Learning by Semantic Similarity Makes Abstractive Summarization Better

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Abstract
By harnessing pre-trained language models, summarization models had rapid progress recently. However, the models are mainly assessed by automatic evaluation metrics such as ROUGE. Although ROUGE is known for having a positive correlation with human evaluation scores, it has been criticized for its vulnerability and the gap between actual qualities. In this paper, we compare the generated summaries from recent LM, BART, and the reference summaries from a benchmark dataset, CNN/DM, using a crowd-sourced human evaluation metric. Interestingly, model-generated summaries receive higher scores relative to reference summaries. Stemming from our experimental results, we first argue the intrinsic characteristics of the CNN/DM dataset, the progress of pre-trained language models, and their ability to generalize on the training data. Finally, we share our insights into the model-generated summaries and presents our thought on learning methods for abstractive summarization.

1 Introduction
Text summarization is a process of automatically generating a compact summary from a document while minimizing the loss of important information. There are two dominant methods for text summarization- namely Extractive and Abstractive. Extractive summarization is a method of creating summaries by extracting important parts from the document (Zhang et al., 2018; Narayan et al., 2018; Liu and Lapata, 2019), whereas abstractive summarization is more like generating sentences using salient information from the document (See et al., 2017; Paulus et al., 2018; Lewis et al., 2019).

For abstractive summarization, reinforcement learning (RL) and supervised learning model are widely used. Reinforcement Learning (RL) based models, using ROUGE metric (Paulus et al., 2018) or neural network (Böhm et al., 2019) as reward, showed remarkable performance. However, the optimization is slow and requires considerable computational effort to converge (Chen et al., 2018; Gehrmann et al., 2018). The supervised learning approach is straight-forward and requires relatively less time to train (You et al., 2019; Gehrmann et al., 2018).

Recently, large-scale pre-trained language models (LM), such as ELMo (Peters et al., 2018), BERT (Devlin et al., 2018), GPT-2 (Radford et al., 2019) and BART (Lewis et al., 2019), demonstrated benefits of contextualized language representations through diverse natural language processing (NLP) tasks, including text summarization (Liu and Lapata, 2019; Zhang et al., 2019a). BART, which is composed of bidirectional transformers (encoder) and auto-regressive transformers (decoder), is designed as a sequence-to-sequence model and has shown advanced performance for CNN/DailyMail dataset.

However, most papers evaluated their model with automatic evaluation metrics such as ROUGE or METEOR. Although automatic evaluation metrics are known to be high correlation with human judgement, they have limitations and may mislead the actual quality of a generated text (Schluter, 2017; Maynez et al., 2020; Gehrmann et al., 2021). Despite the fact that existing researches suggest these drawbacks of current evaluation strategy, papers with comparative analysis on the model-generated summaries and the reference summaries are, to the best of our knowledge, limited.

In this paper, we first investigate and compare the quality of the reference summaries and model generated summaries using crowd-sourcing based manual evaluation, or human evaluation. The human evaluation result indicates that there is a statistically significant difference between reference summaries and the model generated summaries; interestingly,
the latter was better. Normally, quality of reference dataset become a upper-bound for a model trained on a given dataset; model shows sub-optimal performance than its own reference. However, our crowd-source workers preferred model-generated summaries over the reference summaries.

In the rest of our paper, we first address this observation, by discussing the intrinsic characteristics of CNN/DM - how the dataset was built. We also discuss the advance of pre-trained language model structure, and further suggest new perspective of improving text summarization models by sharing our insights on the current learning objective.

Our contributions are as follow:

- We evaluate model generated summary and benchmark dataset through human evaluation bases.  

- We investigate a benchmark dataset, CNN/DM, and suggest the characteristics of the dataset. We further share our insights on the model-generated summaries.

- We present our human evaluation scoring guidelines on 3 criteria; Creativity, Readability and Relevance.

2 Related Work

2.1 Reinforcement Learning

Reinforcement Learning (RL) is a widely used learning technique for text summarization task. Paulus et al. (2018) pointed out that the loss of the supervised model is not closely related to the evaluation metric and therefore, introduced an end-to-end RL model that employs the ROUGE metric (Lin, 2004) as a reworder.

Böhmm et al. (2019) point out the limitations of ROUGE-based rewarders and proposed neural network-based rewarders to predict the similarity between document and summary. Specifically, the model is trained to predict the similarity score between the document and the summaries of various quality. The pre-trained language model BERT is used to encode the input sequences so that the semantics of the two inputs are adequately reflected in the model.

2.2 Supervised Learning

Supervised Learning is an actively researched area in summarization. See et al. (2017) introduced a sequence-to-seq attentional model that combines coverage vector and the copy mechanism. Gehrmann et al. (2018) proposed a bottom-up attention model by incorporating the content selection system that selects the important parts of a document. Liu and Lapata (2019) presented a document-level encoder using BERT (Devlin et al., 2018) and showed benefits of using pre-trained language model (LM) as embeddings. Jeh (2020) developed an approach to stack an additional encoder-decoder network, on top of an attentional encoder-decoder network to alleviate the exposure bias issue that comes from teacher forcing (Williams and Zipser, 1989).

Pre-trained models Recent works on pre-trained language models made significant advances in NLP tasks. BERT (Devlin et al., 2018) is a bidirectional encoder that is pre-trained by predicting the original document with the corrupted document as an input. GPT (Radford et al., 2018) and GPT-2 (Radford et al., 2019) are auto-regressive LMs. BART (Lewis et al., 2019) is a pre-trained language model that combines bidirectional transformer as an encoder and auto-regressive transformers as a decoder. Concurrent to our work, ProphetNet (Yan et al., 2020) and PEGASUS (Zhang et al., 2019b) also use pre-trained LMs to solve text summarization task. Both model shows stunning performance by using encoder-decoder settings.

| System                  | CNN/DailyMail |
|-------------------------|---------------|
|                         | R-1 | R-2 | R-L |
| Böhmm et al. (2019)     | 39.60 | 18.10 | 36.50 |
| Narayan et al. (2018)   | 40.00 | 18.20 | 36.60 |
| Pasunuru and Bansal (2018) | 40.43 | 18.00 | 37.10 |
| Chen and Bansal (2018)  | 40.88 | 17.80 | 38.54 |
| Bae et al. (2019)       | 41.90 | 19.08 | 39.60 |
| Jeh (2020)              | 40.44 | 18.15 | 36.90 |
| Yan et al. (2020)       | 43.68 | 20.64 | 40.72 |
| Zhang et al. (2019b)    | 44.17 | 21.47 | 41.11 |
| BART (Baseline)         | 43.98 | 21.07 | 40.82 |

Table 1: ROUGE (automatic) evaluations on CNN/DailyMail dataset of reinforcement learning (RL) and supervised learning (SL) models.
Table 2: Human Evaluation score of the Systems. Scores are presented in both 1-4 scale and 0-100% percent scale (numbers in parenthesis)

|                          | Creativity | Readability | Relevance | Total (Avg) |
|--------------------------|------------|-------------|-----------|-------------|
| Reference Summary        | 2.70 (56.81%) | 3.05 (68.23%) | 2.68 (55.96%) | 2.81 (60.33%) |
| BART (Baseline)          | 2.80 (60.14%) | 3.39 (79.65%) | 3.12 (70.71%) | 3.10 (70.17%) |

3 Experiments

3.1 Dataset

We used the non-anonymized CNN/DailyMail (CNN/DM) dataset (Hermann et al., 2015; See et al., 2017) to evaluate our approach. CNN/DM dataset is composed of articles and corresponding bullet point summary pairs from the news providers. Following BART, we applied additional preprocessing steps such as replacing escape characters. The preprocessed CNN/DM dataset includes 287k training pairs, 13k validation pairs, and 11k testing pairs.

3.2 Model

We first introduce the underlying structure of BART in Section 3.2.

BART is a denoising autoencoder that uses sequence-to-sequence transformer architecture of Vaswani et al. (2017). The structure of BART consists of two parts: an encoder and a decoder. The encoder part is a bidirectional encoder which corresponds to the structure of BERT (Devlin et al., 2018), and the decoder part is an auto-regressive decoder following the settings of GPT.

During the pre-training process, BART receives the corrupted document as input and performs the task of predicting the original uncorrupted document. In this way, BART can effectively learn contextual representations.

BART can be fine-tuned for various tasks such as token classification, sequence classification and sequence generations. When fine-tuned for summarization task, the bidirectional encoder part encodes the original document and the decoder part predicts the reference summary.

3.3 Settings

Following the setting of original BART paper, we tokenized the input sequences with the byte-pair encoding of RoBERTa (Liu et al., 2019). During the generation process, beam search decoding with a beam size of 4 was used to produce the output summary. Trigram blocking (Paulus et al., 2018), min-len of 55 tokens, max-len of 140 tokens and length penalty were applied during decoding (Lewis et al., 2019).

4 Evaluations

4.1 Automatic Evaluation

We report our automatic evaluation results on the CNN/DM dataset in Table 1. For other models, we report the scores in accordance with their papers. For summarization task, the ROUGE metrics (Lin, 2004) are widely used for evaluations, namely F1 scores of ROUGE-1, ROUGE-2 and ROUGE-L (Paulus et al., 2018; See et al., 2017; Lewis et al., 2019). ROUGE score of BART model was better than reference models using RL approach and the most supervised learning models. Automatic Evaluation results suggest that the BART model is a top-performing model.

4.2 Human Evaluation

4.2.1 Evaluation Criteria

In order to assess model’s proficiency in summarization, we follow the evaluation criteria of International English Language Testing System (IELTS) as it is one of the major English test for non-native speakers across the world. IELTS writing is about summarizing information in a graph or table and writing a letter in response to a problem. Although it has different nature to the summarization task, we believe the fundamental factors should be the same because the model also needs to comprehend the given information, grasp important matters, and write with its own words.
We modified evaluation criteria to Relevance, Readability, and Creativity. Both Relevance and Readability are referred from IELTS’ criteria but Creativity is added specifically for sentence summarization task. Creativity is a meaningful factor because a good summary should not be copied from the original text, but rather translated into the model’s own words to represent the context.

The following questions are asked to adopt score guidelines for our experiment:

- **Creativity** - Is the summary written with its own words and sentence structures?
- **Readability** - Does the summary avoid grammar errors and informal language?
- **Relevance** - Does the summary contain both important and accurate information about the original document?

For more descriptions about score guidelines, please refer to Table 3.

### 4.2.2 Evaluation Setup

We use Amazon Mechanical Turk to evaluate the machine-generated summaries. For qualifications, we required all workers to possess a bachelor’s degree in the United States. Then, we organized a team into ten workers, and each team is requested to answer five questions, where one question includes the original document, the reference summary, and BART model generated summaries. The reference summary and model generated summary are presented in random order. Overall, ten teams are participated for evaluation, meaning 100 people (1 team x 10 people) and 50 examples (5 examples x 10 teams) in total.

Workers are asked to measure the level of summarization quality from 1 to 4 in terms of Relevance, Readability, and Creativity. For these three criteria, the human examiner will judge whether the summary contains key features, avoids grammar errors, and uses its own words and sentence structures. Please consult Appendix for further details about score requirements.

Turk workers in our experiment had Human Intelligence Task (HIT) approval rate of 98% and completed over 10,000 HITs. For five questions, they spent about 1437.69 seconds (24min) on average, and the standard deviation is 782.4 seconds (13min). These statistics suggest that the time it took for workers to complete the questions varied greatly. It is clear that some workers did not respond faithfully, and therefore we excluded workers whose spent time is in the lower 5%, which is 389 seconds. Upon inspection, we realize that these inattentive workers are not biased to a certain team. Instead, there are about 0 to 2 workers in each team, whose spent time is less than 389 seconds for five questions. In this manner, we tried to not only ensure fairness but also assure the quality of human evaluation.
4.2.3 Results

Our human evaluation results are reported in Table 2. The table shows averaged score across all 470 responses (5 examples X 94 people). We convert the human evaluation scores from 1-4 scale to 0-100 scale and reported total score, which is the average of three scores. We compare the scores of BART model and the reference summary. BART was better than reference summaries in terms of Readability (p-value < $10^{-10}$) and Relevance (p-value < $10^{-10}$), but the gain in Creativity was marginal. We calculated p-values using the one-tailed t-test (statistical significance of 0.01).

![Figure 1: An example of CNN/DailyMail dataset.](image)

5 Discussion

5.1 Results Analysis

It is an interesting observation that a model produced a more favorable summaries than the reference summaries. In this section, we take a deeper look into this phenomenon, by focusing on two following aspects: 1) The reference summary is not always an ideal summary of the document and 2) A large-scale language model has a strong ability in text generation.

As a nature of the CNN/DM dataset, some reference summaries are of poor quality and hence, these summaries received low scores compared to those generated by models. Table 4 and Figure 1 show an example of a document-summary pair. This example summary is missing crucial information to comprehend the document: the subject of the article Alessandra Ambrosio and who she is. For this example, reference summaries are made up of bullet points that are appeared as part of the headlines (Figure 1). Headlines are often designed to intrigue readers’ attention, and therefore they usually do not contain enough facts to understand the articles. It is a fatal flaw if the summary is not complete and consequently, such a summary will receive a low score for Readability. We believe that this is one of the reasons why some reference summaries received lower scores than generated summaries.

In general, we assume that the test set and training set are of the same quality because the test set intrinsically has a very similar distribution to the training set. If the test set is a low-quality data, then the training set, which is used for training, would be low quality as well. And this low quality will be reflected eventually when we train a model. Hence, it is rare for the model to produce results that are better than the dataset. However, our model has shown contradicting results: model’s generated summaries are evaluated as better than the reference summaries. We believe that this is due to the transfer learning of large-scale language models. Language models are pre-trained on various corpus and we exploited this advantage. We assume that the performance difference comes from the language model. The idea of the language model is to learn the general understanding of a language during the pre-training process and the specific task during the fine-tuning process. BART is trained to extract salient information by using the encoder and to make a complete sentence by using the decoder. Generating a complete sentence is closely related to providing a readable sentence and this can be achieved by extracting salient information, which can enhance relevance. For these reasons, as shown in the Table 2, BART shows outstanding performance in both Readability and Relevance. The successful use of pre-trained knowledge is the main reason why our model and BART received favorable scores. In addition, by considering that the human evaluation score is subjective, the Readability score of almost 80 is regarded as a high score.

5.2 Learning Strategies and Evaluation Criteria

In this section, we first share our insights on the model-generated summaries. We aim to open a discussion for a better learning strategy and also like to emphasize a need for a better evaluation criteria for text generation tasks.
Brazilian supermodel Alessandra Ambrosio goes back to her roots in an edgy new campaign shot in her home country. The 34-year-old Victoria’s Secret Angel shows off her Latino style and golden tan as she poses in a new campaign for online fashion retailer Dafiti, shot in São Paulo. Dafiti, Latin America’s largest online fashion retailer, has launched its own fashion collection, the Dafiti Collection, and signed Alessandra because they believe she embodies the style of the brand. Scroll down for video. Alessandra Ambrosio, who found fame as a Victoria’s Secret Angel, has been snapped up to front a campaign for online fashion retailer Dafiti, which was shot in São Paulo. The mother-of-two, who is No. 8 on the Forbes list of top-earning models, stars in the advertising...
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