SUPERT: Towards New Frontiers in Unsupervised Evaluation Metrics for Multi-Document Summarization

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Abstract

We study unsupervised multi-document summarization evaluation metrics, which require neither human-written reference summaries nor human annotations (e.g. preferences, ratings, etc.). We propose SUPERT, which rates the quality of a summary by measuring its semantic similarity with a pseudo reference summary, i.e. selected salient sentences from the source documents, using contextualized embeddings and soft token alignment techniques. Compared to the state-of-the-art unsupervised evaluation metrics, SUPERT correlates better with human ratings by 18-39%. Furthermore, we use SUPERT as rewards to guide a neural-based reinforcement learning summarizer, yielding favorable performance compared to the state-of-the-art unsupervised summarizers. All source code is available at https://github.com/yg211/acl20-ref-free-eval.

1 Introduction

Evaluating the quality of machine-generated summaries is a highly laborious and hence expensive task. Most existing evaluation methods require certain forms of human involvement, thus are supervised: they either directly let humans rate the generated summaries (e.g. Pyramid (Nenkova and Passonneau, 2004)), elicit human-written reference summaries and measure their overlap with the generated summaries (e.g. using ROGUE (Lin, 2004a) or MoverScore (Zhao et al., 2019)), or collect some human annotations (e.g. preferences over pairs of summaries (Gao et al., 2019a)) to learn a summary evaluation function. Evaluation in multi-document summarization is particularly expensive: Lin (2004b) reports that it requires 3,000 hours of human effort to evaluate the summaries from the Document Understanding Conferences (DUC)1.

Figure 1: Workflow of SUPERT.

To reduce the expenses for evaluating multi-document summaries, we investigate unsupervised evaluation methods, which require neither human annotations nor reference summaries. In particular, we focus on evaluating the relevance (Peyrard, 2019) of multi-document summaries, i.e. measuring how much salient information from the source documents is covered by the summaries. There exist a few unsupervised evaluation methods (Louis and Nenkova, 2013; Sun and Nenkova, 2019), but they have low correlation with human relevance ratings at summary level: given multiple summaries for the same source documents, these methods can hardly distinguish summaries with high relevance from those with low relevance (see §3).

Contributions. First, to better measure the semantic overlap between source documents and machine-generated summaries, we propose to use state-of-the-art contextualized text encoders, e.g. BERT (Devlin et al., 2019) and its variant Sentence-BERT (SBERT) (Reimers and Gurevych, 2019), which is optimized for measuring semantic similarity between sentences, to develop unsupervised evaluation methods. We measure the relevance of a summary in two steps: (i) identifying the salient information in the input documents, to build a pseudo reference summary, and (ii) measuring the semantic overlap between the pseudo reference and the
summary to be evaluated. The resulting evaluation method is called **SUPERT** (SUmmarization evaluation with Pseudo references and bERT). Fig. 1 illustrates the major steps of SUPERT. We show that compared to state-of-the-art unsupervised metrics, the best SUPERT correlates better with the human ratings by 18-39% (in Kendall’s τ).

Second, we use SUPERT as *reward functions* to guide Reinforcement Learning (RL) based extractive summarizers. We show it outperforms the state-of-the-art unsupervised summarization methods (in multiple ROUGE metrics).

## 2 Related Work

**Reference-based Evaluation.** Popular metrics like ROUGE (Lin, 2004a), BLEU (Papineni et al., 2002) and METEOR (Lavie and Denkowski, 2009) fall into this category. They require (preferably, multiple) human written references and measure the relevance of a summary by comparing its overlapping word sequences with references. More recent work extends ROUGE with WordNet (ShafieiBavani et al., 2018a), word embeddings (Ng and Abrecht, 2015), or use contextualized-embedding-based methods (Zhang et al., 2019; Zhao et al., 2019) to measure the semantic similarity between references and summaries.

**Annotation-based Evaluation.** Some methods directly ask human annotators to rate summaries following some guidelines, e.g. *Responsiveness*, which measures the overall quality (relevance, fluency and readability) of summaries, and *Pyramid* (Nenkova and Passonneau, 2004), which measures summaries’ relevance. Recently, systems have been developed to ease the construction of Pyramid scores, e.g. (Hirao et al., 2018; Yang et al., 2016; Gao et al., 2019b; Shapira et al., 2019), but they still require human-annotated Summary Content Units (SCUs) to produce reliable scores. Besides SCUs, recent work has explored eliciting preferences over summaries (Zopf, 2018; Gao et al., 2018, 2019a) and annotations of important bi-grams (P.V.S and Meyer, 2017) to derive summary ratings.

Some methods collect human ratings on a small number of summaries to train an evaluation function. Peyrard et al. (2017); Peyrard and Gurevych (2018) propose to learn an evaluation function from Pyramid and Responsiveness scores, by using classic supervised learning methods with hand-crafted features. ShafieiBavani et al. (2018b) used the same idea but design corpus based and lexical re-source based word embeddings to build the features. Böhm et al. (2019) train a BERT-based evaluation function with 2,500 human ratings for 500 machine-generated summaries from the CNN/DailyMail dataset; their method correlates better with human ratings than ROUGE and BLEU. However, as their method is designed for evaluating single-document summaries, it correlates poorly with the Pyramid scores for multi-document summaries (see §3).

**Unsupervised Evaluation.** Louis and Nenkova (2013) measure the relevance of a summary using multiple heuristics, for example by computing the Jensen-Shannon (JS) divergence between the word distributions in the summary and in the source documents. Ryang and Abekawa (2012); Rioux et al. (2014) develop evaluation heuristics inspired by the maximal marginal relevance metrics (Goldstein et al., 2000). But these methods have low correlation with human ratings at summary level (see §3). Scialom et al. (2019) propose to generate questions from source documents and evaluate the relevance of summaries by counting how many questions the summaries can answer. However, they do not detail how to generate questions from source documents; also, it remains unclear whether their method works for evaluating multi-document summaries. Sun and Nenkova (2019) propose a single-document summary evaluation method, which measures the cosine similarity of the ELMo embeddings (Peters et al., 2018) of the source document and the summary. In §3, we show that their method performs poorly in evaluating multi-document summaries. SUPERT extends their method by using more advanced contextualized embedded embeddings and more effective text alignment/matching methods (§4), and by introducing pseudo references (§5).

## 3 Datasets, Baselines and Upper Bounds

**Datasets.** We use two multi-document summarization datasets from the Text Analysis Conference (TAC)\(^2\) shared tasks: TAC’08 and TAC’09. In line with Louis and Nenkova (2013), we only use the initial summaries (the A part) in these datasets. TAC’08 includes 48 topics and TAC’09 includes 44. Each topic has ten news articles, four reference summaries and 57 (TAC’08) and 55 (TAC’09) machine-generated summaries. Each news article on average has 611 words in 24 sentences. Each summary has at most 100 words and receives a

\(^2\)https://tac.hist.gov/
TAC’08 | TAC’09 | TAC’09
--- | --- | ---
| r | ρ | τ | r | ρ | τ | r | ρ | τ
Baselines (unsupervised evaluation)
TF-IDF | .364 | .330 | .236 | .388 | .395 | .288 | .388 | .395 | .288
JS | .381 | .333 | .238 | .388 | .386 | .283 | .388 | .386 | .283
REAPER | .259 | .247 | .174 | .332 | .354 | .252 | .332 | .354 | .252
C\textsubscript{ELMo} | .130 | .108 | .076 | .334 | .255 | .183 | .334 | .255 | .183
Böhm19 | .022 | .001 | .001 | .075 | .043 | .031 | .075 | .043 | .031
Upper bounds (reference-based evaluation)
Rouge1 | .747 | .632 | .501 | .808 | .692 | .533 | .808 | .692 | .533
Rouge2 | .718 | .635 | .498 | .803 | .694 | .531 | .803 | .694 | .531
Mover | .760 | .672 | .507 | .831 | .701 | .550 | .831 | .701 | .550

Table 1: Summary-level correlation between some popular evaluation metrics and human ratings. Unsupervised metrics (upper) measure the similarity between summaries and the source documents, while reference-based metrics (bottom) measure the similarity between summaries and human-written reference summaries.

Pyramid score, which is used as the ground-truth human rating in our experiments.

Baselines & Upper Bounds. For baselines, we consider TF-IDF, which computes the cosine similarity of the tf-idf vectors of source and summaries; JS, which computes the JS divergence between the words distributions in source documents and summaries; and the REAPER heuristics proposed by Rioux et al. (2014). In addition, we use the learned metric from Böhm et al. (2019) (Böhm19) and the ELMo-based metric by Sun and Nenkova (2019) (C\textsubscript{ELMo}, stands for cosine-ELMo; see §2). In all these methods, we remove stop-words and use the stemmed words, as we find these operations improve the performance. For C\textsubscript{ELMo}, we vectorize the documents/summaries by averaging their sentences’ ELMo embeddings. As for upper bounds, we consider three strong reference-based evaluation metrics: ROUGE-1/2 and MoverScore (Zhao et al., 2019); note that references are not available for unsupervised evaluation metrics.

We measure the performance of the baselines and upper bounds by their average summary-level correlation with Pyramid, in terms of Pearson’s (r), Spearman’s (ρ) and Kendall’s (τ) correlation coefficients.\footnote{We have also considered the percentage of significantly correlated topics; results can be found in the Github repository.} Table 1 presents the results. All baseline methods fall far behind the upper bounds. Among baselines, the embedding-based methods (Böhm19 and C\textsubscript{ELMo}) perform worse than the other lexical-based baselines. This observation suggests that to rate multi-document summaries, using existing single-document summaries evaluation metrics (Böhm19) or computing source-summary embeddings’ cosine similarity (C\textsubscript{ELMo}) is ineffective.

4 Measuring Similarity with Contextualized Embeddings

In this section, we explore the use of more advanced contextualized embeddings and more sophisticated embedding alignment/matching methods (rather than cosine similarity) to measure summaries relevance. We first extend C\textsubscript{ELMo} by considering more contextualized text encoders: BERT, RoBERTa (Liu et al., 2019), ALBERT (Lan et al., 2019) and SBERT\footnote{Model \texttt{bert-large-nli-stsb-mean-tokens.}}. We use these encoders to produce embeddings for each sentence in the documents/summaries, and perform average pooling to obtain the vector representations for the documents/summaries. We measure the relevance of a summary by computing the cosine similarity between its embedding and the embedding of the source documents. The upper part in Table 2 presents the results. C\textsubscript{BERT} outperforms the other cosine-embedding based metrics by a large margin, but compared to the lexical-based metrics (see Table 1) its performance still falls short.

Zhao et al. (2019) recently show that, to measure the semantic similarity between two documents, instead of computing their document embeddings cosine similarity, minimizing their token embeddings word mover’s distances (WMDs) (Kusner et al., 2015) yields stronger performance. By minimizing WMDs, tokens from different documents are soft-aligned, i.e. a token from one document can be aligned to multiple relevant tokens from the other document. We adopt the same idea to measure the semantic similarity between summaries and
source documents, using RoBERTa and SBERT (denoted by MRoBERTa and MSBERT, respectively). The bottom part in Table 2 presents the results. The WMD-based scores substantially outperform their cosine-embedding counterparts; in particular, MSBERT outperforms all lexical-based baselines in Table 1. This finding suggests that, to rate multidocument summaries, soft word alignment methods should be used on top of contextualized embeddings to achieve good performance.

## 5 Building Pseudo References

WMD-based metrics yield the highest correlation in both reference-based (bottom row in Table 1) and reference-free (bottom row in Table 2) settings, but there exists a large gap between their correlation scores. This observation highlights the need for reference summaries. In this section, we explore multiple heuristics to build pseudo references.

### 5.1 Simple heuristics

We first consider two simple strategies to build pseudo references: randomly extracting N sentences or extracting the first N sentences from each source document. Results, presented in Table 3, suggest that extracting the top 10-15 sentences as the pseudo references yields strong performance: it outperforms the lexical-based baselines (upper part in Table 1) by over 16% and MSBERT (Table 2) by over 4%. These findings confirm the position bias in news articles (c.f. (Jung et al., 2019)).

| Method      | TAC’08 r | TAC’08 ρ | TAC’08 τ | TAC’09 r | TAC’09 ρ | TAC’09 τ |
|-------------|-----------|-----------|-----------|-----------|-----------|-----------|
| Random3     | .139      | .194      | .189      | .123      | .172      | .175      |
| Random5     | .144      | .203      | .199      | .147      | .204      | .206      |
| Random10    | .163      | .228      | .229      | .201      | .279      | .284      |
| Random15    | .206      | .287      | .320      | .185      | .258      | .268      |
| Top3        | .449      | .408      | .295      | .378      | .390      | .291      |
| Top5        | .477      | .437      | .316      | .413      | .421      | .314      |
| Top10       | .492      | .455      | .332      | .444      | .450      | .333      |
| Top15       | .489      | .450      | .327      | .454      | .459      | .340      |

Table 3: Building pseudo references by extracting randomly selected sentences (upper) or the first few sentences (bottom). Results of the random extraction methods are averaged over ten independent runs.

### 5.2 Graph-based heuristics

Graph-based methods have long been used to select salient information from documents, e.g. (Erkan and Radev, 2004; Zheng and Lapata, 2019). These methods build graphs to represent the source documents, in which each vertex represents a sentence and the weight of each edge is decided by the similarity of the corresponding sentence pair. Below, we explore two families of graph-based methods to build pseudo references: position-agnostic and position-aware graphs, which ignore and consider the sentences’ positional information, respectively.

#### Position-Agnostic Graphs

The first graph we consider is SBERT-based LexRank (SLR), which extends the classic LexRank (Erkan and Radev, 2004) method by measuring the similarity of sentences using SBERT embeddings cosine similarity. In addition, we propose an SBERT-based clustering (SC) method to build graphs, which first measures the similarity of sentence pairs using SBERT, and then clusters sentences by using the affinity propagation (Frey and Dueck, 2007) clustering algorithm; the center of each cluster is selected to build the pseudo reference. We choose affinity propagation because it does not require a preset cluster number (unlike K-Means) and it automatically finds the center point of each cluster.

For each method (SLR or SC), we consider two variants: the individual-graph version, which builds a graph for each source document and selects top-K sentences (SLR) or the centers (SC) from each graph; and the global-graph version, which builds a graph considering all sentences across all source documents for the same topic, and selects the top-M sentences (SLR) or all the centers (SC) in this large graph. According to our preliminary experiments on 20 randomly sampled topics, we set K = 10 and M = 90.

#### Position-Aware Graphs

PacSum is a recently proposed graph-based method to select salient sentences from multiple documents (Zheng and Lapata, 2019). In PacSum, a sentence is more likely to be selected if it has higher average similarity with its succeeding sentences and lower average similarity with its preceding sentences. This strategy allows PacSum to prioritize the selection of early-position and “semantically central” sentences. We further extend PacSum by using SBERT to measure sentences similarity (the resulting method is denoted as SPS) and consider both the individual- and global-graph versions of SPS.

Furthermore, we propose a method called Top+Clique (TC), which selects the top-N sentences and the semantically central non-top-N sentences to build the pseudo references. TC adopts
We consider three unsupervised reward functions: two baseline methods REAPER and JS (see §3 and Table 1), and the best version of SUPERT, which selects the top 10 (TAC’08) or 15 (TAC’09) sentences from each source document to build pseudo references and uses SBERT to measure the similarity between summaries and pseudo references.

In addition, we consider a non-RL-based state-of-the-art unsupervised summarizer proposed by Yogatama et al. (2015) (YLS15). We use ROUGE to measure the quality of the generated summaries and leave human evaluations for future work. Table 5 presents the results. We find SUPERT is the strongest reward among the considered rewards: it helps NTD perform on par with YLS15 on TAC’08 and perform significantly better on TAC’09.

7 Conclusion

We explored unsupervised multi-document summary evaluation methods, which require neither reference summaries nor human annotations. We find that vectorizing the summary and the top sentences in the source documents using contextualized embeddings, and measuring their semantic overlap with soft token alignment techniques is a simple yet effective method to rate the summary’s quality. The resulting method, SUPERT, correlates with human ratings substantially better than the state-of-the-art unsupervised metrics.

Furthermore, we use SUPERT as rewards to train a neural-RL-based summarizer, which leads to up to 17% quality improvement (in ROUGE-2) compared to the state-of-the-art unsupervised summarizers. This result not only shows the effectiveness of SUPERT in a downstream task, but also promises a new way to train RL-based summarizers, fundamentally relieving the data-hungriness problem faced by existing RL-based summarization systems.

Table 4: Building pseudo references by position-agnostic (upper) and position-aware (bottom) graphs.

|        | TAC’08 | TAC’09 |
|--------|--------|--------|
|        | $r$    | $\rho$ | $\tau$ | $r$    | $\rho$ | $\tau$ |
| **Position-agnostic graphs** |
| SLR$_1$ | .456   | .417   | .304   | .415   | **.423** | **.311** |
| SLR$_G$ | **.461** | **.423** | **.306** | **.419** | **.423** | **.310** |
| SC$_1$  | .409   | .364   | .261   | .393   | .383   | .280   |
| SC$_G$  | .383   | .344   | .245   | .373   | .365   | .265   |
| **Position-aware graphs** |
| SPS$_3$ | .478   | .437   | .319   | .429   | .435   | .321   |
| SPS$_G$ | .472   | .432   | .313   | .427   | .432   | .318   |
| TC      | **.490** | **.449** | **.329** | **.450** | **.454** | **.336** |

Table 5: Training NTD, a RL-based summarizer, with different rewards (RP: REAPER, SP: SUPERT). NTD performance is averaged over ten runs. $R_{1/2/L}$ stands for ROUGE-1/2/L. *: significant advantage ($p < 0.01$ double-tailed t-tests) over the non-asterisks.

|        | TAC’08 | TAC’09 |
|--------|--------|--------|
|        | $R_1$  | $R_2$  | $R_L$  | $R_1$  | $R_2$  | $R_L$  |
| NTD$_{RP}$ | .348   | .097   | .276   | .360   | .090   | .187   |
| NTD$_{JS}$ | .353   | .090   | .281   | .368   | .095   | .192   |
| NTD$_{SP}$ | **.376** | **.102** | **.296** | **.380** | **.103** | **.194** |
| YLS15   | .375   | .096   | N/A    | .344   | .088   | N/A    |
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