
and XSum references are 59.6% and 87.8%, respec-
tively, indicating that XSum is the most abstractive
dataset.

5.3 Comparison Across Datasets Using NAC

We decode each of the four trained models multiple
times with varying nonlinear abstractiveness con-
straints. Figure 5 plots the resulting abstractiveness
and human-measured factuality, thereby providing
a visual representation of the abstractiveness-
factuality tradeoff for the four models. Table 1 shows
the same 17 MINT and FactH values, along
with QAGS values and the MINT-adjusted factuali-
ties $\mu$FactH and $\mu$QAGS.

XSum. The lower right of Figure 5 shows five
lozenges ($\diamond$). The larger of these represents the
decoding of the test set with our XSum-trained model
using default settings; the other four red points
represent decodings under the same model, but with
different abstractiveness constraints that result in
more extractive ($1/\lambda_i$) or more abstractive ($\lambda_i$)
summaries (Section 2.1). The five red points are as-
associated with a dashed linear trend line. Compared
to the other points in the figure, abstractiveness is
high and factuality low. It took a strong extractive
reward ($1/\lambda_1$), which we did not use for the models
trained on other datasets, to pull this model toward
lower abstractiveness and higher factuality.

Multi-News. Four decodings using the MN-500
model are shown as squares ■. decodings under
the MN-800 model as triangles ▲. The two de-
codings without constraints, denoted by the larger
symbols, are far apart: MN-500 is more abstractive
and less factual, MN-800 is the opposite. This can
be explained by the fact that for MN-500, larger
parts of the input are truncated (Section 5.2) that
the untruncated reference summary in training may
still refer to; the model learns to hallucinate more.
However, the trend lines of MN500 and MN-800 are almost identical. This underscores the value of the trend lines, which reveal the near identical abstractiveness-factuality spectrum of these two models.

**CNN/DM.** The four decodings for CNN/DM are shown as bullets (•). Its default model output without abstractiveness constraint (large bullet) is by far the most extractive (MINT 19.6%); the extraction reward to its left (using $1/\lambda_3$) cannot make it much more extractive; however, there is room to the right, and the abstraction rewards ($\lambda_4$ and $\lambda_2$) move its abstractiveness far into the abstractiveness level of Multi-News and even XSum.

**F@50 Scores.** One of the main takeaways of this study is that different systems can have different factuality rates at the same level of abstractiveness. Previous authors have observed that XSum summaries are highly abstractive and less factual, and that CNN/DM summaries are at the opposite side of that spectrum. We confirm this; however, we add that we can bias the XSum model to create less abstractive summaries and the CNN/DM model to create more abstractive models, so that their abstractiveness becomes comparable, and the factuality rates still differ considerably: Based on the trend line, the F@50 score of the XSum model is 52.6%, while the CNN/DM model’s F@50 is 81.3%. MN-500 and MN-800 lie in the middle, both with F@50 score of 70.5.

**µFactH Scores.** When no abstractiveness constraint is applied (λ=none in Table 1), the CNN/DM and MN models have comparable µFactH scores of 65.7%, 64.3% and 67.9%. The XSum model has a low µFactH score of 54.4%; at its degree of abstractiveness it would need a factuality of 58.3% to match the µFactH score of the CNN/DM model, but its actual FactH score is only 41.3%. The µQAGS scores correlate highly with the µFactH scores.

**Summary Quality and Abstractiveness.** Table 2 lists ROUGE scores for the different decodings, along with multiple abstractiveness metrics; these numbers are measured on the full test sets. Decodings without abstractiveness constraints replicate previous works’ ROUGE scores (Lewis et al., 2020; Fabbri et al., 2019), see Appendix A. The $\lambda_4$ constraint can dramatically increase abstractiveness while leaving ROUGE scores virtually unchanged. To measure summary quality further, we conducted a human evaluation of informativeness and coherence of the summaries generated with the $\lambda_4$ decoding constraint; the results are mixed, where sometimes the default decoding is preferred, sometimes the $\lambda_4$ decoding and sometimes none of them, see Appendix D. The density scores (Grusky et al., 2018) in the table have high correlation with the MINT scores. See Appendix F for fusion scores (Durmus et al., 2020).

### 5.4 Correlating Human and Automatic Factuality Judgements

**Setup.** We analyze the correlation between human and automatic factuality scores, complementing earlier studies in this area (Gabriel et al., 2020). Table 3 describes three groups of correlation results, corresponding to different aggregation of summaries: The “summary sets” group contains the 17 data points whose human factuality scores can be seen in Figure 5; we score the factuality of the same summaries automatically and correlate the 17 score pairs per automatic metric. The “summaries” group contains the 17 x 150 individual factuality scores per summary, so in the “All” column we correlate all 2,550 factuality judgements from human annotators with the automatic metrics. The XSum, MN, and CNN columns contain only the subsets of summaries corresponding to those datasets. The automatic metrics score the full summaries with respect to their inputs. However, recall that we ask human annotators to judge only one summary sentence in context (Figure 4). The “summaries (one sentence)” numbers show the correlations of the 2,550 factuality judgements with the automatic metrics computed based on that same sentence per summary that annotators judged.

**Results.** All automatic metrics have high correlation with the 17 aggregated human judgements per summary set. QAGS and QUALS have almost perfect correlations with human aggreagate judgements, making them suitable to automatically judge the mean factuality of a system. Since QAGS, in particular, uses a [0,1] range like MINT, we combine the two as $\mu QAGS$ (Section 4) and report QAGS and $\mu QAGS$ in Tables 1 and 4. On the basis of individual summaries, overall correlations are moderate at best. For the 2,550 individual sum-
We obtain model outputs of four summarization methods, and compare the abstractiveness-factuality tradeoff of BART: PGConv (See et al., 2017) is a hybrid pointer-generator network that can copy words from the source text via pointing; BERTSum (Liu and Lapata, 2019) is a transformer encoder-decoder model in which only the encoder is pretrained; both BottomUp (Gehrmann et al., 2016; See et al., 2017) and ABSRL (Chen and Bansal, 2018) use separately selected source fragments to constrain an abstractive generation model.

Table 4 shows that, on CNN/DM, BART and ABSRL have the best $\mu QAGS$ scores (61.8 and 61.3), with ABSRL trading some factuality (QAGS) for considerably higher abstractiveness (MINT). Compared to ABSRL, BERTSUM is considerably less abstractive and only slightly more factual, leading to a lower $\mu QAGS$ score (60.1). PGConv and BottomUp rank last ($\mu QAGS$ scores 58.1 and 58.2) for different reasons: PGConv is very extractive while BottomUp is the least factual model. On XSum, BART represents a sizable factuality gain over BERTSum, with a relatively small loss in MINT score. BART’s pretraining of both encoder and decoder may be contributing to its better factuality, in accordance with Maynez et al. (2020).

### 5.5 Comparison Across Different Models

We compare the abstractiveness-factuality tradeoffs of summarization models from the literature. We obtain model outputs of four summarization models other than BART: PGConv (See et al., 2017) is a hybrid pointer-generator network that can copy words from the source text via pointing; BERTSum (Liu and Lapata, 2019) is a transformer encoder-decoder model in which only the encoder is pretrained; both BottomUp (Gehrmann et al., 2018) and ABSRL (Chen and Bansal, 2018) use separately selected source fragments to constrain an abstractive generation model.

Table 4 shows that, on CNN/DM, BART and ABSRL have the best $\mu QAGS$ scores (61.8 and 61.3), with ABSRL trading some factuality (QAGS) for considerably higher abstractiveness (MINT). Compared to ABSRL, BERTSUM is considerably less abstractive and only slightly more factual, leading to a lower $\mu QAGS$ score (60.1). PGConv and BottomUp rank last ($\mu QAGS$ scores 58.1 and 58.2) for different reasons: PGConv is very extractive while BottomUp is the least factual model. On XSum, BART represents a sizable factuality gain over BERTSum, with a relatively small loss in MINT score. BART’s pretraining of both encoder and decoder may be contributing to its better factuality, in accordance with Maynez et al. (2020).

### 6 Related Work

**Abstractiveness-Factuality Tradeoff:** Durmus et al. (2020) observe that the degree of abstractiveness at test time depends on the abstractiveness of the training data and that highly abstractive summaries tend to be less factual. We go a step further: We control for abstractiveness and see that factuality rates between different systems can vary widely at the same levels of abstractiveness. **Increasing Abstractiveness:** Krysciński et al. (2018) use policy gradient with a novelty reward to encourage abstraction in a pointer-generator (PG) network (Gulcehre et al., 2016; See et al., 2017). Weber et al. (2018) penalize the amount of copied tokens during PG decoding. Our decoding technique applies to general sequence-to-sequence models; we penalize contiguous longer extracted fragments more than multiple shorter fragments that add up to the same length, using nonlinear penalties for whole fragments. Finally, Song et al. (2020) control the
amount of copying in training abstractive summarization models by masking the summary tokens with different probabilities, depending on whether they are seen in the input document or not. In contrast, our technique does not require retraining to obtain varying degrees of abstractiveness.

7 Conclusions

We presented a new framework and new metrics for evaluating the relationship of abstractiveness and factuality. As part of this framework, we presented abstractiveness constraints, a general method that enables us to increase or decrease the level of abstractiveness when generating summaries from a summarization model, using nonlinear penalties or rewards based on the length of summary fragments extracted from the source. Through extensive human and automatic evaluations, we shed light on how abstractiveness interacts with factuality, across multiple datasets and models. We proposed new metrics to measure the abstractiveness-factuality tradeoff, incl. F@50 and μQAGS, and established baselines for future research.

References

Ziqiang Cao, Furu Wei, Wenjie Li, and Sujian Li. 2017. Faithful to the original: Fact aware neural abstractive summarization. CoRR, abs/1711.04434.

Daniel Cer, Yinfei Yang, Sheng-yi Kong, Nan Hua, Nicole Limtiaco, Rhommi St. John, Noah Constant, Mario Guajardo-Cespedes, Steve Yuan, Chris Tar, Yun-Hsuan Sung, Brian Strope, and Ray Kurzweil. 2018. Universal Sentence Encoder. EMNLP 2018 - Conference on Empirical Methods in Natural Language Processing: System Demonstrations, Proceedings, pages 169–174.

Boxing Chen and Colin Cherry. 2014. A systematic comparison of smoothing techniques for sentence-level BLEU. In Proceedings of the Ninth Workshop on Statistical Machine Translation, pages 362–367, Baltimore, Maryland, USA. Association for Computational Linguistics.

Yen-Chun Chen and Mohit Bansal. 2018. Fast Abstractive Summarization with Reinforce-Selected Sentence Rewriting. In Proc. of ACL.

Esin Durmus, He He, and Mona Diab. 2020. Feqa: A question answering evaluation framework for faithfulness assessment in abstractive summarization. In Association for Computational Linguistics (ACL).

Günes Erkan and Dragomir R. Radev. 2004. Lexrank: Graph-based lexical centrality as salience in text summarization. J. Artif. Int. Res., 22(1):457–479.

Alexander Fabbri, Irene Li, Tianwei She, Suyi Li, and Dragomir Radev. 2019. Multi-news: A large-scale multi-document summarization dataset and abstractive hierarchical model. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 1074–1084, Florence, Italy. Association for Computational Linguistics.

Tobias Falke, Leonardo F.R. Ribeiro, Prasetya Aji Utama, Ido Dagan, and Iryna Gurevych. 2020. Ranking generated summaries by correctness: An interesting but challenging application for natural language inference. In ACL 2019 - 57th Annual Meeting of the Association for Computational Linguistics, Proceedings of the Conference, pages 2214–2220. Association for Computational Linguistics (ACL).

Lisa Fan, Dong Yu, and Lu Wang. 2018. Robust Neural Abstractive Summarization Systems and Evaluation against Adversarial Information. In NIPS Interpretability and Robustness for Audio, Speech and Language Workshop.

Saadia Gabriel, Asli Celikyilmaz, Rahul Jha, Yejin Choi, and Jianfeng Gao. 2020. Go Figure! A Meta Evaluation of Factuality in Summarization. Technical report.

Shen Gao, Xiuying Chen, Piji Li, Zhangming Chan, Dongyan Zhao, and Rui Yan. 2019. How to write summaries with patterns? learning towards abstractive summarization through prototype editing. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 3741–3751, Hong Kong, China. Association for Computational Linguistics.

Sebastian Gehrmann, Yuntian Deng, and Alexander M. Rush. 2018. Bottom-Up Abstractive Summarization. In Proc. of EMNLP.

Sebastian Gehrmann, Zachary Ziegler, and Alexander Rush. 2019. Generating abstractive summaries with finetuned language models. In Proceedings of the 12th International Conference on Natural Language Generation, pages 516–522, Tokyo, Japan. Association for Computational Linguistics.

Ben Goodrich, Vinay Rao, Peter J Liu Mohammad Saleh, Google Brain, Peter J Liu, and Mohammad Saleh. 2019. Assessing The Factual Accuracy of Generated Text. In International Conference on Knowledge Discovery and Data Mining (KDD).

Max Grusky, Mor Naaman, and Yoav Artzi. 2018. Newsroom: A dataset of 1.3 million summaries with diverse extractive strategies. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pages 708–719, New Orleans, Louisiana. Association for Computational Linguistics.
Caglar Gulcehre, Sungjin Ahn, Ramesh Nallapati, Bowen Zhou, and Yoshua Bengio. 2016. Pointing the unknown words. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 140–149.

Karl Moritz Hermann, Tomáš Kočiský, Edward Grefenstette, Lasse Espeholt, Will Kay, Mustafa Suleyman, and Phil Blunsom. 2015. Teaching machines to read and comprehend. In Proceedings of the 28th International Conference on Neural Information Processing Systems-Volume 1, pages 1693–1701.

Dirk Hovy, Taylor Berg-Kirkpatrick, Ashish Vaswani, and Eduard Hovy. 2013. Learning whom to trust with MACE. In Proceedings of the 2013 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 1120–1130, Atlanta, Georgia. Association for Computational Linguistics.

Wojciech Kryscinski, Nitish Shirish Keskar, Bryan McCann, Caiming Xiong, and Richard Socher. 2019. Neural text summarization: A critical evaluation. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 540–551, Hong Kong, China. Association for Computational Linguistics.

Wojciech Kryściński, Romain Paulus, Caiming Xiong, and Richard Socher. 2018. Improving abstraction in text summarization. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 1808–1817, Brussels, Belgium. Association for Computational Linguistics.

Logan Lebanoff, John Muchovej, Franck Dernoncourt, Doo Soon Kim, Seokhwan Kim, Walter Chang, and Fei Liu. 2019. Analyzing sentence fusion in abstractive summarization. In Proceedings of the 2nd Workshop on New Frontiers in Summarization, pages 104–110, Hong Kong, China. Association for Computational Linguistics.

Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer. 2019. Bart: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. arXiv preprint arXiv:1910.13461.

Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer. 2020. BART: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 7871–7880, Online. Association for Computational Linguistics.

Chin-Yew Lin. 2004. ROUGE: A package for automatic evaluation of summaries. In Text Summarization Branches Out, pages 74–81, Barcelona, Spain. Association for Computational Linguistics.

Yang Liu and Mirella Lapata. 2019. Text Summarization with Pretrained Encoders. In Proc. of EMNLP.

Joshua Maynez, Shashi Narayan, Bernd Bohnet, and Ryan McDonald. 2020. On faithfulness and factuality in abstractive summarization. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 1906–1919, Online. Association for Computational Linguistics.

Feng Nan, Cicero Nogueira dos Santos, Henghui Zhu, Patrick Ng, Kathleen McKeown, Ramesh Nallapati, Dejiao Zhang, Zhiguo Wang, Andrew O Arnold, and Bing Xiang. 2021. Improving Factual Consistency of Abstractive Summarization via Question Answering. In Proc. of ACL.

Shashi Narayan, Shay B. Cohen, and Mirella Lapata. 2018. Don’t give me the details, just the summary! topic-aware convolutional neural networks for extreme summarization. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 1797–1807, Brussels, Belgium. Association for Computational Linguistics.

Joel Larocca Neto, Alex Alves Freitas, and Celso A. A. Kaestner. 2002. Automatic text summarization using a machine learning approach. In Proceedings of the 16th Brazilian Symposium on Artificial Intelligence: Advances in Artificial Intelligence, SBIA’02, page 205–215, Berlin, Heidelberg. Springer-Verlag.

Yixin Nie, Adina Williams, Emily Dinan, Mohit Bansal, Jason Weston, and Douwe Kiela. 2020. Adversarial nli: A new benchmark for natural language understanding. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 4885–4901.

Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. Bleu: a method for automatic evaluation of machine translation. In Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics, pages 311–318, Philadelphia, Pennsylvania, USA. Association for Computational Linguistics.

Thierry Poibeau and Horacio Saggers. 2012. Automatic Text Summarization: Past, Present and Future. In Multi-source, Multilingual Information Extraction and Summarization, pages 3–13.
Alec Radford, Jeff Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. 2019. Language models are unsupervised multitask learners.

Thomas Scialom, Sylvain Lamprier, Benjamin Pivovarski, and Jacopo Staiano. 2019. Answers unite! unsupervised metrics for reinforced summarization models. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 3246–3256, Hong Kong, China. Association for Computational Linguistics.

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

Siamak Shakeri, Cicero Nogueira dos Santos, Henghui Zhu, Patrick Ng, Feng Nan, Zhiguo Wang, Ramesh Nallapati, and Bing Xiang. 2020. End-to-end synthetic data generation for domain adaptation of question answering systems. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 5445–5460. Association for Computational Linguistics.

Kaiqiang Song, Bingqing Wang, Zhe Feng, Ren Liu, and Fei Liu. 2020. Controlling the amount of verbatim copying in abstractive summarization. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 34(05), pages 8902–8909.

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

Noah Weber, Leena Shekhar, Niranjan Balasubramanian, and Kyunghyun Cho. 2018. Controlling decoding for more abstractive summaries with copy-based networks. arXiv preprint arXiv:1803.07038.

Kam-Fai Wong, Mingli Wu, and Wenjie Li. 2008. Extractive summarization using supervised and semi-supervised learning. In Proceedings of the 22nd International Conference on Computational Linguistics (Coling 2008), pages 985–992, Manchester, UK. Coling 2008 Organizing Committee.

Rowan Zellers, Ari Holtzman, Hannah Rashkin, Yonatan Bisk, Ali Farhadi, F. Roesner, and Yejin Choi. 2019. Defending against neural fake news. In NeurIPS.

Jingqing Zhang, Yao Zhao, Mohammad Saleh, and Peter Liu. 2020. PEGASUS: Pre-training with extracted gap-sentences for abstractive summarization. In Proceedings of the 37th International Conference on Machine Learning, volume 119 of Proceedings of Machine Learning Research, pages 11328–11339. PMLR.

Yuhao Zhang, Derek Merck, Emily Bao Tsai, Christopher D. Manning, and Curtis P. Langlotz. 2019. Optimizing the Factual Correctness of a Summary: A Study of Summarizing Radiology Reports.
the supreme court reserved its verdict on a batch of pleas which have raised questions

the supreme court reserved its decision on a batch of pleas that have raised questions

Figure 6: Example of input and highly extractive generated output. The color coding is the same as in Fig. 1.

A ROUGE Scores

The aim of this paper is not to improve ROUGE scores, but to increase insights about the trade-off between abstractiveness and factuality. We do, however, stress that the models we use in our analysis are competitive with the start of the art. We list our ROUGE-1, ROUGE-2 and ROUGE-L $F_1$ scores, as well as their averages; see the RL scores in Table 2 as well:

- For CNN/DM, our $\lambda=\text{none}$ decoding has 44.0/21.0/40.8 with an average of 35.3, compared to an average of 35.4 in Lewis et al. (2020).

- For XSum, our $\lambda=\text{none}$ decoding has 45.3/21.9/36.8 with an average of 34.7, compared to an average of 34.9 in Lewis et al. (2020).

- For Multi-News, our MN-800 $\lambda=\text{none}$ decoding has 50.2/20.5/45.8 with an average of 38.8, compared to improved ROUGE $F_1$ results of 44.5/16.0/40.3 with an average of 33.6 by Fabibri (personal communication) for Fabibri et al. (2019).

B Measuring Abstractiveness with MINT

N-gram Overlap. Each $p_n$, short for $p_n(x, y)$, is the $n$-gram precision of the $n$-grams in $y$ with respect to $x$, i.e., the percentage of $n$-grams in $y$ that are extracted from $x$. For highly abstractive outputs, higher-order $n$-gram precision can be zero, leading to an undefined or zero harmonic mean value. We prevent this by smoothing the $n$-gram counts from which $n$-gram precisions are calculated, such that each $n$-gram count is the average of itself and the smoothed $(n-1)$-gram count and the unsmoothed $(n+1)$-gram count. The smoothed 0-gram count is defined as the 1-gram count plus one. We chose this method for its simplicity and effectiveness; it is described as method 5 in Chen and Cherry (2014).

Harmonic Mean. We use the harmonic mean, in analogy to the definition of the $F_1$ score, as it is a mean function designed to aggregate ratios with different denominators.

For a completely extractive summary that extracts sentences in the original order, the MINT score is 0. The score increases as the order of the extractive fragments is changed with respect to the input, their lengths are decreased and new words and fragments are introduced that are not part of the input $x$. The use of the length-normalized LCS score ($\text{lcsr}$) is inspired by ROUGE-L; it is a useful addition to the $n$-gram precisions as it can detect the extraction of longer $n$-grams broken up by minor edits. As an example, consider the $(x, y)$ pair shown in Figure 6. Only 4 of the 12 summary four-grams match the input, i.e., $p_4=33.3\%$, although very high overlap is apparent due to the fact that a 15-word fragment from the input was extracted with only the words “verdict” and “which” minimally changed. The lcsr score reflects this and measures $12/15=80.0\%$ overlap. On the other hand, the $n$-gram precisions used in the MINT score are valuable in detecting textual overlaps that are not part of the longest common subsequence.

\footnote{MINT has elements of ROUGE (Lin, 2004) and BLEU (Papineni et al., 2002). We do not use the modified $n$-gram precisions, like BLEU does, because $n$-grams extracted multiple times from $x$ should count as such every time.}
C Details on Our Mechanical Turk Setup

We provide additional details on the mitigation strategies we use in Amazon Mechanical Turk. We give detailed instructions to the annotators, with definitions and examples of different factual errors, see Figure 7. We also add a request to write a short explanation when a sentence is judged as not factual.

Tasks with Known Answers. We add a number of tasks with known answers, enabling us to estimate the accuracy of workers who work on multiple of these.

Automatic Quality Checks. Workers who complete the tasks too quickly, write no or very short explanation texts or have low accuracy are automatically removed from our worker pool. Their answers are replaced with new answers.

Bonus. We use a bonus incentive structure. Every worker who passes the automatic quality checks receives a bonus at the end.

Qualification Test. For all our evaluations on Mechanical Turk (see Sec. 3.1), we first set up a short qualification test that can be taken by any worker from a country whose main language is English, who has completed 100 or more HITs so far with an acceptance rate of 95% or higher. The qualification test consists of just three questions from our factual consistency setup; two of which must be answered correctly, along with an explanation text (5 words or more) to explain when “not factually consistent” was chosen. 53% of workers who start the test provide answers to all three questions, and 27.6% of these answer at least two correctly and provide a reasonable explanation text, i.e., only 14.6% of the test takers are granted the qualification.

|                | CNN/DM | MN-800 | XSum |
|----------------|--------|--------|------|
| prefer off     | 40.7   | 44.0   | 20.0 |
| prefer $\lambda_4$ | 46.7   | 38.0   | 17.3 |
| both equal     | 12.7   | 18.0   | 62.7 |

Table 5: Human quality evaluation of summaries generated with no abstractiveness constraint (“off”) versus $\lambda_4$. We asked which summary is more informative or coherent, respectively. MN-800 stands for Multi-News with the input documents truncated to 800 words total (Section 5.2).

The qualification enables workers to work on our factual consistency HITs as well as our HITs judging informativeness and coherence. The rate per HIT differs widely between the two tasks, as the factual consistency task can be done quickly, given the fact that a single summary sentence is evaluated and the related sentences in the article are highlighted. The factual consistency task pays $0.15 per hour with a bonus of $0.05. The task of evaluating informativeness and coherence (see D below) pays $0.50 per hour with a bonus of $0.25, as more text is displayed, compared to the factuality task. These amount to an average pay of $12.50, incl. the bonus. The bonus is paid to workers who spend at least 10 seconds per HIT and who give short explanation texts for their decisions.

D Human Evaluation of Informativeness and Coherence

We conducted a human evaluation to determine the informativeness and coherence of the summaries generated with the $\lambda_4$ decoding constraint (Equation 1), which increases abstractiveness, as compared to not using a abstractiveness constraint. We used the same setup as for the factuality task, incl. a qualification test, three annotators per task and aggregation using MACE. The results are shown in Table 5. We know and expect that factuality decreases with increased abstractiveness. For informativeness and coherence, the results are mixed. For the CNN/DM dataset, for the majority of summaries, $\lambda_4$ is preferred for informativeness but no decoding constrain is preferred for coherence. For Multi-News (MN-800), the preference is reversed. For XSum, the majority of summaries are indistinguishable for both categories.

We used the following definitions of informativeness and coherence for the human evaluation.
Table 6: Train/valid/test split on public datasets.

| Dataset  | Train  | Valid | Test  |
|----------|--------|-------|-------|
| CNN/DM   | 287,227| 13,368| 11,490|
| XSum     | 204,045| 11,332| 11,334|
| Multi-News| 44,972 | 5,622 | 5,622 |

Table 7: Abstractiveness metrics in FEQA (Durmus et al., 2020) for the data points shown in Figure 5. \( \lambda \) values denote decoding constraints (Section 2.1)

| \( \lambda \) | Extraction Sentence | Extraction Span | Extraction Word | Perfect fusion \( k = 2 \) | Perfect fusion \( k \geq 2 \) |
|-------------|---------------------|-----------------|-----------------|----------------|----------------|
| CNN/DM 1/\( \lambda \) | 29.03 | 6.36 | 38.29 | 16.05 | 20.66 |
| 1/\( \lambda \) | 28.27 | 6.28 | 35.07 | 16.39 | 21.8 |
| none | 19.75 | 5.71 | 37.22 | 18.5 | 25.41 |
| \( \lambda \) 1 | 2.24 | 1.31 | 21.2 | 25.51 | 42.71 |
| \( \lambda \) 2 | 0.76 | 0.45 | 7.54 | 14.39 | 31.78 |
| MN-500 1/\( \lambda \) | 8.85 | 8.86 | 11.38 | 11.42 | 17.06 |
| none | 4.78 | 4.64 | 8.66 | 8.41 | 13.43 |
| \( \lambda \) 1 | 1.42 | 1.41 | 3.09 | 5.73 | 10.59 |
| \( \lambda \) 2 | 1.07 | 0.97 | 1.99 | 3.78 | 6.79 |
| MN-800 1/\( \lambda \) | 12.09 | 12.9 | 13.62 | 12.28 | 17.87 |
| none | 7.17 | 7.81 | 9.31 | 9.91 | 15.12 |
| \( \lambda \) 1 | 2.12 | 2.29 | 3.95 | 6.88 | 12.28 |
| \( \lambda \) 2 | 1.44 | 1.5 | 2.32 | 4.42 | 7.74 |
| XSum 1/\( \lambda \) | 1.13 | 0.38 | 0.94 | 1.48 | 10.56 |
| \( \lambda \) 1 | 0.36 | 0.04 | 0.39 | 0.56 | 4.3 |
| \( \lambda \) 2 | 0.16 | 0.03 | 0.22 | 0.23 | 2.43 |
| \( \lambda \) 3 | 0.03 | 0.0 | 0.05 | 0.08 | 1.7 |
| \( \lambda \) 4 | 0.0 | 0.0 | 0.0 | 0.02 | 0.71 |

F Abstractiveness Measures Proposed in FEQA on Three Datasets

The abstractiveness metrics of a generated summary proposed in FEQA (Durmus et al., 2020) fall into three categories: extraction, perfect fusion, and novel \( n \)-grams. The extraction measurements evaluate whether a complete summary sentence, a summary sentence span, and a subset of tokens in a summary sentence are copied from input document(s). The perfect fusion measurements evaluate whether a summary sentence is copied from multiple sentences from input document(s). The novel \( n \)-grams measurements evaluate whether tokens in a summary do not present in input document(s). We observe that these metrics reflect increasing abstractiveness with larger penalty for extractive fragments on Multi-News and XSum datasets. The results on CNN/DM are mixed.

G Additional Experimental Details

We use AWS p3.8x and p3.16x EC2 machines for all our experiments, except we run FEQA on the Multi-News summaries on a p3dn.24xlarge machine, as it requires more memory. The BART model has 406,290,432 parameters. We trained all models for 5 epochs following instructions on the fairseq BART webpage, without further hyper-parameter search. The minimum and maximum length for Multi-News decoding was determined by the lengths of the training reference summaries.

E Dataset Sizes

For all three public datasets, we use the training/validation/test split provided in (Hermann et al., 2015; Narayan et al., 2018; Fabbri et al., 2019). The statistics of the three datasets are described in Table 6.

• Informativeness: the more informative summary is better at expressing the main points of the news story. It contains information that is more relevant and important. It has fewer unimportant details. Its content is more similar to the human-written summary.

• Coherence: the more coherent summary has better structure and flow, is easier to follow. The facts are presented in a more logical order.
Figure 7: Instructions for the factuality annotation task on Amazon Mechanical Turk, as well as the summary and part of the article text shown to the worker.