Understanding the Extent to which Summarization Evaluation Metrics Measure the Information Quality of Summaries

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Abstract

Reference-based metrics such as ROUGE (Lin, 2004) or BERTScore (Zhang et al., 2019) evaluate the content quality of a summary by comparing the summary to a reference. Ideally, this comparison should measure the summary’s information quality by calculating how much information the summaries have in common. In this work, we analyze the token alignments used by ROUGE and BERTScore to compare summaries and argue that their scores largely cannot be interpreted as measuring information overlap, but rather the extent to which they discuss the same topics. Further, we provide evidence that this result holds true for many other summarization evaluation metrics. The consequence of this result is that it means the summarization community has not yet found a reliable automatic metric that aligns with its research goal, to generate summaries with high-quality information. Then, we propose a simple and interpretable method of evaluating summaries which does directly measure information overlap and demonstrate how it can be used to gain insights into model behavior that could not be provided by other methods alone.\footnote{Our code will be available at \url{https://github.com/CogComp/content-analysis-experiments}.}

1 Introduction

The development of a reliable metric that can automatically evaluate the content of a summary has been an active area of research for nearly two decades. Over the years, many different metrics have been proposed (Lin, 2004; Hovy et al., 2006; Giannakopoulos et al., 2008; Louis and Nenkova, 2013; Zhao et al., 2019; Zhang et al., 2019, i.a.).

The majority of these approaches score a candidate summary by measuring its similarity to a reference summary. The most popular metric, ROUGE (Lin, 2004), compares summaries based on their lexical overlap, whereas more recent methods, such as BERTScore (Zhang et al., 2019), do so based on the similarity of the summary tokens’ contextualized word embeddings.

Ideally, metrics that evaluate the content of a summary should measure the quality of the information in the summary. However, it is not clear whether metrics such as ROUGE and BERTScore evaluate summaries based on how much information they have in common with the reference or some less desirable dimension of similarity, such as whether the two summaries discuss the same topics (see Fig. 1).

In this work, we demonstrate that ROUGE and BERTScore largely do not measure how much information two summaries have in common. Further, we provide evidence that suggests this result holds true for many other evaluation metrics as well. Together, these point to a grim conclusion for summarization evaluation: the community has not yet found an automatic metric that successfully evaluates the quality of information in a summary.

Our analysis casts ROUGE and BERTScore into
a unified framework in which the similarity of two summaries is calculated based on an alignment between the summaries’ tokens (§3). This alignment-based view of the metrics enables performing two different analyses of how well they measure information overlap.

The first analysis demonstrates that only a small portion of the metrics’ token alignments are between phrases which contain identical information according to domain experts (§4). The second reveals that token alignments which represent common information are vastly outnumbered by those which represent the summaries discussing the same topic (§5.2). Overall, both analyses support the conclusion that ROUGE and BERTScore largely do not measure information overlap.

Then, we expand our analysis to consider if 10 other evaluation metrics successfully measure information quality or not (§6). The experiments show that all 10 metrics correlate more strongly to ROUGE than to the gold-standard method of manually comparing two summaries’ information, the Pyramid Method (Nenkova and Passonneau, 2004), and that each correlates to the Pyramid Method around the same level as ROUGE. This is evidence that the other metrics measure information overlap no better than ROUGE does.

Finally, we propose a simple and interpretable evaluation method which does directly measure information overlap by calculating metrics on how many tuples of tokens that represent information are common between summaries (§7). Using our methodology, we are able to show that state-of-the-art summarization systems do produce summaries with better content than baseline models, an insight that ROUGE and BERTScore alone could not provide.

The contributions of this work include (1) an analysis which reveals that ROUGE and BERTScore largely do not measure the information overlap between two summaries, (2) evidence that many other evaluation metrics likely suffer from the problem, and (3) a proposal of a simple and interpretable evaluation method which does directly measure information overlap.

2 Understanding Evaluation Metrics

Reference-based evaluation metrics assume that human-written reference summaries have gold-standard content and score a candidate summary based on its similarity to the reference. An ideal evaluation metric that measures the content quality of a summary should score the quality of its information. For reference-based metrics, this means that the comparison between the two summaries should measure how much information they have in common.

Metrics such as ROUGE and BERTScore calculate the similarity of two summaries either by how much lexical overlap they have or how similar the summaries’ contextual word embeddings are (discussed in more detail in §3). Although we understand how their scores are calculated, it is not clear how the scores should be interpreted: Are they representative of how much information the two summaries have in common, or do they describe how similar the summaries are on some other less desirable dimension, such as whether they discuss the same topics? Our goal is to answer this question.

Knowing the answer is critically important. The goal of summarization is to produce summaries which contain the “correct” information (among other desiderata). Automatic metrics are the most frequent method that researchers use to argue that one summarization model generates better summaries than another. If our evaluation metrics are not aligned with our research goals — or if we do not understand what they measure at all — then we do not know whether we are making progress as a community.

3 A Common Framework

The focus of our analysis will be primarily on two evaluation metrics, ROUGE and BERTScore. Although on the surface these two metrics appear to compare two summaries very differently, here we demonstrate how they can both be viewed as calculating a score based on a weighted alignment between the summaries’ tokens. This common framework enables us to reason about how to interpret their scores.

Let $R = r_1, r_2, \ldots, r_m$ and $S = s_1, s_2, \ldots, s_n$ be the tokens of the reference and candidate summaries. ROUGE-1 counts the number of unigrams that are in common between the two summaries:²

\[ M = \sum_{s \in S} \min(c_R(s), c_S(s)) \quad (1) \]

²Our analysis focuses on the unigram variant of ROUGE, called ROUGE-1. We refer to it, where clear, as ROUGE for simplicity.
where \( c(s) \) counts the number of times \( s \) appears in the respective summaries and the summand is over unique unigrams. Then, precision and recall are calculated by dividing \( M \) by \( n \) and \( m \), respectively. When multiple references are available, the precision and recall scores are micro-averaged.

A weighted alignment \( A \) is a set of token alignments \( (i, j, w) \) that map token \( r_i \) to \( s_j \) with weight \( w \in (0,1] \). The weight of an alignment, denoted \( W(A) \), is the sum of the weights of the individual token alignments. ROUGE can be viewed as creating an alignment by pairing \( \min(c_R(s), c_S(s)) \) occurrences of unigram \( s \) in \( R \) and \( S \) with weight 1.0 for all unigrams. It additionally imposes a constraint that each token can be aligned to at most one other token. Since a unigram may appear multiple times in a summary, the alignment may not be unique, however, its weight will equal \( M \).

BERTScore calculates a similarity score between two pieces of text based on the pairwise cosine similarities of their tokens’ BERT embeddings. Let \( B_{ij} \) be the similarity score between the embeddings for \( r_i \) and \( s_j \). To calculate recall, BERTScore first aligns every reference token to its most-similar reference token (Eq. 2). Then, the sum of the corresponding similarities is normalized by the number of reference tokens to get the recall score (Eq. 3).

\[
A_R = \{(i, j, B_{ij}) : \forall i, j = \arg \max_k B_{ik}\} \quad (2)
\]

\[
\text{BERTScoreRecall} = \frac{W(A_R)}{m} \quad (3)
\]

A similar procedure is followed to calculate precision, but instead, every summary token is aligned to its most-similar reference token, and the sum of the similarities is normalized by the number of summary tokens. When multiple references are available, the precision and recall scores are defined to be the maximum respective values across references.

By formulating ROUGE and BERTScore in a framework based on token alignments, we can reason about their behaviors by examining the tokens they align in two different analyses, as described next.

4 SCU-Based Analysis

The first analysis compares the two metrics’ token alignments to annotations derived from the Pyramid Method (Nenkova and Passonneau, 2004).

The Pyramid Method is a technique to manually evaluate the content of a candidate summary by comparing it to a set of reference summaries. The method uses a domain-expert annotator to exhaustively identify atomic units of meaning in the summaries, known as summary content units (SCUs), and mark their occurrences in the reference and candidate summaries. Two phrases marked with the same SCU are considered to express the same information. Since the Pyramid Method annotation is exhaustive, we can assume that any two phrases in the reference and candidate summaries that are not marked with the same SCU do not have the same meaning.

These annotated phrases can be used to reason about ROUGE and BERTScore: If a large portion of their token alignments is between phrases that express the same information, then their scores can potentially be interpreted as representing the summaries’ information overlap. Otherwise, it is evidence that they do not compare summaries based on information.

For this analysis, we use the summaries and Pyramid annotations from the TAC 2008 and 2009 multi-document summarization datasets (Dang and Owczarzak, 2008, 2009). These datasets have 48/44 clusters of around 10 documents, each with 4 reference summaries and 58/55 system summaries that have been annotated with SCUs, respectively.

For each of the system summaries, we calculate the proportion of the total alignment weight that can be explained by matches between identical SCUs, as defined in Eqs. 4 and 5:

\[
A_{SCU} = \{(i, j, w) : (i, j, w) \in A, SCU(i) \cap SCU(j) \neq \emptyset\} \quad (4)
\]

\[
\text{Prop}_{SCU} = \frac{W(A_{SCU})}{W(A)} \quad (5)
\]

where \( SCU(i) \) returns the set of SCUs that are anno-
The second analysis of ROUGE and BERTScore focuses on grouping token alignments into categories (§5.1), then using those categories to reason about how much of the metrics’ scores is explained by information or topic matches (§5.2).

5.1 Token Alignment Categorization

We define a category to be a function $C$ that selects the subset of summary token indices for which that category applies. For example, a “noun” category would select only the token indices that correspond to nouns. $C(S)$ denotes the application of a category to summary $S$.

Each category is used to filter an alignment $A$ used by ROUGE or BERTScore to a category-specific alignment between tokens which belong to that category only, denoted $A_C$:

$$A_C = \{(i, j, w) : (i, j, w) \in A, \quad i \in C(R), j \in C(S)\}$$

(6)

For the “noun” category, $A_C$ would be the subset of token alignments between nouns in $R$ and $S$.

Then, the contribution of $C$ is defined as the ratio between $A_C$ and $A$:

$$\text{Contribution}_C = \frac{W(A_C)}{W(A)}$$

(7)

The contribution of $C$ can be interpreted as the portion of ROUGE or BERTScore’s values cannot be interpreted as a measure of information overlap.

5.2 Category-Based Analysis

Next, we define a set of categories in which each category represents either information or topic matches, then reason about how much of the metrics’ scores can be explained by information or
Joey walked and Reese ran

Figure 5: The VB+NSUBJ category selects tuples of verbs and their corresponding NSUBJ dependents in the dependency tree. In this example, 2/4 of the alignment (the solid lines) can be explained by matches between such tuples. The dashed lines cannot: The “and” alignment is not part of any tuple; Since “ran” and “sprinted” are not aligned, their corresponding tuples are not considered to be aligned, so the “Reese” match does not count toward the total.

Table 1: The contributions (Eq. 7) of every category to ROUGE (R) and BERTScore (BS) on TAC 2008 and CNN/DailyMail indicate the metrics are largely matching nouns and stopwords rather than tuples which express information (e.g., VB+NSUBJ+DOBJ). The contributions do not sum to 100% because more than one category can explain the same token alignment. The NNP and NER for CNN/DailyMail are significantly lower because the candidate summaries were all lower-cased.

| Category       | TAC’08 R | TAC’08 BS | CNN/DM R | CNN/DM BS |
|----------------|----------|-----------|----------|-----------|
| NP-CHUNKS      | 58.7     | 46.1      | 53.6     | 43.0      |
| STOPWORDS      | 54.6     | 32.4      | 48.4     | 28.7      |
| NN             | 17.9     | 13.7      | 31.8     | 24.9      |
| NNP            | 14.9     | 11.3      | 0.3      | 0.2       |
| NER            | 13.5     | 8.5       | 0.1      | 0.1       |
| VB             | 9.0      | 9.3       | 14.1     | 10.6      |
| ADJ            | 4.1      | 2.6       | 6.2      | 4.0       |
| NSUBJ          | 3.9      | 2.2       | 6.3      | 4.1       |
| DOBJ           | 2.0      | 1.4       | 2.8      | 1.7       |
| NUM            | 1.5      | 1.7       | 2.5      | 1.9       |
| VB+DOBJ        | 1.3      | 0.4       | 3.4      | 1.0       |
| ROOT           | 1.1      | 1.5       | 3.3      | 2.5       |
| VB+NSUBJ+DOBJ  | 1.0      | 0.5       | 3.8      | 2.4       |
| ADV            | 0.6      | 0.4       | 1.6      | 0.8       |
| VB+NSUBJ+DOBJ  | 0.3      | 0.1       | 1.5      | 0.5       |

3 Although there are versions of ROUGE that remove stopwords, including them is significantly more common, and therefore we analyze the more popular ROUGE variant.
Table 2: The contributions of different categories of token matches when grouped by whether they represent topics, information, or stopwords. Clearly, the information categories explain only a small proportion of the overall metrics scores on TAC’08 and CNN/DailyMail.

| Category   | ROUGE | BSEA | ∆    | Rel. ∆ |
|------------|-------|------|------|--------|
| Topic      | 70.6  | 57.9 | 75.0 | 59.2   |
| Information| 2.2   | 0.9  | 6.7  | 3.2    |
| Stopwords  | 54.6  | 32.4 | 48.4 | 28.7   |

whereas the dependency tuple with the largest contribution, VB+DOBJ only contributes 1.3%.

When the specific categories are grouped by content type in Table 2, it becomes even more apparent that topic and stopwords matches explain most of ROUGE and BERTScore. Specifically, we find that topic, stopword, and information matches explain 70.1%, 54.6%, and 2.2% of ROUGE’s score on TAC 2008.

The low contribution of information-based categories toward each metric is further evidence that neither metric strongly captures the information overlap between summaries, supporting the results found in §4.

6 Other Evaluation Metrics

The analyses thus far have exploited the structure of ROUGE and BERTScore to reason about the extent to which they measure information overlap between two summaries. Although it is desirable to ask the same question about other evaluation metrics, the metrics may not directly fit into this analysis framework or it would require significant effort to repeat this analysis for each one. Instead, we indirectly reason about how much information overlap other metrics measure through their correlations to ROUGE and the Pyramid Method as follows.

First, we assume that the Pyramid Score is the gold-standard for measuring the information overlap between summaries. This is a relatively safe assumption because the Pyramid Method is annotated by domain experts, and a candidate’s Pyramid Score is based solely on how much information it has in common with a reference. There is no credit given to a candidate for discussing the right topics but with the incorrect information.

Then, the correlations of the other metrics to both ROUGE and the Pyramid Score are calculated and compared. If the correlation to ROUGE is higher than the correlation to the Pyramid Score, then it is more likely that the metric suffers from the same issues that ROUGE does than it is to directly measure information overlap.

Table 4 contains the summary-level correlations of various other evaluation metrics to ROUGE and the Pyramid Score. The other metrics are: AutoSummENG (Giannakopoulos et al., 2008), BEwTE (Tratz and Hovy, 2008), MeMoG (Giannakopoulos and Karkaletsis, 2011), METEOR (Denkowski and Lavie, 2014), MoverScore (Zhao et al., 2019), NPowER (Giannakopoulos and Karkaletsis, 2013), PyrEval (Gao et al., 2019), ROUGE-2, S3 (Peyrard and Eckle-Kohler, 2017), and SUPERT (Gao et al., 2020). These metrics exhibit a variety of different comparison techniques, from n-gram graph comparisons to contextual word-embedding comparisons and other alignment based approaches.

Notably, all of the metrics’ Pearson correlations to ROUGE are higher than to the Pyramid Score.
Table 4: The summary-level Pearson correlations of various metrics to ROUGE-1 and the Pyramid Score (Δ is the difference between them). All of the other metrics correlate more strongly to ROUGE-1 than the Pyramid Score (by around 0.2) and correlate to the Pyramid Score approximately as much as ROUGE-1 does (around 0.6). Together, these results suggest the other metrics are as poor evaluators of information overlap as ROUGE-1 is.

generally by around 0.2 points, suggesting these metrics do not measure information overlap well. Further, their correlations to the Pyramid Score are roughly the same as ROUGE’s, around 0.6. This is means that these metrics correlate to a direct measure of information overlap as well as one would expect a metric which measures information overlap at the level of ROUGE to correlate. Although the results of this experiment are not direct evidence that the other evaluation metrics do a poor job at measuring information overlap, they do strongly suggest it.

An ideal content evaluation metric should measure how much information two summaries have in common, and overall, this experiment indicates that the summarization community has not yet found any such automatic metric.

7 An Interpretable System Comparison

Thus far, we have argued that current evaluation metrics do not strongly measure how much information two summaries have in common. In this Section, we aim to propose a simple and interpretable method of evaluating summaries that does directly measure information overlap.

Instead of evaluating summarization systems with ROUGE or BERTScore, we instead calculate a set of precision and recall scores based on the categories defined in §5.2. We define the category-specific precision and recall as:

$$\text{Recall}_C = \frac{W(AC)}{|C(R)|}$$  (8)

$$\text{Precision}_C = \frac{W(AC)}{|C(S)|}$$  (9)

These can be understood as calculating ROUGE or BERTScore on the subset of tokens defined by $C$. For example, the noun category applied to a ROUGE alignment would calculate the ROUGE-based precision and recall on the two summaries’ nouns.

As long as $C$ is well-understood and interpretable, then so are the category-specific metrics. Therefore, the precision and recall scores of information-based categories can be used to reason about how much information overlap exists between two summaries. Similarly, the differences in these metrics between systems can identify whether one system produces better information than the other.

To demonstrate the utility of this evaluation methodology, we calculated the differences in category-specific $F_1$ metrics between the baseline Pointer-Generator (See et al., 2017) and state-of-the-art BertSumExtAbs model (Liu and Lapata, 2019) on the CNN/DailyMail dataset using ROUGE alignments in Table 3.

Interestingly, some of the largest relative differences between systems are in the information-based categories (e.g., $\text{VB}+\text{NSUBJ}+\text{DOBJ}$). This is evidence that the state-of-the-art model actually does produce summaries with information that is more similar to the ground-truth. In contrast, the topic-based metrics (in particular the noun-related categories), show very little relative improvement, suggesting the baseline model discusses the correct topics nearly as well as the state-of-the art model does.

However, this analysis also reveals that the information-based $F_1$ scores are rather low on an absolute scale. For instance, the $\text{VB}+\text{NSUBJ} F_1$ for the BertSumExtAbs model is only 12.0, whereas the $\text{NN} F_1$ is 40.9 This large gap indicates that there is significant room for improvement in generating summaries with better information.

Although this evaluation methodology is relatively simple, it provides more insights into the systems’ overall behaviors and allows for directly...
Table 5: The Pearson $r$ and Spearman $\rho$ correlations of ROUGE and the NP Chunk category-specific recall (Eq. 8) are very close, demonstrating that a purely topic-based comparison (NP chunks) is a very high baseline for content quality correlations on TAC’08.

The conclusions reached by this evaluation could not have been made by comparing systems using ROUGE or BERTScore alone.

8 Discussion

Responsiveness Correlations Many of the automatic metrics analyzed in this work have demonstrated very high system-level correlations to ground-truth summary responsiveness judgments (Pearson’s $r > 0.8$; Dang and Owczarzak, 2008, 2009), so the results that indicate they do not measure information overlap are somewhat surprising. Since the metrics appear to compare summaries based on the topics they discuss, it is likely that only comparing summary topics is a very strong baseline for these benchmark datasets.

Indeed, we find in Table 5 that evaluating with only the NP chunk category-based recall score (which represents little-to-no information) achieves nearly the same correlations as ROUGE on TAC’08. We hypothesize that further improving correlations to responsiveness judgments will require directly measuring the summaries’ information overlap.

Limitations There are some limitations to our analysis. First, the results are specific to the datasets and summarization models that were used. However, TAC’08 and ’09 are the benchmark datasets for evaluating content quality and have been widely used to measure the performance of different metrics. Further, because the results from §5.2 are consistent across two rather different datasets (TAC and CNN/DailyMail), we believe these results are likely to hold for other datasets as well.

Then, the information categories from §5.2 do not capture all of the information from a summary. A phrase like “the Turkish journalist” expresses that nationality of the journalist, but this information would not be represented by the tuples included in our analysis. However, similar representations of information are used in the OpenIE literature (Etzioni et al., 2008), and we do not believe the addition of more information-based categories is likely to significant change the experimental results.

9 Related Work

Most of the work that reasons about how to interpret the scores of evaluation metrics does so indirectly through correlations to human judgments (Dang and Owczarzak, 2009; Owczarzak and Dang, 2011). However, a high correlation is not conclusive evidence about what a metric measures since it is possible for the metric to directly measure some other aspect of a summary, which is in turn correlated with the ground-truth judgments (see discussion in §8). Our work can be viewed as more direct evidence about what ROUGE and BERTScore measure.

Recent work by Wang et al. (2020) demonstrates that many of the same evaluation metrics covered in this work do not successfully measure the faithfulness of a summary based on low correlations to ground-truth judgments. The results from our experiments offer an explanation for why this is the case: The metrics do not compare summaries based on their information, therefore they cannot determine if a summary is factually consistent with its input.

Metrics which do attempt to directly measure information overlap between summaries are based on the gold-standard comparison technique, the Pyramid Method (Nenkova and Passonneau, 2004). Although it relies heavily on annotations by experts, there have been attempts to crowdsourc (Shapira et al., 2019) or automate all or parts of the Pyramid Method (Passonneau et al., 2013; Yang et al., 2016; Hirao et al., 2018) including PyrEval (Gao et al., 2019), which we analyzed in §6. These metrics have been met with less success than the text overlap-based ones covered by this work, potentially because measuring information overlap is more difficult than comparing summaries by their topics, and topic-based evaluations strongly correlate to responsiveness judgments (see §8).

10 Conclusion

In this work, we argued that ROUGE, BERTScore, and many other proposed metrics for evaluating
the content quality of summaries largely do not compare summaries based on their information overlap. The implications of this result are that the summarization community does not have a reliable metric that aligns with its research goal, to generate summaries with high-quality information. Finally, we proposed a simple and interpretable evaluation methodology which does measure information overlap and provides new insights into model behavior that previous metrics alone could not do.

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