Revisiting Automatic Evaluation of Extractive Summarization Task: Can We Do Better than ROUGE?

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Abstract

It has been the norm for a long time to evaluate automated summarization tasks using the popular ROUGE metric. Although several studies in the past have highlighted the limitations of ROUGE, researchers have struggled to reach a consensus on a better alternative until today. One major limitation of the traditional ROUGE metric is the lack of semantic understanding (relies on direct overlap of n-grams). In this paper, we exclusively focus on the extractive summarization task and propose a semantic-aware nCG (normalized cumulative gain)-based evaluation metric (called Sem-nCG) for evaluating this task. One fundamental contribution of the paper is that it demonstrates how we can generate more reliable semantic-aware ground truths for evaluating extractive summarization tasks without any additional human intervention. To the best of our knowledge, this work is the first of its kind. We have conducted extensive experiments with this new metric using the widely used CNN/DailyMail dataset. Experimental results show that the new Sem-nCG metric is indeed semantic-aware, shows higher correlation with human judgement (more reliable) and yields a large number of disagreements with the original ROUGE metric (suggesting that ROUGE often leads to inaccurate conclusions also verified by humans).

1 Introduction

Text summarization is a difficult NLP task and an automatic evaluation of this task is even more challenging. However, automatic evaluation is vital for large-scale experiments as it acts as a replacement for time consuming and pricey human evaluation. As such, the reliability and robustness of automatic evaluation is very crucial.

The most commonly used metric for evaluating text summarization is ROUGE (Lin, 2004). Although ROUGE has been criticized for considering direct lexical overlap and thus not being semantic-aware, the majority of summarization models’ assessments today are still based on ROUGE scores. In this paper, we revisit the popular ROUGE metric exclusively in the context of evaluating extractive summarization task, a task where phrases and sentences from the original text are extracted to create a summary. As such, if the human-written summary includes more novel words than the original document, ROUGE will provide a poor score to extractive summaries due to a lack of semantic awareness. Another limitation of the ROUGE metric in the context of extractive summarization is the following: while the extractive summarization task is generally framed as a sentence ranking problem, the ROUGE metric was not originally proposed for evaluating the quality of a ranker. Indeed, the heavily used technique behind extractive summarization is to rank sentences from the original document according to how well they reflect the overall description and then create a summary by concatenating the top-ranked sentences. Thus, the “right” evaluation metric for the extractive summarization task should also consider the quality of the sentence ranker. Again think about a human-written summary which is highly abstractive in nature. A good ranker that ranks the most informative sentences at the top may still suffer from low ROUGE scores due to fewer direct lexical overlaps between the system summary and human-written summary.

To address these limitations, we propose an alternative gain-based evaluation metric in this paper (called Sem-nCG) for evaluating extractive summarization tasks, which is both 1) semantic-aware and 2) rewards a system-generated summary based on some groundtruth ranking of sentences from original document. nCG (Normalized cumulative gain) is a widely used metric for evaluating the performance of ranking systems, especially when conducting multi-level relevance judgements (Järvelin and Kekäläinen, 2002). Although nCG evaluation
is not entirely new (Karmaker Santu et al., 2017; Kuzi et al., 2019; Karmaker et al., 2020), one fundamental contribution of this paper is that it demonstrates how we can automatically generate a reliable semantic-aware groundtruth ranking of sentences within a source document, which essentially enables automatic Sem-nCG based evaluation without any additional human intervention. To the best of our knowledge, this work is the first of its kind. To be more specific, given an original document and a human-written summary for evaluation purposes, we used several state-of-the-art sentence embedding techniques (including InferSent, Sentence Transformer, Elmo, Google Universal Sentence Encoding and their ensemble) to prepare groundtruth ranking of sentences from original document by computing semantic similarity between each individual sentence of original document and entire human written summary. Finally, this groundtruth ranking is compared against model-inferred ranking to compute Sem-nCG score, where a higher number means a better extractive summary.

We have conducted extensive experiments with this new metric using the CNN/DailyMail dataset and 6 state-of-the-art extractive summarization models (BERTBase, MobileBERT, DistilBERT, RoBERTa, XLNET, GPT-2). Experimental results show that the new Sem-nCG metric is: 1) semantic-aware, 2) shows higher correlation with human judgement (more reliable), and 3) yields a large number of disagreements with the original ROUGE metric (suggesting ROUGE often leads to inaccurate conclusions). When cross-examined by humans, we found Sem-nCG to be more accurate (62% of the time) than ROUGE on average where the two metrics disagreed on the relative performance of a pair of extractive summarization models. Thus, in response to the question of whether we can do better than ROUGE for evaluating extractive summarization tasks, the answer appears to be “YES”.

2 Related Work

Evaluation of the text summarization task is challenging and has been studied vastly in the past. (Radev and Tam, 2003) proposed the Relative Utility (RU) metric, which evaluates extractive summarization as a ranking task (similar to our formulation), but has not gained much popularity, because their approach requires manual labor to rank each sentence of a document, and it is not practical to manually annotate such large data-sets.

ROUGE (Lin, 2004) is perhaps the most popular metric used today for the evaluation of the automated summarization techniques, mainly because it is a simple and automatic process. However, ROUGE has been criticized a lot for primarily relying on lexical overlap (Nenkova, 2006) of n-grams. Later, (Zhou et al., 2006) suggested using a broad domain-independent paraphrase table derived from a bilingual parallel corpus to enable paraphrase matching for summary evaluation. (Cohan and Goharian, 2016) showed that ROUGE suffers from poor performance in cases of terminology variation and paraphrasing. As of today, around 192 variants of ROUGE have been proposed (Graham, 2015) including ROUGE with word embedding (Ng and Abrecht, 2015) and synonym (Ganesan, 2018), graph-based lexical measurement (ShafieiBavani et al., 2018), Vanilla ROUGE (Yang et al., 2018) and highlight-based ROUGE (Hardy et al., 2019). However, none of the variants of ROUGE considers the ranking quality (core technique of extractive summarization); let alone providing an automatic way to do it, which is the primary goal of our work.

Researchers have also proposed metrics alternative to ROUGE: factoids-based (atomic information units for sentence meaning) (Teufel and van Halteren, 2004) and pyramid-based (Nenkova and Passonneau, 2004) approaches are two of them. Multiple different reference summaries are a must for both approaches, where the pyramid-based approach requires additional manual labor to construct the pyramid. Since the pyramid must be built by hand and gives imprecise scores, this technique failed to gain much attraction. Many enhancements have been made to the pyramid-based approach: precise automated system for calculating pyramid ratings (Passonneau et al., 2013), pyramid evaluation via automated information extraction (Yang et al., 2016), lightweight sampling-based version that is crowdsourcable (Shapira et al., 2019) and facet-aware evaluation (Mao et al., 2020) for better assessment of knowledge coverage in extractive summarization. Still, the pyramid-based approach necessitates significant additional manual labour making it less appealing for large-scale evaluation.

Researchers also attempted to develop methods for evaluating reference-free model summaries (Louis and Nenkova, 2013; Xenouleas et al., 2019). Distance measures between the system summary and reference summary based on word
embeddings have also been proposed (Zhao et al., 2019; Sun and Nenkova, 2019). Moreover, model based evaluation for text generation (also adopted for text summarization) has also been a recent trend (Sellam et al., 2020; Zhang et al., 2020; Yuan et al., 2021). Yet, none of these metrics explicitly assess the quality of ranking performed by an extractive summarization method.

3 Background

\textit{nCG} (Normalized Cumulative Gain) is a popular measure for evaluating information retrieval (IR) systems (Järvelin and Kekäläinen, 2002). Given a query and a ranked list of search results, computation of \textit{nCG} involves summing the gains of the top \(k\) documents, and normalizing by the maximum possible gain that can be obtained for the query. Mathematically:

\[
CG@k = \begin{cases} 
G@1, & \text{if } k = 1 \\
CG@[k-1] + G@k, & \text{otherwise}
\end{cases} \tag{1}
\]

Here, \(k\) is the cutoff position (e.g., \(k = 5\) is a common choice), \(G@k\) and \(CG@k\) are the gain and cumulative gain, respectively, at the \(k\)-th position in the list. \textit{nCG}@\(k\) is \(CG@k\) divided by the maximum achievable \(CG@k\), also called Ideal CG (\textit{ICG}@\(k\)), which is computed from the ideal ranking of the documents with respect to the query. The ideal ranking places the document(s) with the highest gain on the very top, followed by the documents with the next level of gain, etc. Mathematically:

\[
\textit{nCG}@k = \frac{CG@k}{\text{ICG}@k} \tag{2}
\]

4 \textit{Sem-nCG} for Extractive Summary

The main motivation for introducing the \textit{Sem-nCG} metric is to ensure a fair evaluation of the extractive summarization task where the metric is both semantic-aware as well as captures the ranking quality of the extractive summarizer. Indeed, for extractive summarization, sentences in the original document are ranked based on how well they reflect the overall description, and thus, evaluating it with a rank-aware metric like \textit{Sem-nCG} is more equitable. But, how can we develop a \textit{Sem-nCG} metric for the extractive summarization task that was originally designed for Information Retrieval systems? What would be the query in this case? What would be the definition of a document? How do we define the gains? How can we compute the groundtruth ideal ranking? All of these are important questions we need to answer before one can use \textit{Sem-nCG} evaluation for extractive summarization tasks.

\textbf{Problem Formulation:} We formulate extractive text summarization as a ranking problem, where the output is a ranked-list of sentences based on how well they convey the overall content of the original document. Let us assume that, input is a document \(D = [S_1^D, S_2^D, S_3^D, S_4^D, ..., S_{|D|}^D]\), where \(S_i^D\) denotes \(i\)-th sentence of document \(D\) and output is the \textit{Sem-nCG}@\(k\) score for the top-\(k\) sentences extracted from Document \(D\) by the extractive summarization model. Now, in order to compute \textit{Sem-nCG}@\(k\), we need to know what the gains of the top-\(k\) ranked sentences are, as well as the gains of the top-\(k\) ideal (desired) sentences. In other words, without knowing the groundtruth gains for each sentence in the original document, we cannot compute the \textit{Sem-nCG}@\(k\) metric.

\textbf{Groundtruth Gains:} It is indeed a philosophical question to ask what should be the definition of gains in case of the extractive summarization. In this work, we define gain as the following:

\textbf{Definition 4.1} Given document \(D\) and a sentence \(s\) from \(D\), gain of \(s\) with respect to \(D\) is proportional to the degree of how well \(s\) captures the overall semantic meaning of document \(D\).

One way to measure this capturing power is to ask human judges. However, human judgment in this case is problematic for multiple reasons as follows: 1) Human evaluation is time-consuming and expensive, 2) Some human raters have the tendency to give higher ratings than deserved, this is known as the \textit{Leniency} problem, which results in higher variance (Harman and Over, 2004), 3) Natural language descriptions are noisy and ambiguous, which makes manual ordering of sentences by annotators even harder resulting in low inter-rater agreement. This is why we opted for an automated way to create the groundtruth gains without involving humans, as demonstrated by Algorithm 1.

\textbf{Automatic Gain Computation:} How can we automatically infer groundtruth gains in order to automate \textit{Sem-nCG}@\(k\) computation? Fortunately, in most summarization benchmark datasets, one or more reference summaries written by humans are also provided along with the original documents. We leverage these human-written reference summaries to automatically infer groundtruth gains.

The exact process is presented in Algorithm 1, where we utilize the semantic similarity between...
Algorithm 1 Sem-nCG@k Computation

**INPUT:** Document $D$, Reference $R$, Model’s top-k extracted sentences, number of sentences in $D$ as $N$

**OUTPUT:** Sem-nCG@k score

1: **Phase 1:** Groundtruth Gain Computation
2: $GT \leftarrow \emptyset$
3: $GT_{gain} \leftarrow \emptyset$
4: Represent sentences in $D$ and $R$ by embedding vectors
5: for each $S_d \in D$ do
6: for each $S_r \in R$ do
7: $Sim(S_d, S_r) \leftarrow \text{Cosine Similarity}(S_d, S_r)$
8: end for
9: $GT[S_d] \leftarrow \text{mean}(Sim)$
10: end for
11: $GT_{sorted} \leftarrow \text{Sort GT based on mean}(Sim)$
12: $GT_{gain}[S_d] \leftarrow N - \text{rank}(S_d, GT_{sorted}) + 1$
13: Normalize $GT_{gain}$ into a probabilistic gain
14: return $GT_{gain}$

1: **Phase 2:** Sem-nCG@k Computation
2: Compute ICG@k from $GT_{gain}$
3: $M \leftarrow$ Model’s top-k extracted sentences
4: Retrieve $M$’s gain from $GT_{gain}$
5: Compute CG@k for $M$
6: return $\text{Sem-nCG@k} = \frac{CG@k}{ICG@k}$

Algorithm 1 demonstrates the process of computing the Sem-nCG@k metric. Each sentence in the input document and the entire reference summary serves as the groundtruth gains. For semantic similarity, we have experimented with different embeddings, including InferSent, Sentence Transformer, Elmo, Google Universal Sentence Encoding, and their ensembles (details in section 5.3). Specifically, we measure the cosine similarity between each sentence in the original document and each reference sentence and then calculate an average cosine similarity for each source-sentence with respect to the whole reference. This average cosine similarity score is then used to rank all the sentences in the original document and a simple greedy approach is taken to assign the groundtruth gain as follows: sentences are assigned a groundtruth gain of $N, N-1, ..., 1$, sequentially from the top, where $N$ denotes the number of sentences in the document. Later, the gain of each sentence is normalized to probabilistic scores ensuring the range of the Sem-nCG metric to be between 0 and 1. The intuition here is that a higher-ranked sentence gets more rewards than a lower-ranked one.

The gains computed by Algorithm 1 are then used in Equation 1 to compute the corresponding cumulative gain for ideal ranking (ICG@k) and for model’s ranking (CG@k), respectively. The ratio of CG@k and ICG@k, which is nCG@k (equation 2), captures the quality of the system generated ranking with respect to the groundtruth ranking. Figure 1 visually demonstrates the pipeline for computing Sem-nCG@k metric.

5 Experimental Setup

5.1 Dataset

We conducted extensive experiments with our proposed Sem-nCG metric using the popular CNN/DailyMail (Hermann et al., 2015) benchmark dataset. The CNN/DailyMail dataset provides a collection of news articles and related highlights, and these highlights are somewhat extractive in nature (a few bullet points providing a brief overview of the article) (Liu and Lapata, 2019). We collected the dataset from huggingface (Wolf et al., 2020). As we are not explicitly doing any training/fine-tuning of the summarizer models, we have only used the testing set for our experimental evaluation. We excluded any sample that has a sentence count less than 5 from our analysis as we report Sem-nCG@5 scores. There were 64 such samples in the testing set, which brings
our sample size to 11, 426 (Details can be found in Table 1).

| Feature          | Description                        |
|------------------|-------------------------------------|
| Train/Validation/Test | 287113/13368/11490                 |
| #Mean Tokens     | 781 per Article/56 per Highlights  |
| Reference Strategy| Single                              |
|                  | Extractive                          |

Table 1: Overview of CNN/DailyMail Dataset

5.2 Extractive Summarization Models

We collected six pre-trained models: BERT$_{base}$ (Liu and Lapata, 2019), MobileBERT (Sun et al., 2020), DistilBERT (Sanh et al., 2019), RoBERTa (Liu et al., 2019), XLNet (Yang et al., 2019), GPT-2 (Radford et al., 2019), from hugging-face that were fine-tuned on the CNN/DailyMail dataset for the extractive summarization task. We then evaluated these six models using both our proposed Sem-nCG@k metric and traditional ROUGE metric.

5.3 Embedding Sensitivity

We recognize that the groundtruth gains we considered are not absolute since they are derived from a pre-trained sentence embedding. Therefore, we investigated the sensitivity of the gains by varying eight cutting-edge sentence embedding techniques. Specifically, we experimented with Inference (v1&v2) (Conneau et al., 2017), Semantic Textual Similarity benchmark (STSb - bert/roberta/distilbert) (Reimers and Gurevych, 2019), Elmo (Peters et al., 2018) and Google Universal Sentence Encoder (USE) (Cer et al., 2018): i) enc-2 (Iyyer et al., 2015) based on the deep average network ii) enc-3 (Vaswani et al., 2017) based on transformers. We also created an ensemble method to aggregate the gains (in terms of raw similarity, rank and relevance) provided by different embeddings and combine them into a single gain with an expectation that the ensemble technique will provide a more reliable way for preparing the groundtruth gains. Furthermore, we have also experimented with 3 different variations of the ensemble technique: Ensemble$_{sim}$, Ensemble$_{rank}$ and Ensemble$_{rel}$, with the hope of obtaining more robust groundtruth gains. Specifically, Ensemble$_{sim}$ aggregates the cosine similarity first and then gives gains according to Algorithm 1, Ensemble$_{rank}$ generates a sentence ranking for each embedding variation and then aggregates the ranking to create a more robust ranking and then provide the gains according to Algorithm 1 and Ensemble$_{rel}$ calculates the gain first according to Algorithm 1 for all embedding variations and then takes an average over the gains. Please note that we compare sentences from original documents with highlights (written by humans) to prepare these groundtruth gains.

6 Quantitative Evaluation

6.1 ROUGE is not Robust to Perturbation

One of the major criticisms of ROUGE is that it is not semantic-aware. Table 2 confirms that the ROUGE score highly varies if the original document is perturbed with synonyms. Clearly, this is not desired from a “good” summary evaluation metric. Indeed, humans have various ways to express the same thing and often humans write summaries in their own words rather than picking the same key words from the original document (for example if the document uses “vacation”, human references can have “trip”, “tour”, “break” etc.). For our experiments, we substituted around 20% of the words (excluding stop words) of the original document with their synonyms and computed ROUGE scores for these perturbed documents using the CNN/DailyMail dataset, assuming a 5-sentence summary. We utilized wordnet from nltk.corpus to perform synonym replacement. As seen from Table 2, for ROUGE-1 and ROUGE-3, the score drop was around 5-7%, where for ROUGE-L it was around 3-5%. Interestingly, for ROUGE-2, the score drop was 5-16%.

As the groundtruth gain computation of Sem-nCG is dependent of embedding techniques, we have also inspected whether the ROUGE variant with word embedding (ROUGE-we) (Ng and Abrecht, 2015) is also sensitive to perturbation. Interestingly, table 2 shows ROUGE-we scores are also sensitive to perturbation. For all ROUGE-we-\{1,2,3\}, the score drop was around 5-6%. One can reasonably expect that the score drop would be more significant if more words are replaced in original document (> 20%).

6.2 Sem-nCG is Robust to Perturbation

We have conducted the same experiment mentioned in Section 6.1 with Sem-nCG metric for

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3The objective was to reduce the lexical overlap between extractive summary and reference. The reference can also be perturbed to do this experiment.
4www.nltk.org/howto/wordnet.html
5More evidence are included in Appendix
would recommend utilizing the STSb-distilbert embedding for our proposed Sem-nCG. The findings reveal that the Sem-nCG@5 sentence embedding technique is Robust across Multiple sentence embeddings. Among non-ensemble techniques, STSb-distilbert seems to be the most robust. If computational time is a bottleneck (Table 4), we can see that Ensemble techniques (especially for ROUGE) can offer substantial gains. Specifically, we experimented with eight different sentence embedding variations. Table 2: ROUGE and ROUGE-we scores (Precision, Recall and F1) for the extractive summarization models (BERT\textsubscript{base}, MobileBERT, DistilBERT, RoBERTa, XLNet, GPT-2) on CNN/DailyMail test dataset. The results are for top-5 extracted sentences when the outputs are in actual and perturbed. Table 3: Sem-nCG@5 scores for the top-5 sentences of the extractive summarization models (BERT\textsubscript{base}, MobileBERT, DistilBERT, RoBERTa, XLNet, GPT-2) on CNN/DailyMail test dataset for different embedding variations. 6.3 Sem-nCG is Robust across Multiple Sentence Embedding Techniques In this experiment, we tested the sensitivity of the proposed Sem-nCG metric with respect to the sentence embedding used to create the groundtruth gains. Specifically, we experimented with eight different sentence embedding techniques (Table 3). The findings reveal that the Sem-nCG@k score is stable across different sentence embeddings as evident from the low standard deviation of both Sem-nCG@5 scores for the top-5 extracted sentences. Also, the relative performance of the models always remains same (DistilBERT > BERT\textsubscript{base} > MobileBERT > XLNet > GPT-2 > RoBERTa) for all embedding variations.

6.4 Sem-nCG often disagrees with ROUGE Although ROUGE and Sem-nCG@k agree on relative performances of multiple summarization models in the average case, as we explored further, we discovered that the agreement does not hold for individual document samples. As shown in Table 5, there is a considerable amount of disagreements between ROUGE and Sem-nCG@k for each pair of models. Here, disagreement means when comparing Model\textsubscript{A} > Model\textsubscript{B}, Sem-nCG@k in-
dicates ModelA’s output is better, while ROUGE implies ModelB’s output is better and vice-versa. To resolve these conflicts, we further involved humans to perform meta-evaluation of ROUGE and Sem-nCG@k, where human judgement agreed with Sem-nCG@k most of the time (see Section 7).

7 Human Evaluation

7.1 Human judgment favors Sem-nCG over ROUGE in case of disagreements

We next took a deeper look into the cases where Sem-nCG disagreed with ROUGE (Table 5) while comparing two extractive summarization models. We asked humans to blindly evaluate the quality of the summaries generated by two models and make a judgement on which summary was better as suggested by (Peyrard, 2019) as well. Specifically, we considered 5 pairs of models (BERTbase vs. MobileBERT, MobileBERT vs. DistilBERT, DistilBERT vs. RoBERTa, RoBERTa vs. XLNet, and XLNet vs. GPT-2) and provided humans with outputs for each pair of models, hiding the model’s name. We took 10 conflicting examples between Sem-nCG and ROUGE-L for each pair of models. This means that humans evaluated $10 \times 2 = 20$ summaries, each 5 sentences long, for each model pair. In total, annotators labeled $5 \times 20 \times 5 = 500$ sentences for model output, after reading around $5 \times 10 \times 50 = 2500$ sentences for articles and $5 \times 10 \times 3 = 150$ sentences for highlights. We asked the annotators to say which extractive summary is better and matched their decision against both ROUGE and Sem-nCG@k’s conclusions. Our annotators were three doctoral students all working in NLP. We took the majority voting judgement from annotators and the results are reported in Table 6. As summarized in Table 6, blind evaluation by humans indicated Sem-nCG@k was more accurate than ROUGE in the case of disagreements between the two, thus confirming that Sem-nCG@k captures semantics better than ROUGE.

7.2 Meta-Evaluation of Sem-nCG

We further performed meta-evaluation of the Sem-nCG metric using data provided by (Fabbri et al., 2021). The dataset includes summaries generated by 16 models (both extractive and abstractive) from 100 source news articles (1600 summaries in total). For our experiments, we only considered the extractive summaries and omitted samples containing less than 3 sentences (as we report Sem-nCG@3), and that resulted in 252 samples. Each of these summaries was annotated by 5 independent crowd-source workers and 3 independent experts (8 annotations in total). Summaries were evaluated across 4 dimensions: consistency, fluency, coherence, relevance after looking into the CNN/DailyMail reference and 10 additional crowd-sourced reference summaries. As mentioned in (Gillick and Liu, 2010), non-expert annotation can be risky, so we only considered expert annotations as followed by (Fabbri et al., 2021) as well. Next, we computed kendall’s tau correlation between the Sem-nCG score and each of consistency, fluency, coherence, relevance scores rated by humans in the case of single reference setting for the following 3 different scenarios (example in Table 8):

- **Less Overlapping Reference (LOR):** Highly abstractive references with fewer lexical overlap with the original document.
- **Medium Overlapping Reference (MOR):** Somewhat extractive references (CNN/DailyMail) with moderate lexical overlap.
- **Highly Overlapping Reference (HOR):** Highly extractive references with high lexical overlap.

Table 7 shows that our proposed metric outperforms ROUGE in terms of consistency (the most crucial dimension perhaps) for all 3 types of references (even for HOR) with a considerable margin. Interestingly, we found that there is not a clear winner among the embedding choices. However, the STSb-distilbert embedding shows good performance in the consistency dimension both for less overlapping and high overlapping references. Note that STSb-distilbert also takes less computation time (Table 4) and can be a better choice for low-resource evaluation scenarios.

Along the fluency dimension, our proposed sem-nCG@k correlates better with humans for all types of references (except for less overlapping references with a comparable performance). Of particular interest from Table 7 are the more abstractive (LOR) references with little overlaps, where sem-nCG@k correlation is higher than ROUGE for 3 dimensions, including consistency, coherence, and relevance. For medium and highly overlapping references, ROUGE correlation along the coherence and relevance dimension was higher, which is somewhat expected, since ROUGE mainly computes lexical overlaps. These results suggest that,
Paired with 4296 3917 4251 4458
XLNet 4040 3759 4147 4282
5 pairs (BERT
4772 4489 4923 4725
BERTbase
3853 4121 4447 4643
4380 3989 4376 4478
4820 4471 4850 4693
GPT-2
4911 4583 5008 4787
XLNet and XLNet vs. GPT-2) evaluated by humans.

Table 6: Statistics for Sem-nCG@5

| Model    | Paired with | R1   | R2   | R3   | RL   |
|----------|-------------|------|------|------|------|
| BERTbase | MobileBERT  | 6478 | 6258 | 6401 | 6397 |
|          | DistilBERT  | 6443 | 6326 | 6486 | 6336 |
|          | RoBERTa     | 4408 | 3994 | 4345 | 4511 |
|          | XLNet       | 3853 | 4121 | 4447 | 4643 |
|          | GPT-2       | 4380 | 3989 | 4376 | 4478 |
| MobileBERT | DistilBERT  | 6152 | 5999 | 6040 | 5850 |
|          | RoBERTa     | 5397 | 5027 | 5261 | 5269 |
|          | XLNet       | 5533 | 5024 | 5222 | 5287 |
|          | GPT-2       | 5488 | 5050 | 5250 | 5286 |
| DistilBERT | RoBERTa     | 7786 | 7800 | 4173 | 4285 |
|          | XLNet       | 4296 | 3917 | 4251 | 4458 |
|          | GPT-2       | 4040 | 3759 | 4147 | 4282 |
| RoBERTa  | XLNet       | 5772 | 4489 | 4923 | 4725 |
|          | GPT-2       | 4911 | 4583 | 5008 | 4787 |
| XLNet    | GPT-2       | 4820 | 4471 | 4850 | 4693 |

Table 5: Disagreement between Sem-nCG@5 (with Ensemble\(_{eq}\)) and ROUGE (F1) out of 11426 samples for different extractive summarization model pairs.

Table 6: Statistics for Sem-nCG@5 vs. ROUGE (%)

| Win | Lose | Tie |
|-----|------|-----|
| 62% | 36%  | 2%  |

while there may not be a clear winner between sem-nCG and ROUGE when the testing corpus mostly contains medium and highly overlapping references, however, sem-nCG@k is clearly a superior metric when evaluating summaries against a more abstract (low overlap) reference.

8 Discussions and Conclusion

In this paper, we revisited the problem of automatic evaluation for the extractive summarization task, exclusively focusing on the popular ROUGE metric. We first argued that any summary evaluation should be more semantic-aware and demonstrated that ROUGE fails to capture semantics through comprehensive experiments. Indeed, ROUGE score drops (5-7%) even only for small percentages (20%) of synonym perturbation, and thus is not optimal for evaluating any summarization task.

Next, we argued that a “good” metric for evaluating extractive summarization task should assess its core ranking quality, which ROUGE does not. To address this issue, we proposed a new metric called Sem-nCG which is both semantic-aware and considers ranking quality. More importantly, Sem-nCG provides an automated way to compare a set of top-ranked model-extracted sentences (the system-extracted summary) against an ideal ranking of sentences, where the ideal ranking is automatically inferred by computing gains based on some human-written summary. This saves us from tedious process of manual annotation of each sentence within the original document, thus making it practically suitable for large scale automated evaluation.

The correctness of the Sem-nCG metric depends largely on the reliability of the groundtruth gains computed by algorithm 1. Therefore, to verify the quality of the groundtruth gains, we conducted extensive quantitative evaluations which confirm that the Sem-nCG metric is stable across multiple sentence embedding techniques (very robust) [section 6.2]. Through additional experiments, we have demonstrated the following as well: 1) Sem-nCG correlates better with humans [section 7.2]; 2) Sem-nCG often disagrees with ROUGE for pairwise comparison of summarization methods [section 6.4]; 3) In the cases of such disagreements, further verification from human judges confirmed that Sem-nCG is more reliable than the ROUGE metric [section 7.1]; and 4) Sem-nCG is a superior metric when evaluating summaries against a more abstract (low overlap) reference [section 7.2]. To conclude, we recommend the following practice:

- For extractive summarization evaluation, please refrain from overemphasizing a substantial improvement over ROUGE solely.
- While evaluating extractive summaries, mitigate the limitations of the ROUGE metric by reporting additional metrics which are semantic-aware and can generate reliable gains from human references (e.g., Sem-nCG), especially when the human-references are more abstractive in nature.
- Human judgment must still be the gold standard, and while making a conclusion of making substantial improvement over previous work, make sure it is backed by human evaluation.

We recognize that our proposed Sem-nCG metric overlooks redundancy when computing groundtruth gains; thus, our immediate future goal is to design a redundancy-aware Sem-nCG, as well as expand Sem-nCG for multi-references and multi-document summarization settings.
Table 7: Kendall’s tau correlation coefficients of expert annotations computed at single reference setting for ROUGE and Sem-nCG along four quality dimensions (for top-3 sentences). The correlation was demonstrated for low overlapping references (LOR), Medium Overlapping CNN/DailyMail Reference (MOR), and high overlapping references (HOR) chosen from 11 reference summaries per example. The outperformed correlated values in each column have been bolded both for Sem-nCG and ROUGE.

Table 8: An example of the three scenarios highlighted in the human evaluation.

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A.2 Various Sentence Embeddings used for summarization

**A.1 Extractive Summarization Models**

**BERT**: Transformer models achieve state of the art performance on different NLP tasks. A simple variant of BERT for extractive summarization has been shown in paper (Liu and Lapata, 2019) which consists of 2 parts: a BERT encoder and a summarization classifier. The BERT model here consists of the pretrained BERT encoder from masked language model by (Devlin et al., 2019).

**MobileBERT** (Sun et al., 2020): In an effort to make BERT available for low resource devices, MobileBERT has been proposed which is a thin version of BERT, with carefully designed balance between self-attentions and feed-forward.

**DistilBERT** (Sanh et al., 2019): Model size reduction has been studied extensively in the literature due to huge computational expenses of large models. DistilBERT uses knowledge distillation during pre-training to reduce the size of BERT model. It has 40% less parameter than BERT and runs 60% faster while achieving 97% of BERT’s performance.

**RoBERTa** (Liu et al., 2019): RoBERTa is another variant of BERT that modified key hyperparameters and removed the next sentence prediction objective while training with larger mini batches and learning rates. The authors have shown the importance of design choices in BERT architecture while improving the performance.

**XLNet** (Yang et al., 2019): While BERT has been pre-trained on mask language model, XLNet proposes a generalized autoregressive method for pre-training and an extension of the Transformer-XL that outperforms BERT on 20 NLP tasks.

**GPT-2** (Radford et al., 2019): GPT-2 is similar to decoder only transformer but trained on a very large dataset which outperforms BERT on NLP tasks like question answering, reading comprehension, summarization.

A.2 Various Sentence Embeddings used for summarization

**InferSent** (Conneau et al., 2017): BiLSTM network with max-pooling generates 4096-
dimensional sentence embedding. Infersent-v1 (trained with GloVe) and Infersent-v2 (trained with fastText) are the two versions of Infersent sentence embedding.

**Semantic Textual Similarity benchmark (STSb)** *(Reimers and Gurevych, 2019)*: Sentence Transformer allows to generate dense vector representations of sentences. We considered three of the best available models that were optimized for semantic textual similarity (STSb-bert, STSb-roberta and STSb-distilbert).

**Elmo** *(Peters et al., 2018)*: A fixed mean-pooling of all contextualized word representations with shape 1024 has been considered, effectively transforming the contextualized word-embedding into a sentence embedding.

**Google Universal Sentence Encoder (USE)** *(Cer et al., 2018)*: USE converts the input text to a 512-dimensional vector. There are two kinds available, i) enc-2 *(Iyyer et al., 2015)* based on the deep average network ii) enc-3 *(Vaswani et al., 2017)* based on transformer.

### A.3 Sem-nCG@k and ROUGE Scores for Top-3 Sentences

To generalize our remarks, we repeated the same experiments (mentioned in Section 5) for ROUGE and Sem-nCG@k for the top-3 sentences. Table 10 demonstrates that ROUGE is sensitive to synonym perturbation for the top-3 sentences of extractive models. Table 11, on the other hand, confirms that Sem-nCG@k is merely sensitive to sentence perturbation (especially Ensemblerel) and also robust across various sentence embedding variations (confirms from lower standard deviation).

### A.4 Dimensions of Human Evaluation

We have considered four quality dimensions following *(Fabbri et al., 2021)* to measure the Kendall’s tau rank correlation between Sem-nCG@3 and ROUGE.

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| Model       | Layers | Hidden Units | Parameters | Size  |
|-------------|--------|--------------|------------|-------|
| BERT_base   | 12     | 768          | 108M       | 100%  |
| MobileBERT  | 24     | 128          | 25.3M      | 25%   |
| DistilBERT  | 12     | 768          | 66M        | 60%   |
| RoBERTa     | 12     | 768          | 125M       | 113%  |
| XLNet       | 12     | 768          | 110M       | 100%  |
| GPT-2       | 24     | 1024         | 355M       | 328%  |

Table 9: Summary of the Model Architecture
Table 10: **ROUGE** scores for the extractive summarization models (BERT_{base}, MobileBERT, DistilBERT, RoBERTa, XLNet, GPT-2) on CNN/DailyMail test dataset. The results are for top-3 extracted sentences when the outputs are in actual and perturbed.

| Model          | ROUGE-1 | ROUGE-2 | ROUGE-3 | ROUGE-L |
|----------------|---------|---------|---------|---------|
|                | Precision | Recall | F1     | Precision | Recall | F1     | Precision | Recall | F1     | Precision | Recall | F1     |
| BERT-base      | 36.64   | 52.8    | 41.72  | 16.67   | 9.77   | 11.01  |
| MobileBERT     | 30.24   | 46.46   | 35.3   | 10.68   | 4.84   | 5.62   |
| DistilBERT     | 35.2    | 50.66   | 39.93  | 22.34   | 12.71  | 10.06  |
| RoBERTa        | 29.15   | 44.6    | 33.9   | 15.58   | 6.79   | 5.97   |
| XLNet          | 37.77   | 53.19   | 42.67  | 19.07   | 14.64  | 11.79  |
| GPT-2          | 30.97   | 46.75   | 35.93  | 11.58   | 7.4   | 8.38   |

Table 11: **Sem-nCG@3** scores for the top-3 sentences of the extractive summarization models (BERT_{base}, MobileBERT, DistilBERT, RoBERTa, XLNet, GPT-2) on CNN/DailyMail test dataset for different embedding variations.

| Model          | BERT-base | MobileBERT | DistilBERT | RoBERTa | XLNet | GPT-2 |
|----------------|-----------|------------|------------|---------|-------|-------|
|                | Precision | Recall     | F1         | Precision | Recall | F1     |
| InferSent-v1   | 78.03     | 73.33      | 71.14      | 79.25    | 75.17 | 72.72 |
| InferSent-v2   | 77.75     | 72.31      | 70.59      | 79.64    | 75.99 | 72.02 |
| STSB-bert      | 78.08     | 72.93      | 71.35      | 79.46    | 78.91 | 72.93 |
| STSB-robusta   | 77.66     | 72.88      | 71.44      | 79.06    | 78.42 | 72.79 |
| STSB-distilbert| 76.95     | 71.98      | 70.42      | 78.38    | 77.78 | 72.02 |
| Elmo           | 77.28     | 72.33      | 68.79      | 78.34    | 70.52 | 71.7  |
| USE-enc2       | 79.43     | 73.11      | 71.27      | 81.52    | 71.44 | 73.93 |
| USE-enc3       | 78.37     | 72.37      | 70.14      | 80.28    | 79.53 | 71.97 |
| Ensemble_{max} | 80.17     | 74.5       | 73.15      | 81.91    | 72.2   | 74.69 |
| Ensemble_{rel} | 80.17     | 74.5       | 73.15      | 81.91    | 72.2   | 74.69 |
| Ensemble_{std} | 81.2      | 80.98      | 75.7       | 82.81    | 82.46 | 75.56 |
| std            | 1.38      | 2.69       | 1.15       | 1.83     | 1.55  | 3.43  |

Table 10 and Table 11: ROUGE scores and Sem-nCG@3 scores for the extractive summarization models (BERT_{base}, MobileBERT, DistilBERT, RoBERTa, XLNet, GPT-2) on CNN/DailyMail test dataset.