Play the Shannon Game With Language Models: A Human-Free Approach to Summary Evaluation

Nicholas Egan, Oleg Vasilyev, John Bohannon
Primer AI
{negan, oleg, bohannon}@primer.ai

Abstract
The goal of a summary is to concisely state the most important information in a document. With this principle in mind, we introduce new reference-free summary evaluation metrics that use a pretrained language model to estimate the information content shared between a document and its summary. These metrics are a modern take on the Shannon Game, a method for summary quality scoring proposed decades ago, where we replace human annotators with language models. We also view these metrics as an extension of BLANC, a recently proposed approach to summary quality measurement based on the performance of a language model with and without the help of a summary. Using transformer based language models, we empirically verify that our metrics achieve state-of-the-art correlation with human judgement of the summary quality dimensions of both coherence and relevance, as well as competitive correlation with human judgement of consistency and fluency.

1 Introduction
With the ever-expanding development of new summarization algorithms in the NLP community, metrics that reliably measure summary quality are more important than ever. And yet, the most popular method for summary quality estimation remains the ROUGE (Lin 2004) family of metrics, which require human written reference summaries for comparison and measure summary quality through simple token overlap, ignoring the syntax and semantics governing the way humans use language.

The goal of a summary is to concisely state the most important information conveyed by a document. Examining summarization through this lens, one should be able to determine summary quality by measuring how much information from the document is represented in the summary. Put another way, when comparing alternative summaries of similar length, the information we gain from reading the original document should be minimal given the best summary.

The idea of measuring this difference in information content was proposed as the Shannon Game by Hovy and Lin (1998): they assign 3 humans the task of guessing a document letter by letter, where the first human is allowed to look at the document, the second human is allowed to look at a summary of the document, and the third human is given nothing at all. By measuring how many tries it takes the second human to guess the document compared to the other humans, you can evaluate how much information about the document is communicated in the summary, and therefore measure how good the summary is.

Contributions This paper proposes a new summarization evaluation metric, the Shannon Score, that performs the Shannon Game with a language model such as GPT-2 (Raford et al. 2019). By using a language model to autoregressively generate a document both with and without a summary as a prompt, we measure the information provided by the summary. One can view this method as a more theoretically driven extension to the recently proposed BLANC metric (Vasilyev, Dharnidharka, and Bohannon 2020), which measures the accuracy of unmasking document tokens with and without a summary. In addition to the Shannon Score, we also propose a variant we call Information Difference.

To understand the empirical performance of this method as a summary evaluation technique, we performed experiments to correlate our metrics against human judgement. We found that our metrics perform strongly on the SummEval benchmark (Fabbri et al. 2021), achieving state-of-the-art correlation with human judgement of summary coherence and relevance, and competitive correlation with human judgement of summary consistency and fluency.

2 Methods

2.1 Computing Information
Language models are probability distributions over documents, giving us \( p(D) \) for some document \( D \). Autoregressive language models do this by predicting next token probabilities given prior tokens, modeling

\[
p(x_t | x_1, \ldots, x_{t-1})
\]

where our input document is broken into tokens \( \{x_1, \ldots, x_n\} \). The Shannon information content, or surprisal, of event \( E \) with probability \( p(E) \) of happening is defined as \( I(E) = -\log p(E) \), so we can compute the information of a document according to our language model as

\[
I(D) = -\log p(x_1) - \log p(x_2 | x_1) - \ldots - \log p(x_n | x_1, x_2, \ldots, x_{n-1})
\]
2.2 Conditional Information

Suppose we had a conditional language model $p(D|S)$ that gives us a probability distribution of documents that could correspond to a given summary $S$. Using this conditional language model, we could compute the conditional information content $I(D|S)$ as the amount of information we gain from the document $D$ if we are already given the information of summary $S$.

If $S$ is a satisfactory summary of $D$, then $I(D|S) < I(D)$, as documents that have little to do with the summary should be much less likely than documents that are relevant to the summary after conditioning the language model. If the summary fluently describes people, ideas, or relationships that appear in the document, then that should decrease the information one learns from subsequently reading the document.

Thus we can define an Information Difference metric of summary quality as:

$$ID(D, S) = I(D) - I(D|S)$$

The Information Difference tells us the change in document information between using the summary and not using the summary, and it is equivalent to the log likelihood ratio between the document and the document given the summary. While it is unbounded, it should be positive unless a summary does such a bad job that it makes the document more confusing to read.

Considering the fact that the summary that best preserves the information of a document is the document itself, we can view $I(D|D)$ as a lower bound on $I(D|S)$. Since this idea of having a third evaluator who has the document itself as help is inspired by the Shannon Game, we can compute the Shannon Score metric as:

$$s(D, S) = \frac{I(D) - I(D|S)}{I(D) - I(D|D)}$$

The Shannon Score gives us the ratio between how helpful the summary was and how helpful the document itself was. While this formula in theory is unbounded, it usually should be in the range 0 to 1, unless the summary makes the document more confusing or somehow explains the document better than the document itself.

2.3 Approximating Conditional Information

To the extent of our knowledge, there is no easy way to exactly condition a pretrained language model such as GPT-2 on a summary, even though there has been work on conditioning language models on fixed control codes (Keskar et al. 2019), bags of words, or discriminators (Dathathri et al. 2020). We also have a strong motivation not to train such a model because we want our method to be universal and robust, while summarization datasets are much smaller and more restricted in domain than the massive datasets that modern language models require.

We approximate $p(D|S)$ by computing the probability that $D$ is generated when we provide $S$ as a prompt to a language model. We intuitively justify this idea by the fact that in real-world documents the most important information is often summarized at the top as an introduction, and then described in more detail in body paragraphs. This setup resembles the BLANC-help metric (Vasilyev, Dharmidharka, and Bohannon 2020), which measures language model token unmasking accuracy for a document when a summary is prepended. An alternative setup would be to finetune a language model on the summary which was also explored by Vasilyev, Dharmidharka, and Bohannon (2020), but we don’t explore that method in this paper. We use the GPT-2 small language model (Radford et al. 2019) for our experiments, but investigate the use of other language models in section 5.4.

An issue we run into when computing information with GPT-2 is that the model can only be given a maximum of 1024 tokens, making many documents too large to fit in at once. To get around this, we approximate document information with an independence assumption between sentences in the document, meaning that only the preceding tokens within a sentence are provided when generating the next token in the sentence. In section 5.2, we investigate the effects of prompting the language model with additional upstream sentences of context.

3 Understanding Our Metrics

3.1 Information Visualization

A toy illustration of our methodology is shown in Figure 1. We picked a document excerpt in the CNN/DailyMail (Hermann et al. 2015) dataset and paired it with two abstractive summaries we wrote. While both of these summaries are grammatically correct and mostly consist of words from the document, one of the summaries is of high quality and the other is of low quality. The figure shows the information content of each token in the document as estimated by GPT-2 in 4 scenarios: $I(D)$ (the document on its own), $I(D|D)$ (the document given the document), $I(D|S)$ (the document given a summary) for the high quality summary, and $I(D|S)$ for the low quality summary. A darker background color denotes higher information according to the model.

As you can see, the model gained less information from words like “gray” and “Varvara” after seeing those words in the high quality summary. We can also see that words like “Pacific” and “journey,” which do not appear in the high quality summary, became more likely to appear in the document due to their association with concepts in the summary. The low quality summary may have helped the model predict words like “CNN,” but it is unhelpful for words like “mammal” and “website” that are confusingly used in the summary. Very little information was gained from reading a document that was already read, except for the first token or two for each sentence. This is an artifact of our autoregressive language modeling setup, so measuring $I(D|D)$ is useful for normalizing our Shannon Scores.

We used a truncated document and toy summaries here to demonstrate the Shannon Score in a concise way, but we included visualizations of real, full-length documents and summaries from the SummEval dataset in the appendix.
I(D) = 580

A North Pacific gray whale has earned a spot in the record books after completing the longest migration of a mammal ever recorded. The whale, named Varvara, swam nearly 14,000 miles (22,500 kilometers), according to a release from Oregon State University, whose scientists helped conduct the whale-tracking study. Varvara, which is Russian for "Bar bara," left her primary feeding ground off Russia’s Sakhalin Island to cross the Pacific Ocean and down the West Coast of the United States to Baja, Mexico. Varvara’s journey surpassed a record listed on the Guinness World Records website. It said the previous record was set by a humpback whale that swam a mere 10,190-mile round trip.

I(D|S) = 482 for this high quality summary:
Varvara the gray whale traveled from Russia to Mexico, a swim of record breaking length.

I(D|D) = 52

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I(D|S) = 540 for this low quality summary:
The round humpback has told CNN mammals that Baja was a previous Pacific website for "Guinness."

Figure 1: A comparison of token-wise information content within a document as estimated by GPT-2 in 4 scenarios: the document on its own, the document given the document, the document given a high quality summary, and the document given a low quality summary. Tokens with a darker background color have more information.

Figure 2: Distributions of Shannon Score and Information Difference on 100 summaries from the CNN/DailyMail dataset. Three different summaries are used: the original human-written reference summary (in blue), the original summary with words scrambled (in orange), and a reference summary for a different document in the dataset (in green).

3.2 Baseline Validation

As a simple validation of our information-based metrics, we sampled 100 documents with their corresponding reference summaries from the CNN/DailyMail dataset (Hermann et al. 2015), and created two “bad” summaries per document: a version of the reference summary with all the words randomly shuffled, and a reference summary for a different document in the dataset.

Figure 2 shows the distributions of the Shannon Score and Information Difference for these three summaries. As expected, the original summaries have the highest scores, followed by shuffled summaries and wrong summaries. It is good to see that there is full separation between original summaries and wrong summaries for both metrics. The fact that the original summaries and shuffled summaries are almost completely separated demonstrates the importance of syntax to our metrics, a quality that metrics like the Jensen-Shannon divergence (Louis and Nenkova 2009) and ROUGE-1 (Lin 2004) lack.

We also verified that there are no documents for which the shuffled summary or wrong summary score better than the original summary for either of the metrics. Despite the fact that the Shannon Score has no lower bound, we can see
that it doesn’t go far below zero for even the most unreasonable of summaries. And despite the fact that the Shannon Score has no upper bound, even high quality human reference summaries are unable to achieve a score above 0.4.

4 Evaluation of Our Metrics

4.1 SummEval

| Metric | Coher. | Consi. | Fluen. | Relev. |
|--------|--------|--------|--------|--------|
| Shannon | 0.4118 | 0.6324 | 0.5240 | 0.6029 |
| Info Diff | 0.4706 | 0.6324 | 0.5683 | 0.6618 |
| rouge-1 | 0.2500 | 0.5294 | 0.5240 | 0.4118 |
| rouge-2 | 0.1618 | 0.5882 | 0.4797 | 0.2941 |
| rouge-3 | 0.2206 | 0.7059 | 0.5092 | 0.3529 |
| rouge-4 | 0.3088 | 0.5882 | 0.5535 | 0.4118 |
| rouge-L | 0.0735 | 0.3617 | 0.2583 | 0.2353 |
| rouge-su* | 0.1912 | 0.2941 | 0.4354 | 0.3235 |
| rouge-w | 0.0000 | 0.3971 | 0.3764 | 0.1618 |
| rouge-we-1 | 0.2647 | 0.4559 | 0.5092 | 0.4265 |
| rouge-we-2 | -0.0147 | 0.5000 | 0.3026 | 0.1176 |
| rouge-we-3 | 0.0294 | 0.3676 | 0.3026 | 0.1912 |
| S3-pyr | -0.0294 | 0.5147 | 0.3173 | 0.1324 |
| S3-resp | -0.0147 | 0.5000 | 0.3321 | 0.1471 |
| BertScore-p | 0.0588 | -0.1912 | 0.0074 | 0.1618 |
| BertScore-r | 0.1471 | 0.6618 | 0.4945 | 0.3088 |
| BertScore-f | 0.2059 | 0.0441 | 0.2435 | 0.4265 |
| MoverScore | 0.1912 | -0.0294 | 0.2583 | 0.2941 |
| SMS | 0.1618 | 0.5588 | 0.3616 | 0.2353 |
| SummaQA | 0.1176 | 0.6029 | 0.4059 | 0.2206 |
| SuPERT | 0.1029 | 0.5882 | 0.4207 | 0.2353 |
| BLEU | 0.1176 | 0.0735 | 0.3321 | 0.2206 |
| CHRF | 0.3971 | 0.5294 | 0.4649 | 0.5882 |
| CIDER | 0.1176 | -0.1912 | -0.0221 | 0.1912 |
| METEOR | 0.2353 | 0.6324 | 0.6126 | 0.4265 |

Table 1: Kendall tau-b system-level correlation between expert annotations of coherence, consistency, fluency, and relevance and various automated metrics, adapted from Fabbri et al. (2021). * denotes reference-free metrics. The five highest correlations per column are in bold, with ties for consistency and relevance. Coefficients with a magnitude above 0.36 are significant at the \( \alpha = 0.05 \) level.

The SummEval (Fabbri et al. 2021) benchmark was established as a comprehensive evaluation tool for summary evaluation metrics. It consists of 100 English-language documents from the CNN/DailyMail dataset, each paired with system summaries from 17 different summarization systems: 3 extractive models, 13 abstractive models, and a lead-3 baseline. All models were published in 2017 or later. Each of these 1700 system summaries were scored by a panel of 3 experts in the field of summarization on the qualities of coherence (the collective quality of all sentences), consistency (the factual alignment between the summary and document), fluency (the quality of individual sentences), and relevance (selection of important content from the source). The experts achieved an inter-annotator agreement kappa coefficient of 0.7127.

Fabbri et al. (2021) scored each summary using these evaluation metrics: ROUGE (Lin 2004), ROUGE-WE (Ng and Abrech 2015), S3 (Peyrard, Botschen, and Gurevych 2017), BertScore (Zhang et al. 2020), MoverScore (Zhao et al. 2019), Sentence Mover’s Similarity (SMS) (Clark, Celikyilmaz, and Smith 2019), SummaQA (Scaiolo et al. 2019), BLANC (Vasilyev, Dhamdhere, and Botham 2020), SUPERT (Gao, Zhao, and Eger 2020), BLEU (Papineni et al. 2002), CHRF (Popovic 2015), METEOR (Lavie and Agarwal 2007), and CIDEr (Vedantam, Lawrence Zitnick, and Parikh 2015). They also measure the Grusky, Naman, and Artzi (2018) statistics of summary length, extractive fragment coverage (coverage), compression ratio, average length of extractive fragments (density), proportion of n-grams in summary that aren’t in the document (novel n), and n-grams repeated in summary (repeat n).

Table 1 shows the correlation between expert annotations and the automated evaluation metrics. Following Fabbri et al. (2021), we use Kendall tau-b system-level correlation for comparison. Our metrics of Shannon Score and Information Difference are the only metrics to be in the top 5 for every category of summary quality. Additionally, our metrics achieve state-of-the-art performance for the qualities of coherence and relevance.

4.2 Coverage

The coverage score (Lin and Hovy 2003) is a human evaluation method that measures a system summary’s recall of semantic units that appeared in a reference summary, weighed by how well the system summary was able to capture each semantic unit as judged by the human labeler. The 2001 and 2002 Document Understanding Conferences (DUC) provide datasets of English-language system and reference summaries for news documents with human coverage labels, on both single-document and multi-document levels.

Table 2 shows the correlation of various metrics to these coverage scores for the single-document summaries. System-level Spearman correlation is used following Louis and Nenkova (2013). The reference-free metrics perform similarly, except for Jensen-Shannon Divergence (Louis and Nenkova 2009) which performs particularly well on DUC 2001 and Info Diff which performs particularly poorly on DUC 2002. The metrics using reference benefits from the coverage bias that the coverage itself was measured with respect to the reference summary, so as expected, they have higher correlations with the coverage than the reference-free metrics.
Table 2: System-level Spearman correlation of various summary quality metrics with human-judged coverage scores on the DUC 2001 and 2002 single-document summary datasets. The last seven metrics make use of reference summaries, while the first four metrics have to rely only on the original document itself. DUC 2001 coefficients above 0.60 and DUC 2002 coefficients above 0.55 are significant at the $\alpha = 0.05$ level.

| Metric         | DUC 2001 | DUC 2002 |
|---------------|---------|---------|
| Shannon Score | 0.2909  | 0.5714  |
| Info Diff     | 0.3000  | 0.4835  |
| Jensen-Shannon| 0.4455  | 0.5440  |
| BLANC-help    | 0.2727  | 0.5769  |
| ROUGE-1       | 0.9636  | 0.9066  |
| ROUGE-2       | 0.8273  | 0.9121  |
| ROUGE-L       | 0.7455  | 0.9176  |
| ROUGE-Lsum    | 0.9455  | 0.9066  |
| BERTScore-P   | 0.4636  | 0.5989  |
| BERTScore-R   | 0.8545  | 0.9451  |
| BERTScore-F1  | 0.6091  | 0.7308  |

Table 4: Kendall tau-b system-level correlations between expert annotations of coherence, consistency, fluency, and relevance and our Shannon Score and Information Difference metrics with the choice of different language models on the SummEval dataset. Scores at least as high as GPT-2 S are bold. Coefficients above 0.36 are significant at the $\alpha = 0.05$ level.

| Model      | Coher. | Consi. | Fluen. | Relev. |
|------------|--------|--------|--------|--------|
| Shannon Score |        |        |        |        |
| GPT-2 S     | 0.4118 | 0.6324 | 0.5240 | 0.6029 |
| GPT-2 M     | 0.3529 | 0.6618 | 0.4945 | 0.5441 |
| GPT-2 L     | 0.3676 | 0.6471 | 0.5092 | 0.5588 |
| GPT-2 XL    | 0.3824 | 0.6324 | 0.4945 | 0.5735 |
| GPT         | 0.0294 | 0.5147 | 0.3469 | 0.1912 |
| XLNet       | 0.4265 | 0.5882 | 0.4945 | 0.6471 |
| TransfoXL   | 0.3529 | 0.5441 | 0.4502 | 0.5441 |

Figure 3: The average document information and document information given summary as estimated by different sizes of GPT-2 for the SummEval dataset.
other language models.

It is also interesting to see that bigger GPT-2 models do not necessarily perform better. Figure 3 shows the relationship between model size and average document info with and without the help of a summary. We can see that as the model gets larger, both average $I(D)$ and average $I(D|S)$ decrease together. Larger models should be better at autoregressive token prediction, as reflected in the plot of $I(D)$, but it is interesting to see that $I(D|S)$ decreases at around the same rate. We suspect this is because larger models may not be more suitable at utilizing a summary to predict a document under our setup.

5.2 Upstream Sentences

As described in section 2.3, we are making an independence assumption between sentences in a document when estimating $I(D)$, $I(D|S)$, and $I(D|D)$ by feeding each sentence into the model individually. We could alternatively assume that each sentence in the document is dependent on the $k$ previous sentences, where $k = 0$ refers to our current approach and $k = \infty$ (or the maximum number of sentences in a document) drops the sentence independence assumption altogether. One could reason that this would better allow us to quantify the information in a document, which may lead to a more effective metric.

As shown in table 3 using $k > 0$ leads to an improvement in consistency at the expense of the other summary dimensions, and increasing $k$ beyond 1 does not yield any significant gains in performance. Figure 4 shows that increasing $k$ from 0 is more helpful at decreasing $I(D)$ than it is at decreasing $I(D|S)$. We could draw a similar conclusion as we did in section 5.1 that increasing $k$ is helpful for autoregressive token prediction, but it doesn’t help our model with utilizing a summary to predict a document in our setup.

5.3 BLANC-Shannon

Our metrics bear similarity to the BLANC-help metric \cite{Vasilyev2020}, which measures the accuracy of the BERT language model on the task of guessing masked tokens with and without a summary prepended to a document. The BLANC score is measured as a boost in unmasking accuracy $a_{\text{help}} - a_{\text{base}}$ when masking various sets of $M$ evenly spaced tokens, where $a_{\text{help}}$ is the accuracy when the summary is provided as help and $a_{\text{base}}$ is the accuracy when no help is provided. Our metrics differ from BLANC in that we measure information instead of raw accuracy, we generate documents autoregressively instead of masking, and we typically use GPT-2 instead of BERT.

To study the utility of measuring document information as opposed to raw accuracy counts, we define BLANC-Shannon to be the boost in accuracy when generating document tokens given the summary. On the SummEval benchmark, BLANC-Shannon achieves Kendall tau-b system-level correlations of 0.3676, 0.6765, 0.5092, and 0.5588 for the expert annotations of coherence, consistency, fluency, and relevance respectively. These scores are an improvement on the consistency dimension over the Shannon Score and Information Difference metrics at the expense of every other dimension. We can only hypothesize that accuracy may be more sensitive to wrongly generated tokens and hence to consistency, but it would be interesting to compare BLANC-Shannon to the other metrics on an even larger dataset than SummEval.

### Related Work

#### The Shannon Game

The Shannon Game \cite{Hovy1998} was proposed over two decades ago as a way to use humans to measure the information retention between document and summary. In the original formulation, humans need to guess a document letter by letter given the summary, document, or nothing, and they measure the total number of guesses that were required to reconstruct the document. The authors ran a small-scale experiment where they conducted this game using human subjects, and they found a clear order of magnitude difference between the number of guesses that each human required, as expected. However, they also found that reconstructing the original document with no help (the task of human 3) was extremely time-consuming, sometimes taking over 3 hours, making the Shannon Game prohibitively expensive as a human evaluation method.

#### Automated Summary Evaluation

The most popular automatic summarization evaluation method is the ROUGE family of metrics \cite{Lin2004, Lin2004b}, which measure word overlap between the system summary and one or more reference summaries. The two biggest problems we see with ROUGE as a metric are 1) that it relies on human written reference summaries, and 2) that it measures simple word overlap, which means that a perfectly paraphrased

| Metric         | Info Diff | Shannon Score | Coherence | Consistency | Fluency | Relevance |
|----------------|-----------|---------------|-----------|-------------|---------|-----------|
| Length         | 0.5425    | 0.4291        | 0.0615    | 0.0886      | -0.0105 | 0.2054    |
| Novel 1        | -0.1140   | -0.0962       | 0.1340    | -0.2719     | -0.1924 | 0.0267    |
| Novel 2        | -0.2935   | -0.2849       | -0.0248   | -0.3693     | -0.2674 | -0.0733   |
| Novel 3        | -0.3324   | -0.3297       | -0.0781   | -0.3840     | -0.2755 | -0.1035   |
| Coverage       | 0.2163    | 0.1896        | 0.0144    | 0.3369      | 0.2431  | 0.0688    |
| Compression    | -0.0879   | -0.6086       | -0.0041   | -0.0697     | -0.0084 | -0.1155   |
| Density        | 0.4591    | 0.4517        | 0.1991    | 0.4035      | 0.2738  | 0.2019    |

Table 3: Spearman correlation of our metrics and human judged quality metrics with various statistics describing summaries across the 1700 SummEval summaries.
Table 5: Kendall tau-b system-level correlations between expert annotations of coherence, consistency, fluency, and relevance and our Shannon Score and Information Difference metrics with different choices of $k$ (the number of upstream sentences to provide the model) on the SummEval dataset. Scores at least as high as those of $k = 0$ are bold. Coefficients above 0.36 are significant at the $\alpha = 0.05$ level.

| $k$ | Coher. | Cons. | Fluen. | Relev. |
|-----|--------|-------|--------|--------|
| 0   | 0.4118 | 0.6324| 0.5240 | 0.6029 |
| 1   | 0.3529 | 0.6618| 0.4945 | 0.5441 |
| 2   | 0.3235 | 0.6618| 0.4945 | 0.5147 |
| 3   | 0.3235 | 0.6618| 0.4945 | 0.5147 |
| 4   | 0.3235 | 0.6618| 0.4945 | 0.5147 |

Many solutions have been proposed to remedy issue #2 without solving issue #1, such as BERTScore (Zhang et al. 2020), MoverScore (Zhao et al. 2019), Sentence Mover Similarity (Clark, Celikyilmaz, and Smith 2019), Word Mover Similarity (Kusner et al. 2015), and ROUGE-WE (Ng and Abrechet 2015). All of these metrics involve the idea of using soft overlap or embedding/token distance between the system and reference summaries. Louis and Nenkova (2009) suggested measuring the Jensen-Shannon divergence between word distributions used in the system summary and original document, which suffers from issue #2 while fixing issue #1. Sun and Nenkova (2019) and Gao, Zhao, and Eger (2020) perform reference-free summary evaluation using language model word embeddings with promising results. Other have used question generation and question answering models to evaluate summaries (Scialom et al. 2019; Chen et al. 2018), but we argue that these metrics are only as good as the datasets the models were trained on, and may have problems generalizing. Beyond summarization, there have been many metrics proposed for Natural Language Generation more generally (Sai, Mohankumar, and Khapra 2020).

Our methods are most similar to BLANC (Vasilyev, Dharmidharka, and Bohannon 2020; Vasilyev et al. 2020), which measures the accuracy boost of BERT (Devlin et al. 2019) on the Cloze task (Taylor 1953) when a summary is prepended to a document or the model is finetuned on the summary. This paper contributes to the study of BLANC-like metrics by extending them to new language models, giving them a theoretical motivation, and performing more robust experiments to better understand their behavior. The information-theoretic motivations of our metrics are similar to that of Peyrard (2019) who formally defined some metrics based on distributions of semantic units, which contrasts with our use of pretrained language models.

7 Conclusion

In this work, we successfully show that a universal language model performing the basic language modeling task is an effective reference-free evaluator of summary quality. This work extends the Shannon Game from using humans as evaluators to using machines, and extends the work on BLANC-like metrics to new language models and theoretical interpretations. We experimentally showed that our metrics strongly correlate with expert judgement of summary quality, and hope that they will serve as useful tools for the future development of summarization models. As next steps, it would be interesting to see if our metrics are useful for summarization model training, or evaluation in tasks beyond standard summarization, such as paraphrasing or query-focused summarization. Our code is available on GitHub.

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A Experimental Setup

| Model   | HF Name   | Params | sec |
|---------|-----------|--------|-----|
| GPT-2 S | gpt2      | 124M   | 13  |
| GPT-2 M | gpt2-medium| 355M   | 28  |
| GPT-2 L | gpt2-large| 774M   | 43  |
| GPT-2 XL| gpt2-xl   | 1558M  | 59  |
| GPT     | openai-gpt| 117M   | 15  |
| XLNet   | xlnet-base-cased| 117M | 40  |
| TransfoXL | transfo-xl-wt103 | 285M | 49  |

Table 6: Additional information about each language model used in our experiments: HuggingFace model hub name, number of model parameters, and number of seconds it takes to compute the Shannon Score on average for SummEval without batching.

In our experiments, we used the Transformers library\(^2\) (Wolf et al. 2020) for implementations of GPT-2, GPT, XLNet, and Transformer-XL. Sentence tokenization was performed with the NLTK Punkt sentence tokenizer\(^3\). We computed our metrics using a single NVIDIA V100 GPU. Our code will be published on GitHub and linked in this paper after blind review.

Table 6 shows information about each language model we used in our experiments: the HuggingFace model hub\(^4\) name for the model, number of parameters in the model, and the number of seconds it takes to compute the Shannon Score for a given document-summary pair on average for SummEval when using the model. Our implementation did not include any batching since we had no need for it, but if we batched together document sentences for model inference we could greatly improve our runtime.

B Full Doc Information Visualizations

Tables [7] and [9] show full document information visualizations for 3 different CNN/DailyMail documents. Each of these documents were paired with 2 SummEval system summaries: one that humans judged to be of high quality, and one that humans judged to be of low quality. The visualizations show the information content of each token in the document as estimated by GPT-2 in 4 scenarios: \(I(\mathcal{D})\) (the document on its own), \(I(\mathcal{D}|\mathcal{D})\) (the document given the document), \(I(\mathcal{D}|\mathcal{S})\) (the document given a summary) for the high quality summary, and \(I(\mathcal{D}|\mathcal{S})\) for the low quality summary. A darker background color denotes higher information according to the model.

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\(^2\)https://github.com/huggingface/transformers
\(^3\)https://www.nltk.org/api/nltk.tokenize.html
\(^4\)https://huggingface.co/models
I(D) = 1787

Priscilla Presley will serve as a witness at the first wedding to be held at an all-new chapel of love in Las Vegas. The 69-year-old collaborated with NBC’s Today show to launch a contest for one Elvis-related prize, which is to be awarded to the winners of a contest. The winning duo—announced next Monday—will tie the knot at Elvis Presley’s Graceland Wedding Chapel in Las Vegas. The 69-year-old collaborated with NBC’s Today show to launch a contest for one Elvis-related prize, which is to be awarded to the winners of a contest. The winning duo—announced next Monday—will tie the knot at Elvis Presley’s Graceland Wedding Chapel in Las Vegas.

I(D|S) = 1265 for this high quality summary:

Priscilla Presley will serve as a witness at the first wedding to be held at Elvis Presley’s Graceland Wedding Chapel in Las Vegas. The 69-year-old collaborated with NBC’s Today show to launch a contest for one Elvis-related prize, which is to be awarded to the winners of a contest. The winning duo—announced next Monday—will tie the knot at Elvis Presley’s Graceland Wedding Chapel in Las Vegas.

I(D|S) = 1426 for this low quality summary:

The winning couple will tie the knot at Elvis Presley’s Graceland Wedding Chapel inside the Westgate Hotel on Thursday, April 23. 'I am so excited to be a part of this,' she said. 'It is going to be a great experience for me and my family.' The bride's mother, Doris Presley, is also a part of the group that will receive a $1 million cash prize.

Continued on the next page
The winning duo announced next Monday - will tie the knot at Elvis Presley’s Graceland Wedding Chapel inside the Westgate Hotel on Thursday, April 23. No vel idea: Priscilla Presley will serve as a witness at the first wedding to be held at an all-new chapel of love in Las Vegas. The 69-year-old collaborator with NBC’s Today show to launch a contest for one Elvis -obsessed couple to win the “ultimate wedding.” The winning duo - announced next Monday - will tie the knot at Elvis Presley’s Graceland Wedding Chapel inside the Westgate Hotel on Thursday, April 23. No vel idea: Priscilla Presley will serve as a witness at the first wedding to be held at an all-new chapel of love in Las Vegas. The 69-year-old collaborator with NBC’s Today show to launch a contest for one Elvis -obsessed couple to win the “ultimate wedding.”

Table 7: A comparison of token-wise information content within a document as estimated by GPT-2 in 4 scenarios: the document on its own, the document given the document, the document given a high-quality summary, and the document given a low-quality summary. Tokens with a darker background color have more information.
Italy is coping with a rising wave of desperate migrants from Africa and Middle East hoping to make it to Europe. From Friday to Monday, a total of 8,480 migrants were rescued, according to the Italian coast guard, which said it received on Monday – alone – SOS calls from 20 boats in distress. On Tuesday, a spokesman with Save the Children told CNN the group fears 400 migrants could be missing, citing testimony from survivors who said their ship carrying 550 people capsized in the Mediterranean Sea about 80 miles off the Libyan coast. The Italian coast guard, however, told CNN that while it is taking the report seriously, it cannot confirm such an incident and has not yet found evidence at sea to indicate a migrant boat carrying approximately 550 has capsized with 145 rescued. An operation that included boats and planes did not find any survivors, nor bodies, nor any evidence to indicate a particular boat capsized, Coast Guard official Filippo Marini said. There has been a recent upsurge in migrant boats crossing the Mediterranean into Italy and an increase in rescues performed by the Italian Coast Guard to aid migrant boats. Why migrants are dying trying to reach Italy According to the International Organization for Migration, Italy registered more than 10,000 migrants arriving in the first three months of 2015, and about 2,000 were rescued at sea during the first weekend of April in the Channel of Sicily. Most migrants recorded this year come from countries in West Africa as well as Somalia and Syria, the IOM said. They use Libya as a country of transit. At least 480 migrants have died while crossing the Mediterranean since the beginning of the year, often because of bad weather and overcrowded vessels used by smugglers, the IOM said. Sometimes the captains and crews abandon the ships, leaving passengers to fend for themselves. Last week: 978 migrants rescued in one day in Mediterranean Sea. CNN’s Ralph Ellis contributed to this report.

For this high quality summary:

$I(D) = 1352$

$I(D|S) = 1137$ for this high quality summary:

A Save the Children spokesman says a ship carrying 550 people capsized off the Libyan coast. The Italian coast guard says it cannot confirm such an incident. There has been a recent upsurge in migrant boats crossing the Mediterranean. Italy registered more than 10,000 migrants arriving in first three months of 2015. CNN’s Ralph Ellis contributed to this report.

For this low quality summary:

$I(D) = 118$

$I(D|S) = 1168$ for this low quality summary:

Italy’s coast guard says it has rescued 8,480 migrants since Friday, more than 1,000 of whom are believed to have died. Migrant crisis in the Mediterranean. The IOM says that of the 8,480 migrants rescued by Italian coast guard vessels, 5,943 were women and children, and 1,852 were men. The IOM says that of the 1,852 women and children, 781 were from Eritrea. Continued on the next page.
Italy is coping with a rising wave of desperate migrants from Africa and Middle East hoping to make it to Europe. From Friday to Monday, a total of 8,480 migrants were rescued, according to the Italian coast guard, which said it received SOS calls from 20 boats in distress. On Tuesday, a spokesman with Save the Children told CNN the group fears 400 migrants could be missing, citing testimony from survivors who said their ship carrying 550 people capsized in the Mediterranean Sea about 80 miles off the Libyan coast. The Italian coast guard, however, told CNN that while it is taking the report seriously, it cannot confirm such an incident and has not yet found evidence at sea to indicate a migrant boat carrying approximately 550 has capsized with 145 rescued. An operation that included boats and planes did not find any survivors, nor bodies, nor any evidence to indicate a particular boat capsized.

Coast Guard official Filippo Marini said, "There has been a recent upsurge in migrants crossing the Mediterranean into Italy and an increase in rescues performed by the Italian Coast Guard to aid migrant boats. Why migrants are dying trying to reach Italy? According to the International Organization for Migration, Italy registered more than 10,000 migrants arriving in the first three months of 2015, and about 2,000 were rescued at sea during the first weekend of April in the Channel of Sicily. Most migrants recorded this year come from countries in West Africa as well as Somalia and Syria, the IOM said. They use Libya as a country of transit. At least 480 migrants have died while crossing the Mediterranean since the beginning of the year, often because of bad weather and overcrowded vessels used by smugglers, the IOM said. Sometimes the captains and crews abandon the ships, leaving passengers to fend for themselves. Last week: 978 migrants rescued in one day in Mediterranean Sea CNN's Ralph Ellis contributed to this report.

Table 8: A comparison of token-wise information content within a document as estimated by GPT-2 in 4 scenarios: the document on its own, the document given the document, the document given a high quality summary, and the document given a low quality summary. Tokens with a darker background color have more information.
Sir Bradley Wiggins will bid for cycling’s hour record on June 7 at London’s Olympic Velodrome. The four-time Olympic champion and 2012 Tour de France winner, who is 35 on April 28, will attempt to add to his accomplishments by riding the furthest distance in 60 minutes at the Lee Valley Velodrome. The Hour Record is a holy grail for cyclists,” Wiggins said. Four-time Olympic champion Bradley Wiggins will bid to break cycling’s hour record in June. Wiggins finished his Team Sky career in the Paris - R ou ba ix 253. 5 km one-day race on Sunday Australian rider Rohan Dennis poses after breaking the world hour record on February 8 in Grenoble. ”It’s been fought over too much by now. It’s time for me to have a crack at it.” Wiggins said. “I like the idea of challenging myself and want to motivate people to do the same - so why not get your bike out of the shed and see how far you can go in an hour? We’re going to try and set a mark which will last for some time.” Wiggins will hope for a capacity of 6,000 crowd to spur on his attempt, with tickets going on sale from April 19, while the event will be broadcast live on Sky Sports. In June, Wiggins will hope to race in front of a sell-out crowd at London’s Olympic Velodrome. Wiggins (left) alongside his Team Sky colleague Luke Rowe after the pair raced the Paris - R ou ba ix. Wiggins will look to beat the record of Dennis (pictured), who managed to cycle 52.491 km in an hour. The Brit on finished his Team Sky career at Paris - R ou ba ix last Sunday and will ride in next month’s inaugural Tour de Yorkshire for his.eponomous team before preparing for the Hour as part of his return to the track. The world time trial champion is targeting a British record eighth Olympic medal - he has four gold, one silver and two bronze at the 2016 Rio Olympics in the four-man, four-kilometre team pursuit. The current Hour record is 52.491 km, set by Australian Rohan Dennis in February after the UC1, cycling’s world governing body, reformed regulations, reigniting interest in the event. German Jens Voigt was the first to make an attempt last September, recording 51.115 km, a mark which stood for six weeks before Austria’s Matthias Brandl rode 51.852 km, while Jack Bobridge was the first to fall short in his attempt. Dennis’ mark will come under threat from Briton Alex Dowsett, who will make his attempt on May 2 in Manchester having had to postpone it previously after suffering a broken collar bone. Tickets to watch Sir Bradley Wiggins attempt to break the UC1 Hour Record at the Lee Valley Velodrome on June 7 will go on sale to the general public through Sky Tickets from Friday, April 19 (10 am) price £49, £39 and £29, on line sale only through the Sky Ticket website. Continued on the next page
Sir Bradley Wiggins will bid for cycling ’s hour record on June 7 at London ’s Olympic Velodrome. The four - time Olympic champion and 2012 Tour de France winner , who is 35 on April 28 , will attempt to add to his accomplishments by riding the furthest distance in 60 minutes at the Lee Valley Velodrome. ’The Hour Record is a holy grail for cyclists,’ Wiggins said. Four - time Olympic champion Bradley Wiggins will bid to break cycling ’s hour record in June Wiggins finished his Team Sky career in the Paris - Roubaix. Wiggins will look to break the record of Dennis ( pictured ), who managed to cycle 152.7 km in an hour. The Brit finished his Team Sky career at Paris - Roubaix last Sunday and will ride in next month ’s inaugural Tour de Yorkshire for his eponyymous team before preparing for the Hour as part of his return to the track. The world time - trial champion is targeting a British record eighth Olympic medal - he has four golds, one silver and two bronze - at the 2016 Rio Olympics in the four - man, four kilometer team pursuit. The current Hour record is 52.491 km, set by Australian Rohan Dennis in February after the UCI ’s world governing body, reformed regulations, reigniting interest in the event. German Jens Voigt was the first to make an attempt last September, recording 51.115 km, a mark which stood for six weeks before Austria ’s Matthias Brandle rode 51.185 km, while Jack Bobridge was the first to fall short in his attempt. Dennis ’ mark will come under threat from Briton Alex Dowsett, who will make his attempt on May 2 in Manchester having had to postpone it previously after suffering a broken collar bone. Tickets to watch Sir Bradley Wiggins attempt to break the UCI ’s Hour Record at the Lee Valley Velodrome on June 7 will go on sale to the general public through Sky Tickets from Friday, April 19 (10 am) and price £49, £39 and £29, on line sale only through the Sky Tickets website.

Table 9: A comparison of token-wise information content within a document as estimated by GPT-2 in 4 scenarios: the document on its own, the document given the document, the document given a high quality summary, and the document given a low quality summary. Tokens with a darker background color have more information.