End-to-end Semantics-based Summary Quality Assessment for Single-document Summarization

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Abstract

ROUGE is the de facto criterion for summarization research. However, its two major drawbacks limit the research and application of automated summarization systems. First, ROUGE favors lexical similarity instead of semantic similarity, making it especially unfit for abstractive summarization. Second, ROUGE cannot function without a reference summary, which is expensive or impossible to obtain in many cases. Therefore, we introduce a new end-to-end metric system for summary quality assessment by leveraging the semantic similarities of words and/or sentences in deep learning. Models trained in our framework can evaluate a summary directly against the input document, without the need of a reference summary. The proposed approach exhibits very promising results on gold-standard datasets and suggests its great potential to future summarization research. The scores from our models have correlation coefficients up to 0.54 with human evaluations on machine generated summaries in TAC2010. Its performance is also very close to ROUGE metrics\textsuperscript{7}.

1 Introduction

ROUGE is the de facto criterion for summarization research \cite{Celikyilmaz2018, Amplayo2018, Dohare2018, Cao2018}. Despite its wide use, previous work \cite{Ng2015, Liu2008, Liu2016, Shang2018} has agreed on its two major drawbacks: 1) it favors lexical similarity, not semantic similarity, and 2) it requires a reference summary.

The first drawback makes ROUGE unfit when heavy rewrite happens, which is not so rare, especially for abstractive/generative summarization \cite{Shang2018, Celikyilmaz2018, Amplayo2018}. Some attempts introduce word semantics into ROUGE, including replacing exact-word-matching with the dot product of the word embeddings \cite{Ng2015}. But bounded by the grammar-based framework of ROUGE, such word-level fixes cannot be effective because the meaning of a sentence is not only defined by words comprising it.

The second drawback significantly limits summarization research because reference summaries are expensive to obtain \cite{Zopf2018}. Instead of simply labeling the data with numbers or categorical tags in many other supervised learning problems, a human annotator for summarization tasks needs to generate a substantial amount of data. Current summarization research is limited to a handful of datasets, which are dominantly in the news domain. With ROUGE, it is hard to expand the study to new domains, or even new datasets, that do not come with reference summaries.

To tackle the two drawbacks rooted in the design of ROUGE, we hypothesize that it is possible to assess the quality of summary through a semantic document-summary comparison. As the first step toward this goal, this paper studies the feasibility to predict how proper a given summary matches a given document. In order to instantiate, we train end-to-end models in supervised machine learning fashion by leveraging recent advances in sentence embedding, which demonstrate that semantically similar sentences are close in the embedding space \cite{Yang2018}. This could help the trained model to consider more on high-level semantic similarity instead of only lexical similarity.

Such a supervised learning task is not trivial because no datasets can be directly used here: existing datasets do not contain mis-matching summaries but only human-composed reference summaries that well match documents. We hence develop two negative sample generation approaches to prepare two datasets by swapping and mutating summaries, respectively.

Experimental results show that our methods can accurately tell whether a summary matches a given document with a 96.2% accuracy, or tell how much a summary is mutated with irrelevant words with a correlation coefficient over 0.95. Additional cross-domain analyses show that models trained in our approach can capture the meaning.

In summary, our contributions are as follows:

- a feasibility study on semantics-based summary quality assessment without using reference summaries,
- two negative sample generation methods from existing datasets, and
- extensive and promising empirical evidences, especially the correlation between the output of our model and human evaluation scores for machine-generates summaries in TAC2010.

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2 Approach

2.1 Model Architecture

We formulate the problem as a supervised learning problem. Formally, given an input document, and a candidate summary, the goal is to compute a score about the quality of the summary w.r.t. the input document.

As depicted in Figure 1, our model has two stages. First both the document and the summary are transformed into a vector representation. Then a neural network is trained to estimate a summary quality score from the vector representation. Our study covers two approaches to convert text into its vector representation, detailed as follows.

The first approach, based on sentence embedding, views the document \( d = [a_1, \ldots, a_n] \) and the summary \( s = [a_1', \ldots, a_m'] \) as two sequences of \( n \) and \( m \) sentences, respectively. A vector representing both of them is then the concatenation of sentence embeddings of all sentences in them

\[
V = [e_1 \oplus \cdots \oplus e_n \oplus e_1' \oplus \cdots \oplus e_m']
\]

where

\[
e_i = \text{Emb}(a_i), \forall i \in [1..n],
\]

and \( \text{Emb} \) is a sentence encoder. We employed two sentence encoders: Google’s Universal Sentence Encoder (USE) [Cer et al., 2018] and Facebook’s InferSent Sentence Encoder [Conneau et al., 2017], to study the impact of sentence embedding on the task.

The second approach, based on BERT [Devlin et al., 2018], views the document \( d \) and the summary \( s \) as two sequences of tokens, i.e., \( d = [t_1, t_2, \ldots] \) and \( s = [t_1', t_2', \ldots] \). The tokens, plus two control tokens, [CLS] and [SEP], are then concatenated:

\[
T = [[\text{CLS}], t_1, t_2, \ldots, [\text{SEP}], t_1', t_2', \ldots, [\text{SEP}]]
\]

before being fed into the BERT network. The output of BERT corresponding to the special token CLS can be regarded the representation of both the document and the summary:

\[
V = \text{BERT}(T)|_{[\text{CLS}]}.
\]

Then, the vector \( V \) is fed into a neural network that predicts the score. For the \( V \) constructed using sentence encoders, three standard neural networks, namely a fully-connected (FC) network, a convolutional neural network (CNN), and a long short-term memory (LSTM) network, are chosen as examples to prove the concept of our framework. In the last two networks, in line with common practices, there is an FC network in the last stage. For the BERT-based document-summary representation, only the FC network is used. Details of the networks are provided in Section 3.

2.2 Negative Sample Generation

To train a said supervised model, besides summaries that match documents well, we also need summaries that match documents poorly, including negatively. However, existing summarization datasets contain only the former ones, the human-composed reference summaries. So we introduce two approaches, random mutation and cross pairing, to create negative samples.

![Figure 1: Model architecture. When the document and the summary perfectly match, the expect score is 1. When they are totally irrelevant, the expect score is 0.](image)

![Figure 2: Training sample generation by mutation. Mutated text in dark blocks while original text in the summary in gray blocks. Sizes are out of scale.](image)

**Random mutation**, illustrated in Figure 2, alters the content of a reference summary by: 1) adding random tokens drawn from the vocabulary to random locations, or 2) deleting random tokens; or 3) replacing random tokens with random words. The complement of the percentage of mutation is the score to be predicted by the model. For example, if 30% of the tokens in a reference summary are deleted, then the model is expected to predict 0.7 when the corresponding document and the mutated summary are fed into the model. In particular, when no mutation, i.e., the original reference summary, the label is 1. Therefore, the model
to be trained is a regression model, and Mean Square Error (MSE) is chosen as the loss metric.

One caveat of such word-level mutation is that the structure of the text may be destroyed, producing ill-formed data. Hence, we introduce the second approach, cross-pairing.

Another concern is using the amount of mutation to approximate the quality of a summary, e.g., replacing words by synonyms does not change the meaning much. However, we can rely on the small chance that a word mutated retains the meaning. Second, the chances that a word mutated retains the meaning are very low due to the randomness.

Cross-pairing, illustrated in Figure 3, is inspired by how word2vec [Mikolov et al., 2013] generates fake context words. Given a document and its reference summary, we create negative data by pairing the document with reference summaries of other documents. We assign the label 0 to such document-summary pairs, and the label 1 to any original pair of document and (reference) summary. This renders the problem into a binary classification problem. We use binary cross-entropy as the loss function.

3 Experiments
3.1 Data
We evaluate our approach on three widely used summarization datasets:

- CNN/DailyMail dataset [Hermann et al., 2015] Nallapati et al., 2016
- Newsroom Grusky et al., 2018
- Big-Patent Sharma et al., 2019

The first two datasets belong to news article domain while the third is formed from patent documents and their abstracts.

Results on data prepared in different methods introduced in Section 2.2 will be reported separately. For each dataset, we randomly pick 30,000 samples, and report the result on each dataset individually. Later, we also study how well a model trained on one dataset can perform on the other.

For each data preparation method, we generate one fake sample per article, thus we have a total of 60,000 samples. Data is split into 80%/10%/10% as training/validation/testing set. The splitting procedure also ensures that no article in test set appears in training set.

3.2 Settings
As it is interesting to study the impact of different text sequence encoding schemes to our task, we evaluate the results on four text sequence encoder settings:

- Universal Sentence Encoder (USE) Cer et al., 2018 with Deep Averaging Networks (DAN)
- USE Cer et al., 2018 with Transformer (USE-Trans)
- InferSent Conneau et al., 2017, and
- BERT Devlin et al., 2018 which pre-trains a transformer using a large web corpus.

For the first 3 sentence encoders, we apply padding to both documents and summaries to unify the input dimensions. The dimensions are limited to the length of 80% of the data, or equivalently, 47 sentences for documents and 3 sentences for summaries. For BERT, we limit the total token number at 512. Should a pair of document and summary together exceed or fall short of 512 tokens, we pad or truncate the document and summary in parallel to meet the dimension requirement.

As a baseline, we also test a model (denoted as "GloVe" in Table 1) trained on top of word embedding using GloVe Pennington et al., 2014. We use pretrained 100d GloVe matrix. The padding/truncation lengths are set to 1091 and 55 words, respectively for documents and summaries, according to the 80% rule above.

As mentioned in Section 2.1, embeddings are fed into 3 kinds of networks: a fully-connected network (FC-only), a CNN, and an LSTM. The FC-only network has a single hidden layer of 128 neurons fully connected to the flattened input embeddings and a single output node. The CNN is stacked from a 2D convolutional layer, a max-pooling layer, and lastly a fully-connected layer resulting in a single output neuron. We use 128 kernel filters of a dimension 5 × d where d is the dimension of word/sentence embeddings, so that convolutions do not cross word/sentence boundaries. The filter size of the max-pooling layer equals to the dimension of the output of the convolutional layer. The max-pooling layer output is fully connected to the single output neuron. In LSTM setting, we use one layer of 25 and 128 LSTM units for word and sentence models, respectively. These units are connected to a single output neuron in fully-connected manner. For all architectures, we use RMSProp optimizer with NAG learning rate. Early-stopping is used to determine the desired number of epochs, and stop training if validation loss is not improving in three epochs.

As for the BERT model, we consider the pre-trained 12-layer transformer as our model. Each token of the input sequence including [CLS] is encoded into an embedding vector with a dimension of 768 by using BERT. The FC-only network for BERT-based model also has a single hidden layer of 128 neurons fully connected to the [CLS] embedding and a single output node.

3.3 Base Model Performance on Cross-pairing
The results of our base models on samples generated using cross-pairing are given in Table 1. Each row corresponds to one network architecture, and each column corresponds to one text-to-vector scheme.

First of all, the framework has phenomenal success on telling how well a summary matches a document. On predicting whether a document-summary pair is true using data prepared by cross pairing, the accuracy can be up to 96,2%
word embeddings cannot capture sentence similarities [Liu et al., 2015] and the structure. This finding aligns well with other studies that primitively combining word embeddings into sentence embedding based models over-perform word embedding ones. In particular, InferSent and USE-Trans models achieve 96.2% and 93.5% accuracy, respectively, while GloVe-based models seem to struggle with up to 72.2% accuracy (for mutation-add, mutation-delete, and mutation-replace) when using USE-Trans + LSTM, and up to 95.3/94.6/98.4 when using BERT. Second, sentence embedding models consistently outperform word embedding ones on mutated-deletion data where all models perform comparably. Lastly, USE-Trans and BERT based models are generally better than USE-DAN and Glove, while the pre-trained transformer architecture such as BERT has shown the best performance. This shows the transformer architecture especially the pre-trained transformer such as BERT model may capture some fundamental linguistic semantics.

### 3.4 Base Model Performance on Mutation

We proceed to evaluate our model performance on mutation in Tables 2 where the three variants of mutation are denoted as mutation-add, mutation-delete, and mutation-replace. The results are similar to the cross-paired datasets. In general, the results are encouraging. The framework can help to tell how well a summary matches a document. For example on predicting how much the reference summary is mutated, the correlation coefficient can be up to 95.5/93.0/96.9 (for mutation-add, mutation-delete, and mutation-replace respectively) when using USE-Trans + LSTM, and up to 95.3/94.6/98.4 when using BERT. Second, sentence embedding models consistently outperform word embedding ones except on mutated-deletion data where all models perform comparably. Lastly, USE-Trans and BERT based models are generally better than USE-DAN and Glove, while the pre-trained transformer architecture such as BERT has shown the best performance. This shows the transformer architecture especially the pre-trained transformer such as BERT model may capture some fundamental linguistic semantics.

### 3.5 Cross-domain Analysis

By cross-domain analysis, we mean that the training and test data are from two different domains (e.g., news articles vs. patents, or two different kinds of news articles). The domain on which the model is trained is called the source domain while the domain on which the model is tested is called the target domain. A good summary assessment model is expected to have a consistent performance across domains, even on text from a domain that differs from those used in training. Because domain-transferability is not a focus of this paper, we use samples generated in cross-pairing only in this part. The only model used here is BERT-based.

**Cross-domain performance.** By using the CNN/DailyMail dataset as the target domain, we test the transferability of
different source domains. Here we use the Big-patent [Sharma et al., 2019] and Newsroom [Grusky et al., 2018] datasets as the source domains.

As shown in Table 3, the performance on the CNN/DailyMail drops when training on other domains like Big-patent and Newsroom, showing that domain difference exists. But since the performance drop is very small, around 1% and 0.3% for Big-patent and Newsroom respectively, this means the proposed method has relatively good transferability across different domains.

Cross-domain performance w.r.t. domain size. We continue to examine the effect of target domain size on the cross-domain performance. We sample data from the CNN/DailyMail dataset with different sample sizes, 30k, 100k, and 300k, to test the transferability from another domain and itself.

As shown in Table 4 for training in-domain (CNN/DM as the source), the performance increases slightly with the data size. For transferring (Newsroom as the source), the performance is relatively stable, as all the results are around 98.3%. A good thing is that the domain difference is not large as the transferability from Newsroom to CNN/DailyMail is generally good in all cases.

| Target domain size | CNN/DailyMail | Big-Patent | Newsroom |
|--------------------|---------------|------------|----------|
| 30k                | 98.5          | 97.5       | 98.2     |
| 100k               | 98.6          | 98.3       | 99.2     |
| 300k               | 98.4          | 98.3       | 98.3     |

Hence we can conclude the model built in our approach has consistent performance across domains, and across different domain sizes, and thus suitable to handle summaries from various sources.

### 3.6 Alignment with human evaluation

The last, but probably the most exciting, part of the evaluation is on how well the scores from our models correlate or align with human evaluation or judgment of summaries.

#### Data and setup

Because there is no released single-document summarization dataset that includes human evaluation on the summaries, we use the data from TAC2010 [2010 guided summarization competition, a multi-document summarization task, to approximate. The human evaluation result from TAC2010 is distributed by NIST.

In TAC2010 guided summarization task, there are 43 machine summarizers and 4 human summarizers. Given a document set, consisting of 10 news articles about the same event, each summarizer generates a summary. Because there are 46 document sets and 47 summarizers, we have a total of $46 \times 47 = 2,162$ document-summary pairs.

For each summary generated, a group of human evaluators score it from multiple aspects, resulting in 4 scores: the Pyramid score, the modified score, the linguistic quality, and the overall score. The meaning of the scores can be found from TAC2010 dataset. Because the Pyramid score is not available for human-composed summaries and it is also based on overlaps, this part of the study focuses on the last 3 scores.

Given a document $d$, and a corresponding summary $s$ (machine-generated or human-composed), denote the score from our framework as $f(d, s)$. Because a document set (denoted as $D$) has 10 articles which all correspond to the same summary, we define the score for the summary as $\sum_{d \in D} f(d, s)$, and compute its correlation with 3 human scores. Our model $f$ is trained using samples generated from 30k CNN/DailyMail data only.

#### Results

Because BERT-based model has the best performance in previous experiments, we use BERT-based model in this last part of the experiment. The results are given in Table 5 (in Pearson’s correlation coefficient) and Table 6 (in Spearman’s correlation coefficient).

Among the 4 methods to generate samples, crosspairing produces the samples that train a model that best align with human evaluation scores, reaching 0.3426 (Pearson’s) and 0.3993 (Spearman’s) with modified score. We think this is a promising result given the limited amount of data (30k news articles) used in training.

Models trained with 3 mutation-generated samples have
very poor alignment with human evaluation scores, especially deletion based. Using samples generated from deletion, the Pearson’s or Spearman’s correlation coefficients between our model’s score and human evaluation scores are below 0.1. One possible reason is that the model trained in deletion-generated samples is influenced by the length of the summary heavily rather than the information or writing of it.

Among three human evaluation scores, our model has the lowest correlation with linguistic quality. This might indicate that current sentence or document embedding approaches focus on the semantics but not the writing styles.

If we mix the samples generated in all 4 methods together to train a new model, the model’s alignment with human evaluation can be boosted significantly. For example, the Pearson’s and Spearman’s correlation coefficients between the mixed model and modified score are as high as 0.4496 and 0.5024, respectively.

Lastly, we are particularly interested in testing our approach on machine-generated summaries in TAC2010 because an important use of our approach is to judge automated summarizers. On machine-generated summaries, our mixed model’s Pearson’s and Spearman’s correlation coefficients with modified score are 0.5191 and 0.5387, respectively, and those with overall score are 0.4274 and 0.3844, respectively.

So in conclusion, we think that our approach achieves very promising initial results given the small amount of data and training epoch.

Comparison with ROUGE
We then compare our best model with the ROUGE metrics, the de facto standard in summarization study, to see whether our model or ROUGE aligns with human evaluation better. Because ROUGE is a set of metrics, we pick 4 in this part of the study: ROUGE-1, ROUGE-2, ROUGE-4, and ROUGE-W-1.2. They measure the overlap between the summary and the document in terms of n-grams and skip-gram. The ROUGE scores are computed by NIST and distributed in the TAC2010 dataset. They are for machine-generated summaries only.

The results in Pearson’s and Spearman’s correlation coefficients are given in Tables 7 and 8 respectively. The suffixes P, R, and F after each ROUGE metric denote Precision, Recall, and F1 score, respectively. In terms of Pearson’s correlation coefficient, on modified score and overall score, our best model outperforms ROUGE-4, such as 0.5191 vs. 0.4765 and 0.4274 vs. 0.3513 in Table 7. And our method achieves slightly (below 0.1) inferior performance than those of ROUGE-1, ROUGE-2, and ROUGE-W-1.2, in most cases. It closes the gap with ROUGE metrics further on linguistic quality. In particular, it has almost equal performance with ROUGE-2 in linguistic quality. Similar results can be observed in Spearman’s correlation coefficient as well.

Therefore, despite that our approach cannot fully defeat ROUGE in terms of correlation with human evaluation of summary quality, the initial result is still promising in that our approach’s performance is close to ROUGE’s after training with a small amount of data and epoch.

4 Conclusion
In this paper, we propose an end-to-end approach that can potentially assess summary quality by its semantic similarity to the input document, without needing a reference summary. Two methods to prepare negative samples for training such end-to-end models are developed. Extensive experiments under various settings, including different neural network architectures, show that our approach can consistently and accurately tell whether or how much a summary is about the input document. Cross-domain analyses further show that a model trained in our approach can be used to judge summary quality in an unseen domain. Finally, our model shows moderate correlation with human evaluation to summaries, with a performance close to or equal to ROUGE metrics'. Our approach is a step toward designing better metrics to supplement the widely used, lexical-based ROUGE.
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