Counterfactual Data Augmentation improves Factuality of Abstractive Summarization

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Abstract
Abstractive summarization systems based on pretrained language models often generate coherent but factually inconsistent sentences. In this paper, we present a counterfactual data augmentation approach where we augment data with perturbed summaries that increase the training data diversity. Specifically, we present two augmentation approaches based on replacing (i) entities from other and the same category and (ii) nouns with their corresponding WordNet hypernyms. We show that augmenting the training data with our approach improves the factual correctness of summaries without significantly affecting the ROUGE score. We show that in two commonly used summarization datasets (CNN/DailyMail and XSum), we improve the factual correctness by about 2.5 points on average.

1 Introduction
Hallucinations or generating facts that can’t be substantiated with evidence from the input is still an uphill challenge for generative models (Cao et al., 2018; Falke et al., 2019; Goyal and Durrett, 2021). Standard maximum likelihood training (MLE) has been shown as the reason that models produce inconsistent summaries, making them prone to hallucinations (Cao et al., 2020; Nan et al., 2021b; Cao and Wang, 2021). In this work, we explore (i) three augmentation approaches for improved factual consistency and (ii) whether we can improve factuality without modifying the original MLE objective. We present the following augmentation strategies where we replace (i) entities with random entities and entities with random entities from the same category and (ii) nouns with their corresponding hypernyms from an ontology. We transform each of the above transformation by transforming the input via a control code (§2). Figure 1 shows an example of our overall approach. In contrast to the findings from literature (Nan et al., 2021b), we show that we do not need to modify the original MLE objective. In this work, we explore (i) three augmentation approaches for improved factual consistency and (ii) whether we can improve factuality without modifying the original MLE objective.

We present the following augmentation strategies where we replace (i) entities with random entities and entities with random entities from the same category and (ii) nouns with their corresponding hypernyms from an ontology. We transform each of the above transformation by transforming the input via a control code (§2). Figure 1 shows an example of our overall approach. In contrast to the findings from literature (Nan et al., 2021b), we show that we do not need to modify the original MLE objective.

Table 1: Sample input document and output summary from our baseline and our approach. Despite showing comparable ROUGE scores, we see that the more factually correct summary is produced by our approach.

| Input | Reference | No Augmentation | Our Work |
|-------|-----------|-----------------|----------|
| ..He had not really spoken about his injuries, she said, although he was aware of the extend of them. “I don’t think he’s ready”, she said.... | A bus driver was seriously hurt when a steam engine fell off a lorry into the path of his vehicle remains really poorly, his wife has said. | A bus driver who was seriously injured when he was hit by a steam engine is making good progress, his wife has said. | A bus driver who suffered serious injuries when he was hit by a steam engine is not ready to return to work, his wife has said. |

1All the code and data will be released soon.
Input: Philip had not really spoken about his injuries, she said, although he was aware of the extent of them. “I don’t think he’s ready”, she said...

Output: Philip, a bus driver was seriously hurt when a steam engine fell off a lorry into the path of his vehicle remains “really poorly”, his wife has said.

Input: Philip had not really spoken about his injuries, she said, although he was aware of the extent of them. “I don’t think he’s ready”, she said...

Output: US Chamber of Commerce, a bus driver was seriously hurt when a steam engine fell off a lorry into the path of his vehicle remains “really poorly”, his wife has said.

Input: Philip had not really spoken about his injuries, she said, although he was aware of the extent of them. “I don’t think he’s ready”, she said...

Output: Norton, a bus driver was seriously hurt when a steam engine fell off a lorry into the path of his vehicle remains “really poorly”, his wife has said.

Input: Philip had not really spoken about his injuries, she said, although he was aware of the extent of them. “I don’t think he’s ready”, she said...

Output: Philip, a (vehicle) (operator) was seriously hurt when a steam engine fell off a (heavy vehicle) into the path of his vehicle remains “really poorly”, his wife has said.

Figure 1: Overview of our data augmentation approach. (1) denotes the original dataset while (2), (3), and (4) denote different augmentation strategies. (2) replaces entity in summary with a random entity (3) replaces entity in summary with an erroneous entity of the same category (in this example, another name) and in (4) we replace randomly selected nouns from the summary and replace it with their corresponding WordNet hypernyms. The control code $c$ for each transformation are emphasized.

The MLE objective, which is commonly cited as the reason for increased hallucinations.

Our empirical results show that inducing diversity by proposed augmentation improves the factual correctness of summaries without significant change in ROUGE score. In experiments in two commonly used summarization datasets CNN/DailyMail and XSum using the T5-LARGE model, our approach outperforms the original model that is trained only to generate summaries for factual consistency. We show an average of ~3 points improvement in both the CNN/DailyMail and ~2 points improvement in XSum with the recently proposed strong E2E NLI metric for factuality (Honovich et al., 2021). In summary, our results show that counterfactual data augmentation via inducing entity errors and replacing nouns with hypernyms lead to improved factuality.

2 Approach

Data augmentation approaches for learning with augmentation (Zhang et al., 2019) often rely on transforming the input such that the model is introduced to training data variations during learning. In such an approach, a transformation $t$ is applied to an input sample $x$ (with a corresponding output $y$) to get a modified sample $\tilde{x} = t(x)$. For our approach, we propose a simple transformation where we augment a control code $c$ to $x$ and correspondingly augment the output $\tilde{y}$ in accordance with the control code as shown in Figure 1. For the summarization task, we formulate this as a learning task where the model learns to optimize the following loss function:

$$L_S = \frac{1}{M} \sum_{j=1}^{M} L_{CE}(x_j, y_j) + L_{CE}(\tilde{x}_j, \tilde{y}_j)$$

where $L_{CE}$ stands for the cross-entropy loss and $(x_j, y_j)$ an input document, summary pair and $(\tilde{x}_j, \tilde{y}_j)$ a transformed document, summary pair for $M$ samples.

2.1 Data Augmentation

Factuality in summarization comprises of a diverse range of inconsistencies as described in Pagnoni et al. (2021). The prominent errors among them are entity errors that captures errors where wrong entities are used as primary arguments and circumstance errors where arguments are mistakenly generated. Inspired by this, we propose the following three transformations for our approach to tackle such errors:

Entity Replacement (ER): In this perturbation, we replace entities in a reference summary with another random entity in the training dataset that is not present in the current input sample. An example is shown in Figure 1 (2), where a PERSON entity Philip is replaced by a random entity US Chamber of Commerce, an ORGANIZATION. Each of the erroneous sample was augmented with a control code “generate a wrong summary” to the input document.
### Dataset Augmentation

| Dataset       | Augmentation | E2E NLI | ROUGE-1 | ROUGE-2 | ROUGE-L | ΔR-L  | ΔNLI  |
|--------------|--------------|---------|---------|---------|---------|-------|-------|
| CNN/DailyMail| Original     | 61.0    | 42.5    | 19.6    | 39.8    | -     | -     |
|              | ER           | 62.3    | 41.3    | 19.3    | 38.8    | -1.0  | +1.3  |
|              | CAT-ER       | 63.9    | 41.9    | 19.6    | 38.3    | -1.5  | +2.9  |
|              | WN-HYPER     | 64.2    | 41.1    | 19.3    | 38.8    | -1.0  | +3.2  |
| XSum         | Original*    | 10.2    | 42.0    | 19.8    | 34.6    | -     | -     |
|              | ER           | 10.8    | 40.8    | 18.9    | 33.7    | -0.9  | +0.6  |
|              | CAT-ER       | 11.9    | 40.8    | 18.9    | 33.7    | -0.9  | +1.7  |
|              | WN-HYPER     | 11.2    | 41.6    | 20.1    | 34.3    | -0.3  | +1.0  |

Table 2: Results for different augmentation approaches compared to the Original model. Note that all models are trained for the same number of steps and with 5 random seeds (reporting the average). *- denotes our reproduction of the results with the preprocessed dataset as described in §3.1. ΔR-L and ΔNLI refer to difference in the ROUGE-L and E2E NLI scores of the augmented models versus the original, accordingly. Note: Each row specifies individual augmentation.

#### Categorical Entity Replacement (CAT-ER)

Inspired from the previous entity swap, we replace entities with other entities from similar category. An example is shown in Figure 1 (3) where a PERSON entity Philip is replaced by Norton, another entity of the same PERSON category. The categorical entity replacement also uses the same control code as entity replacement due to their similar nature of perturbation.

#### WordNet Hypernym Replacement (WN-HYPER)

We also try an augmentation strategy that does not rely on introducing errors in reference summaries. In this approach, we replace a fraction of nouns in each reference summary y with their corresponding lexical category from an ontology. For this, we rely on WordNet (Fellbaum, 2000) hypernym for noun replacement. Correspondingly, we use the control code “generate a general summary” as shown in Figure 1 (4), where a noun such as bus, driver, lorry is replaced by their corresponding lexical categories - namely vehicle, operator, heavy vehicle. We hypothesize that this transformation provides additional semantics to arguments (predominantly nouns) during generation.

### 3 Experiments

With the training data, consisting of \((x, y)\) and augmented \((\bar{x}, \bar{y})\) samples, we minimize the loss \(L_S\). For all our experiments, we use the transformer based T5-LARGE (Raffel et al., 2020) as our base model with learning rate of \(1e-03\), batch size of 32, a dropout of 0.1 with the adafactor optimizer.

#### Metrics

We use the standard ROUGE metric (Lin, 2004) to compare against the baselines. To measure the factual correctness, we adopt the E2E NLI metric proposed by Honovich et al. (2021). In this metric, we use an NLI model trained on SNLI (Bowman et al., 2015) to assess whether each sentence of the summary can be inferred from the input document. Towards this, we use the RoBERTa (Liu et al., 2019) model trained on the SNLI corpus. For each predicted summary \(y_p\), we assign a score of 1 if the NLI model predicts a entailment and a score of 0 if the model predicts either neutral or contradiction. Finally, we average these scores across all the test set to yield an overall factuality score.

### 3.1 Datasets

We select the CNN/DailyMail and XSum dataset for our experiments since their factual inconsistency is well documented (Kryscinski et al., 2020).

#### CNN/DailyMail

This dataset proposed by See et al. (2017) is composed of summaries from the news websites CNN and Dailymail.

#### XSum

The XSum dataset (Narayan et al., 2018) is also a news summarization dataset but targeted towards summaries that are extremely short, thus more challenging. We compare our model settings with the variation of the model where the original dataset is not augmented (the Original setting). All models were train on 16 TPUv3 slices. For fair comparison, baseline and proposed approach were trained for

- We use entire dataset for both CNN/DailyMail and XSum.
the same number of steps (110000), with 5 random seeds and the results are averaged.

**Preprocessing** : We follow the preprocessing steps outlined in Nan et al. (2021a) for the XSum dataset as following: we remove (i) all sentences from the source document that include only noisy strings such as “Share this with Email, Facebook, Messenger” and (ii) all sentences in summaries that has an entity that is not present in the source document. For CNN/DailyMail, we follow the standard dataset processing without any special preprocessing steps.

### 3.2 Results

We compare our different augmentation strategies to training the model without augmentation. The results are shown in table 2. The ROUGE scores are comparable to the model that was trained on the original dataset without augmentation. We also observe that augmentation uniformly improves factuality across various augmentation settings. For the CNN/DailyMail dataset, WN-HYPER augmentation performs the best, improving by about 3 points compared to the baseline. We observe a similar trend in the XSum dataset where augmentation achieves improvement in factuality.

### 3.3 Analysis

An abstractive summary (Rush et al., 2015; Gehrmann et al., 2019) paraphrases the input document copies less fragments of text from the input compared to an extractive summary (Neto et al., 2002; Erkan and Radev, 2004). While recent state-of-the-art methods for summarization methods focus of abstractive methods, it is shown that as degree of abstractiveness is an important indicator of hallucinations in summarization models, and often higher hallucinations correlated with higher ROUGE scores for such models (Dreyer et al., 2021).

To understand in-depth the nature of the samples where the factuality improves, we sampled 100 random datapoints from development set of XSum dataset. Among those samples, we found that about 68% summaries are similar without significant variance in ROUGE and have the same E2E NLI score. From the rest of the samples, we observed the following: (i) **Specificity** : Models trained on augmented data often had more named entity information, in effect making them more specific. Table 3 show some qualitative examples from the model (ii) **Factually Correct with reduced ROUGE** : In about 9% of the samples, despite being factually correct, resulted in lower ROUGE scores compared to the original model. In our inspection of these samples, we found that the gold news summaries often omit specific details in the input document and tend to be less extractive, and extractive summaries are often more factual than abstractive summaries since they copy higher ratio of phrases from the input document. We observe the same phenomenon as Dreyer et al. (2021) that degree of abstractiveness affects the factuality inversely. We believe that this contributed to the lower ROUGE scores and improve factuality scores in Table 2. We show some qualitative examples in Table 3.
4 Related Work

To generate factually correct summaries, several approaches have been proposed recently. A line of work focuses on post-correcting summaries after they are generated Dong et al. (2020); Cao et al. (2020). Zhu et al. (2021) propose adding a graph based layer to existing transformer network to improve factuality by modifying the architecture. Contrastive learning approaches Nan et al. (2021b); Cao and Wang (2021); Cao et al. (2020) have also been proposed with data perturbation that introduces additional loss components for improving factuality with the assumption that MLE objective leads to inconsistent summaries. Our approach proposes a data-augmentation alternative to current approaches but we do not require to modify the loss term during fine-tuning or add special layers to the model.

5 Conclusion

Overall, we propose a counterfactual data augmentation approach to improve factuality in summarization systems. We achieve this using a simple data augmentation approach by perturbing the summaries via inducing errors in entities and replacing nouns with their corresponding WordNet hypernyms. Our results show this simple, yet effective technique, leads to improvements in the factual correctness of the generated summaries.

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