Revisiting the Evaluation Metrics of Paraphrase Generation

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Abstract

Paraphrase generation is an important NLP task that has achieved significant progress recently. However, one crucial problem is overlooked, 'how to evaluate the quality of paraphrase?'. Most existing paraphrase generation models use reference-based metrics (e.g., BLEU) from neural machine translation (NMT) to evaluate their generated paraphrase. Such metrics' reliability is hardly evaluated, and they are only plausible when there exists a standard reference. Therefore, this paper first answers one fundamental question, 'Are existing metrics reliable for paraphrase generation?'. We present two conclusions that disobey conventional wisdom in paraphrasing generation: (1) existing metrics poorly align with human annotation in system-level and segment-level paraphrase evaluation. (2) reference-free metrics outperform reference-based metrics, indicating that the standard references are unnecessary to evaluate the paraphrase's quality. Such empirical findings expose a lack of reliable automatic evaluation metrics. Therefore, this paper proposes BBScore, a reference-free metric that can reflect the generated paraphrase's quality. BBScore consists of two sub-metrics: S3C score and SelfBLEU, which correspond to two criteria for paraphrase evaluation: semantic preservation and diversity. By connecting two sub-metrics, BBScore significantly outperforms existing paraphrase evaluation metrics.

1 Introduction

Paraphrases are texts that convey the same meaning while using different words or sentence structures, and the generation of paraphrases is a longstanding problem for natural language learning (NLP). Paraphrasing is widely applied in versatile NLP tasks, such as question answering (Dong et al., 2017; Lan and Xu, 2018; Gan and Ng, 2019; Abujabal et al., 2019), machine translation (Madnani et al., 2012; Apidianaki et al., 2018; Kajiwara, 2019), and semantic parsing (Herzig and Berant, 2019; **?**; Cao

et al., 2020). Moreover, it is also a good way for data augmentation (Kumar et al., 2019; Feng et al., 2021; Hegde and Patil, 2020). Although paraphrase generation systems have progressed significantly and performed much more human-like skills in recent years (Sun et al., 2021; Huang and Chang, 2021; Kumar et al., 2020), automatically measuring the quality of paraphrase candidates is still an open and under-explored research problem.

Most existing paraphrase generation systems evaluate the generated paraphrases with neural machine translation (NMT) evaluation metrics (e.g., BLEU (Papineni et al., 2002), METEOR (Banerjee and Lavie, 2005), and Rouge (Lin, 2004)). These NMT metrics are reference-based, and measure the degree of word overlap between the paraphrase candidate and its corresponding reference. However, paraphrase generation is a **one-to-many** task, which means that there are several suitable references for one source sentence, so a high-quality paraphrase may have a low BLEU score towards the standard reference.

Therefore, this paper first examines whether such NMT metrics align well with human annotations. To evaluate the performance of existing metrics, we build the benchmark called Twitter-Para. Specifically, we make comprehensive experiments to show the correlation between NMT metric score and human annotation in segment-level and system-level evaluation. Based on the results, we present two surprising conclusions: (1) existing NMT metrics fail to align with human judgments in segment-level and system-level evaluation (with around 0.1-0.2 Spearman correlation). (2) reference-free metrics better align with human judgments than reference-based metrics, which indicates that the reference is not indispensable during evaluation.

Such two conclusions reveal an urgent need for a reliable paraphrase metric. Therefore, this paper then proposes the BERT-BLEU Score (BBScore),

a reference-free metric that consists of two interpretable sub-metrics combined in a configurable manner. Rather than relying on a gold reference paraphrase, unsupervised metrics can better match the **one-to-many** nature of the paraphrase generation task and better align with human judgments. BBScore's motivation origins from two principal purposes for the generated paraphrases, which guarantee the quality of the generated paraphrases:

- Semantic Preservation: the generated paraphrase should possess similar semantics with the source sentence.

- Diversity: the generated paraphrase should be as different from the source as possible.

Technically, BERT-BLEU Score is the difference of two components: Self-supervised cosine similarity score and Self-BLEU score:

- Self-supervised cosine similarity (S3C Score): we optimize the PLM with a contrastive learning objective and apply it for computing the cosine similarity between the paraphrase candidate and source sentence. Higher S3C Score corresponds to better semantic preservation.

- Self-BLEU: the BLEU score between the generated paraphrase and source sentence, higher Self-BLEU corresponds lower diversity.

As such, BBScore (1) resolves the problem of existing metrics that they fail to match the one-to-many nature of paraphrase generation task (2) produces interpretable measures for desirable properties of generated paraphrase. (3) compared to existing NMT evaluation metrics, the BBScore strongly better correlates with human judgment on both system-level and segment-level evaluation. (system-level Spearman: 0.572, segment-level Spearman: 0.571). The strong performance across various evaluation setting validates that the BBScore is valuable for the paraphrase generation field.

Our main contributions are as follows:

- We argue that existing paraphrase evaluation metrics mismatch the one-to-many nature of the paraphrasing task. Thus, We revisit the existing metrics and find that they fail to align well with human judgments.

- We evaluate both reference-free and reference-based metrics and discover that reference-free metrics better align with human judgment,

which supports our argument that paraphrasing owns a one-to-many nature and reference might not be necessary during the evaluation.

- We propose BBScore, a strongly-correlated, unsupervised, and reference-free metric for evaluating paraphrase generation. Comprehensive experiments demonstrate its superiority towards existing baselines.

2 Related Work

2.1 Paraphrase Generation

Recent advances have been using neural models for paraphrase generation. From the modeling perspective, there are roughly two categories: unsupervised and supervised methods. Unsupervised models do not use parallel paraphrases during training. (Wieting et al., 2017) and (Wieting and Gimpel, 2018) use back-translation to generate paraphrases. (Huang and Chang, 2021) propose a transformer-based model SynPG for paraphrase generation. Besides unsupervised paraphrase generation, another paradigm is supervised paraphrase generation, which means that we require parallel paraphrases during training. Previous supervised paraphrase models are mostly RNNbased models, including SCPN (Iyyer et al., 2018), CGEN (Chen et al., 2019) and SGCP (Kumar et al., 2020). Such models suffer from generating long sentences and do not utilize the power of recent pretrained language models. (Goyal and Durrett, 2020) is a concurrent work with ours that also builds on BART to generate paraphrases but has a different model design. For syntactic control, (Goyal and Durrett, 2020) use target syntactic parses to reorder source sentences to guide the generation, while other works, including AESOP, directly use target syntactic parses to guide the generation. Moreover, AESOP (Sun et al., 2021) retrieves target syntactic parses automatically and achieves state-of-the-art performance in supervised paraphrase generation.

2.2 Automatic Evaluation in Paraphrase Generation

Existing paraphrase evaluation can be divided into three groups: reference-based metric, reference-free metric, and hybrid metric. Existing reference-based metrics are commonly NMT metrics like BLEU (Papineni et al., 2002), Rouge (Lin, 2004), and METEOR (Banerjee and Lavie, 2005). BLEU utilizes all samples in the dataset as references

for each generated sentence. METEOR (Banerjee and Lavie, 2005) measures sentence quality based on the harmonic mean of the unigram precision and recall. Some variants of METEOR also consider surface forms, stemmed forms, and meanings. ROUGE (Lin, 2004) calculates n-gram recall in text generation tasks. Besides, some reference-free metrics have also been proposed recently. Self-BLEU measures the BLEU score between the generated paraphrase and source sentence, reflecting the generated paraphrase's diversity. Besides, Self-iBLEU takes a weighted harmonic mean of the BERT-score and one minus self-BLEU. Please note that reference-based metrics can also be transformed into reference-free metrics by substituting the reference with the source sentence. The hybrid metric takes both source and reference into evaluation. Specifically, the iBLEU score penalizes repeating the source sentence in the generated paraphrase. However, existing works neither investigate whether such auto metrics are reliable in paraphrase evaluation nor their superiority to each other. This paper will present empirical results to investigate both two issues.

3 Problem formulation of the metrics for paraphrase generation

In a standard supervised paraphrase generation scenario, given a source sentence S, a model f generates the paraphrase candidate P, and the standard reference of S is R. For an evaluation metric $l(\cdot)$, if it is reference-based, then it follows a formation of $l(P, R)$; if it is reference-free, then it follows a formation of $l(P, S)$; if it is hybrid, then it follows a formation of $l(P, S, R)$.

4 Are existing metrics reliable for paraphrase generation?

In this section, we revisit the existing metrics for paraphrase quality evaluation by answering one question: "Are existing metrics reliable for paraphrase generation?" A straightforward and commonly-accepted approach is to observe how perfectly they align with human judgments. Therefore, we first build Twitter-Para, a benchmark for evaluating the reliability of paraphrase metrics.

4.1 A brief introduction for Twitter-Para

We build Twitter-Para by collecting the paraphrases from Twitter dataset (Xu et al., 2014,

#source	#candidate	#reference	avg candidate
761	7159	761	9.41

Table 1: The statistics of Twitter-Para. There are 761 source sentences and each source sentence corresponds to one standard reference. Besides, there are 7159 paraphrase candidates totally, and each source sentence owns 9.41 paraphrase candidates averagely.
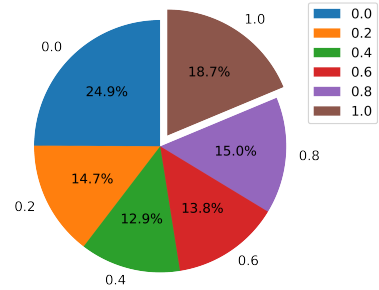

Figure 1: An overview of the human-annotation score distribution in Twitter-Para.

2015). Formally, there are two kinds of sentence pairs in the dataset. (1) source-candidate pair (S_i, P_{ij}, h_{ij}): each source sentence S_i corresponds to several candidates P_{ij} with corresponding human-annotated scores h_{ij}. (2) source-candidate pair (S_i, P_{ij}, g_{ij}): each source sentence S_i has one corresponding standard reference R_i with the corresponding human-annotated scores g_{ij}. Specifically, the human-annotated score ranges from 0∼1.0, 0.8∼1.0 score represents good paraphrase pairs while 0∼0.4 indicates non-paraphrase pairs. The basic statistics of Twitter-Para are listed in Table 1 and Figure 1.

4.2 Evaluation settings

The performance of an evaluation metric is usually measured by its correlation with the human judgment. Following conventional paradigms on evaluating the evaluation metrics in NMT and dialogue generation, we make evaluations in two settings: **system-level** and **segment-level**.

Segment-level evaluation measures the correlation between metric to human-annotation in a sentence-pair paradigm. Formally, given a evaluation metric $l(\cdot)$, we get the metric score m_{ij} for each source-candidate pair (S_i, P_{ij}, h_{ij}), then segment-level evaluation measures the correlation between m_{ij} and h_{ij}. System-level evaluation mea-

sures the correlation between metric to human-annotation in a pair-set paradigm. Formally, given a evaluation metric $l(\cdot)$, we get the metric score m_{ij} for each source-candidate pair (S_i, P_{ij}, h_{ij}), then we calculate the system-level metric score m_i^* and system-level human-annotation score h_i^* as follows:

$$m_i^* = \frac{\sum_{k=1}^{k=j} m_{ik}}{j}; h_i^* = \frac{\sum_{k=1}^{k=j} h_{ik}}{j} \qquad (1)$$

then system-level evaluation measures the correlation between m_i^* and h_i^*.

4.3 Baseline Metrics

We compare the following reference-based metrics by their match degree with human annotation, which are commonly used in the modern paraphrase quality evaluation. Moreover, we make comparisons under both segment-level and system-level settings.

Metric	Sys-level		Seg-level	
	Pr.	Spr.	Pr.	Spr.
BLEU-1	-0.101	-0.145	-0.110	-0.106
BLEU-2	-0.240	-0.245	-0.099	-0.106
BLEU-3	-0.244	-0.243	-0.122	-0.107
BLEU-4	-0.234	-0.226	-0.120	-0.107
Rouge-1	0.268	0.299	0.278	0.283
Rouge-2	0.196	0.194	0.183	0.145
Rouge-L	0.257	0.272	0.255	0.246
METEOR	-0.079	-0.122	-0.087	-0.094
BERTScore(B)	0.500	0.498	0.471	0.470
BERTScore(R)	0.362	0.365	0.369	0.361
BARTScore	0.331	0.340	0.314	0.310

Table 2: The Pearson (Pr.) and Spearman (Spr.) correlations with both segment-level and system-level human judgments on Twitter-Para. Specifically, BERTScore(B) and BERTScore(R) represent BERTScore based on BERT (Devlin et al., 2019) and RoBERTa (Liu et al., 2019), respectively. As we can see, most of existing NMT metrics fail to align well with human annotation.

BLEU (Papineni et al., 2002): it is a well-known word overlap metric that computes n-gram precision between the generated sequence and the reference. **ROUGE** (Lin, 2004): it identifies the common subsequence between the generated and reference sequence to better account for sentence-level structure when computing word overlap. **METEOR** (Banerjee and Lavie, 2005): it was designed

as an improvement on BLEU using a harmonic mean of precision and recall, as well as stemming and synonyms. **BERTScore** (Zhang et al., 2019): it uses a pretrained model (Devlin et al., 2019; Liu et al., 2019) to greedily match each word in a reference response with one word in the generated sequence. **BARTScore** (Yuan et al., 2021): it proposes a different paradigm of evaluation of text generation by modeling evaluation as a text generation problem based on BART (Lewis et al., 2020).

4.4 Results

The results of reference-based metrics are demonstrated in Table 2, from where we can observe that most of the existing NMT metrics fail to align well with human annotation. Metrics like BLEU even possess a negative correlation towards human annotation. Besides, ROUGE and METEOR have a low correlation, thus failing to reflect the paraphrase quality precisely. Such popular n-gram metrics all show a low correlation with human judgments. We noticed that in the conditional generation tasks, the word level overlap constitutes a considerable ratio of a meaningless word such as pronoun and Be Verb. Such NMT metrics suffers from low overlap in the open-ended text generation like paraphrase generation task.

Generally, the metrics (e.g., BERTScore) based on a PLM (Pre-trained Language Model) outperform the metrics (e.g., BLEU) without a PLM. However, there is also one significant issue for the metrics based on a PLM: they only measure the semantic similarity between reference and source sentence, which fails to demonstrate the diversity of paraphrase. A simple counterexample is that we can directly take the source sentence as the generated paraphrase and obtain a high BERTScore. Therefore, we have the conclusion that existing reference-based metrics fail to quantify the quality of paraphrasing comprehensively.

5 Is reference-based metrics better than reference-free ones?

As mentioned above, we compare various widely-used reference-based metrics for paraphrase generation, and we conclude that existing metrics fail to reflect the paraphrase quality comprehensively. This section revisits the reference-free and hybrid metrics for paraphrase generation and finds that reference-free metrics better align with human annotation than reference-based metrics.

Metric	System-level		Segment-level	
	Pearson	Spearman	Pearson	Spearman
SelfBLEU-1	-0.115 (+0.014)	-0.159 (+0.014)	-0.107 (-0.003)	-0.104 (-0.002)
SelfBLEU-2	-0.231 (-0.005)	-0.246 (+0.001)	-0.102 (+0.003)	-0.105 (-0.001)
SelfBLEU-3	-0.235 (-0.009)	-0.243 (+0.000)	-0.118 (-0.004)	-0.105 (-0.002)
SelfBLEU-4	-0.239 (+0.005)	-0.240 (+0.014)	-0.122 (+0.002)	-0.105 (-0.002)
SelfRouge-1	0.335 (+0.067)	0.357 (+0.058)	0.298 (+0.020)	0.304 (+0.021)
SelfRouge-2	0.310 (+0.114)	0.300 (+0.106)	0.232 (+0.049)	0.192 (+0.047)
SelfRouge-L	0.332 (+0.075)	0.340 (+0.068)	0.274 (+0.019)	0.260 (+0.014)
SelfMETEOR	-0.084 (+0.005)	-0.092 (-0.030)	-0.085 (-0.002)	-0.092 (+0.005)
SelfBERTScore(B)	**0.555 (+0.055)**	**0.554 (+0.056)**	**0.493 (+0.022)**	**0.490 (+0.020)**
SelfBERTScore(R)	0.401 (+0.039)	0.385 (+0.020)	0.378 (+0.009)	0.364 (+0.003)
SelfBARTScore	0.343 (+0.003)	0.346 (+0.006)	0.304 (-0.009)	0.295 (-0.015)
BERT-iBLEU(R,1)	0.391	0.368	0.337	0.326
BERT-iBLEU(R,2)	0.392	0.372	0.360	0.348
BERT-iBLEU(R,3)	0.394	0.375	0.366	0.354
BERT-iBLEU(R,4)	0.396	0.379	0.369	0.357
BERT-iBLEU(B,1)	0.545	0.540	0.489	0.488
BERT-iBLEU(B,2)	0.545	0.540	0.489	0.488
BERT-iBLEU(B,3)	0.545	0.541	0.489	0.488
BERT-iBLEU(B,4)	0.546	0.543	0.489	0.488
iBLEU(0.1)	-0.231	-0.222	-0.003	0.028
iBLEU(0.2)	-0.227	-0.216	-0.227	-0.216
iBLEU(0.3)	-0.220	-0.208	0.007	0.030

Table 3: The Pearson and Spearman correlations with both segment-level and system-level human judgments on Twitter-Para. Specifically, BERTScore(B) and BERTScore(R) represent BERTScore based on BERT (Devlin et al., 2019) and RoBERTa (Liu et al., 2019), respectively. BERT-iBLEU(R,1) means the encoder is RoBERTa (Liu et al., 2019) and β is 1.0. iBLEU(0.1) indicates α is set as 0.1. Moreover, the number in the parenthesis are the changes of absolute value of correlations, **'Red'** indicates improvement and **'Blue'** means degradation.

5.1 Baseline Metrics

Following the experimental settings in Sec 4.2, we compare the following widely-used reference-free metrics by their match degree with human annotation. Also, we make comparisons under both segment-level and system-level settings.

SelfBLEU (Papineni et al., 2002): it is a word overlap metric that computes n-gram precision between the generated sequence and the source sentence. **SelfROUGE** (Lin, 2004): it identifies the common subsequence between the generated and source sentence to better account for sentence-level structure when computing word overlap. **SelfME-TEOR** (Banerjee and Lavie, 2005): it was designed as an improvement on BLEU using a harmonic mean of precision and recall, as well as stemming and synonyms. **SelfBERTScore** (Zhang et al., 2019): it uses a pretrained model (Devlin et al., 2019; Liu et al., 2019) to greedily match each word in a source sentence with one word in the generated sequence. **SelfBARTScore** (Yuan et al., 2021): it replaces the reference with source sentence in BARTScore (Yuan et al., 2021). **BERT-iBLEU** (Niu et al., 2021): it takes a weighted harmonic mean of the BERT-score and one minus SelfBLEU,

which is defined as follows:

$$\text{BERT-iBLEU} = \frac{\beta + 1.0}{\beta \cdot \text{BERTScore}^{-1} + 1.0 \cdot (1 - \text{SelfBLEU})^{-1}} \quad (2)$$
$$\text{SelfBLEU} = \text{BLEU}(\text{source}, \text{candidate})$$

where β is a constant (usually set as 4). **iBLEU** (Siddique et al., 2020; Liu et al., 2020): it is a hybrid metric that computes the difference between BLEU and SelfBLEU, which is defined as follows:

$$\text{iBLEU} = \text{BLEU} - \alpha \cdot \text{SelfBLEU} \quad (3)$$

where α is a constant (usually set as 0.3).

5.2 Results

The results of reference-free metrics are demonstrated in Table 3. Specifically, we also compare the performance change of metrics between reference-based and reference-free paradigms, and the performance changes are colored in the table. Similar to the reference-based paradigm, in the reference-free paradigm, the n-gram metrics still perform badly to correlate with human annotation, and the PLM-based metrics have better performances. Specifically, SelfBLEU owns a negative correlation score with human judgment. A higher SelfBLEU score

means higher word overlap with the source sentence, thus leading to a lower diversity of the generated paraphrase and worse paraphrase quality.

The results demonstrate that the reference-free metrics generally better aligns with human annotation, which indicates that we can evaluate the paraphrase quality without a reference. This phenomenon also matches the one-to-many nature of the paraphrase generation task because one standard reference is too impotent to comprise the diversity of paraphrasing. Moreover, the hybrid metrics also fail to reflect the quality of paraphrasing.

6 BBscore: A more human-like metric for paraphrase evaluation

As previous experimental results show, most existing widely-used paraphrase evaluation metrics are transported from NMT and are not paraphrase-specific, thus failing to reflect paraphrase quality. This section introduces BBScore, an unsupervised, reference-free evaluation metric for paraphrase quality evaluation. BBScore is designed to be reference-free because there are multiple suitable paraphrases due to the inherent one-to-many nature of paraphrasing.

Though there are multiple suitable paraphrases for a single source sentence, paraphrase generation has two principal purposes: (1) semantic preservation: the generated paraphrase should express similar semantics with the source sentence. (2) diversity: the generated paraphrase should be different from the source sentence. Therefore, we propose two sub-metrics: S3C Score and Self-BLEU, which correspond to such two purposes and build our BBScore.

Formally, given a source sentence and one candidate paraphrase the BBScore is formulated as follows:

$$\text{BBScore(src,can)} \qquad (4)$$
$$= \text{S3C(src,can)} - \text{Self-BLUE(src,can)}$$

6.1 S3C Score

S3C (Self-supervised cosine similarity) Score is a metric to judge the degree of semantic matching between the two sentences, and leverages a PLM (e.g., BERT (Devlin et al., 2019)) to compute similarity. Considering that two sentence can have high semantic similarity even with low word overlapping, we use a self-supervised training procedure to bring similar sentence pair's embedding closer and push away dissimilar sentences' embedding.

We leverage contrastive learning to achieve this goal, it is also a common choice to enhacne sentence representation. Formally, given a set of sentence pairs $\mathcal{D} = \left\{ \left(x_i, x_i^+\right) \right\}_{i=1}^{m}$, where x_i and x_i^+ are semantically similar. We follow the contrastive framework in (Gao et al., 2021) and take a cross-entropy objective with in-batch negatives: let $\mathbf{h}_i$ and $\mathbf{h}_i^+$ denote the representations of x_i and x_i^+, the training objective for $\left(x_i, x_i^+\right)$ with a mini-batch of N pairs is:

$$L_i = -\log \frac{e^{\cos\left(\mathbf{h}_i, \mathbf{h}_i^+\right)/\tau}}{\sum_{j=1}^{N} e^{\cos\left(\mathbf{h}_i, \mathbf{h}_j^+\right)/\tau}} \qquad (5)$$

where τ is the temperature and $\cos\left(\cdot\right)$ represents the cosine similarity computation. Specifically, in our case, we get the positive sample h_i^+ by randomly cropping[1] 10% embedding of h_i. Then the PLM is optimized following Eq 5.

After the contrastive learning, the model is used to compute the cosine similarity between embedding the source sentence and the candidate as the S3C Score. Note that there is one principal difference between S3C Score and BERTScore: BERTScore calculates the score based on the fine-grained similarity while S3C Score simply computes the cosine similarity between two sentences' embeddings.

6.2 Self-BLEU

Self-BLEU serves as a sub-metric to measure the diversity from a n-gram overlapping perspective, and Higher Self-BLEU indicates lower diversity. Given a source sentence and a paraphrase candidate, the SelfBLEU is computed as follows:

$$\text{Self-BLUE} = \text{BLUE(src,can)} \qquad (6)$$

6.3 Correlation with human judgement

In this section, we investigate whether BBScore correlates with human judgment better. Specifically, we select the best-performing metrics from both reference-based and reference-free metric groups. The results are shown in Table 4. BBScore has the highest correlation with human judgment among all metrics across segment-level and system-level evaluation. In all evaluation settings, BBScore is shown to outperform all existing metrics when evaluating paraphrase qualities. This is because

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[1] set the randomly selected embeddings as zero

BBScore balances two aspects of paraphrase generation: diversity and semantic preservation. Interestingly, the best non-BBScore metric is consistently the BERTScore, possibly because both methods are adept at comparing synonyms during evaluation, thus better capturing the semantic overlap between the source sentence and the paraphrase candidate.

Metric	Sys-level		Seg-level	
	Pr.	Spr.	Pr.	Spr.
Reference-based				
BERTScore(B)	0.500	0.498	0.471	0.470
BERTScore(R)	0.362	0.365	0.369	0.361
BARTScore	0.331	0.340	0.314	0.310
Reference-free				
SelfBERTScore(B)	0.555	0.554	0.493	0.490
BERT-iBLEU(B,3)	0.545	0.541	0.489	0.488
BERT-iBLEU(B,4)	0.546	0.543	0.489	0.488
BBScore	0.569	0.572	0.563	0.571

Table 4: The Pearson (Pr.) and Spearman (Spr.) correlations with both segment-level and system-level human judgments on Twitter-Para. Specifically, we highlight the best performance with **'Red'**. Generally, our BBScore achieves the best performance.

Metric	Sys-level		Seg-level	
	Pr.	Spr.	Pr.	Spr.
BBScore				
BBScore	0.569	0.572	0.563	0.571
-S3C	0.239	0.240	0.122	0.105
-SelfBLEU	0.534	0.537	0.514	0.520
Other combination				
BERTScore+SelfBLEU	0.521	0.512	0.504	0.509
BARTScore+SelfBLEU	0.408	0.402	0.393	0.394
BERT-iBLEU(B,3)+SelfBLEU	0.501	0.512	0.468	0.472

Table 5: Ablation study on the BBScore. '-S3C' means removing S3C score from BBScore. 'BERTScore+SelfBLEU' means combining BERTScore and SelfBLEU for evaluation. Specifically, we highlight the best performance with **'Red'** and our BBScore achieves the best result in all evaluation settings.

6.4 Ablation studies

There are two sub-metrics in our BBScore: S3C Score and Self-BLEU. We conduct an ablation study on Twitter-Para to investigate the effectiveness of the two sub-metrics, and the results are listed in Table 5. Moreover, we use some existing

paraphrase metrics to replace the S3C Score. We found that both sub-metrics contribute to the evaluation performance of BBScore. Specifically, the S3C Score possesses a significantly greater contribution than Self-BLEU. Furthermore, when replacing the S3C Score with existing PLM-based metrics, the performance degrades significantly, which indicates the superiority of our S3C Score.

6.5 Robustness analysis

We also tested the robustness of BBScore. We first created four kinds of paraphrase candidates on the test set of Twitter-Para dataset, and then evaluate these paraphrase candidates with various paraphrase metrics. The five types of paraphrases are as following:

- Standard reference (SR). Given the source sentence, each one owns a standard paraphrase reference. This is used to test metric performance for high-quality paraphrase generation.

- Source sentence (SC). By leveraging source sentences as paraphrase candidates, we can see whether the metrics tend to over-value the word-level overlapping.

- Lexical different paraphrase (LDP). Given the source sentence, we created a reasonable paraphrase while avoiding using words from the standard reference.

- Human writing paraphrase with better quality (HWPBQ). Given the source sentence and the reference, we created a paraphrase that is of better quality than the original reference.

- Adversarial paraphrase (AP). Given the source and the reference, turkers modify the original reference as little as possible to create a non-paraphrase candidate.

We randomly selected 100 source sentences from Twitter-Para and created such five kinds of paraphrase candidates. We show the various metric scores in the robustness check, and the results are shown in Table 6. Specifically, different metric owns a different score scale (e.g., BERTScore has a small scale between 0.8~1.0, BARTScore even produces negative scores), so we rescale them to 0.0~1.0. The scaling does not affect the ranking between scores and increases readability.

As shown in Table 6, the first column means using the gold reference as paraphrase candidates, so

the metric should generate a higher score. The reference-based metrics generate the full score since the GR paraphrase candidate matches the gold reference perfectly. Among reference-free metrics, BBScore shows the best performance. The second column uses the source sentence as a paraphrase candidate, so the metric should generate a lower score. When evaluating SC paraphrase candidates, metrics like SelfBLEU generate a 1.00 score, indicating that they regard the source sentence as a good paraphrase, which is unfeasible. Specifically, BBScore achieves the best performance among all other metrics. The third column is the high-quality paraphrase candidates different from references, so the metric should generate a higher score on them. As we can see, all reference-based metrics generate an extremely low score, implying that such candidates are non-paraphrases, which contradicts the ground truth that such candidates are high-quality paraphrases. However, BBScore significantly outperforms other metrics due to its compatibility with the one-to-many nature of the paraphrase generation task. In the fourth column, the paraphrase candidates own even better qualities than the standard reference, so the metric should score as high as possible. Specifically, BBScore achieves the best performance since it considers semantic preservation and diversity of the paraphrase, thus better reflecting its quality. In the final column, the paraphrase candidates belong to non-paraphrases that lexically similar to standard references, so metric should provide low scores. As we can see, all n-gram-based metrics fail to recognize that such candidates are non-paraphrases since they only capture the word overlapping between two sentences, which is powerless to judge whether they are semantically similar. However, PLM-based metrics significantly outperform n-gram-based metrics since the PLM can capture one sentence's semantics more precisely. Moreover, among the PLM-based metrics, BBScore performs the best.

7 Discussion and Limitation

BBScore achieves statistically significant better correlations with human judgment than existing paraphrase metrics. The results hold across two evaluation paradigms, segment-level, and system-level. Besides, BBScore is configurable. Notably, it is composed of two specific paraphrase quality sub-metrics. These sub-metrics are combined in a configurable manner that corresponds to two prin-

Metric	SR($\uparrow$)	SC($\downarrow$)	LDP($\uparrow$)	HWPBQ($\uparrow$)	AP($\downarrow$)
Reference-based metrics					
BLEU	1.00	0.68	0.12	0.41	0.86
Rogue	1.00	0.59	0.21	0.47	0.79
BERTScore	1.00	0.62	0.31	0.51	0.50
BARTScore	1.00	0.56	0.28	0.30	0.51
Reference-free metrics					
SelfBLEU	0.62	1.00	0.21	0.44	0.64
SelfRogue	0.65	1.00	0.28	0.46	0.55
SelfBERTScore	0.52	1.00	0.37	0.54	0.50
SelfBARTScore	0.41	0.81	0.41	0.33	0.44
BERT-iBLEU(B,4)	0.76	0.35	0.43	0.53	0.46
BBScore	0.81	0.00	0.58	0.62	0.37

Table 6: Robustness analysis results on Twitter-Para. GR is short for standard reference; SC is short for source sentence; LDP is short for lexical different paraphrase; HWPBQ is short for human writing paraphrase with better quality; AP is short for Adversarial paraphrase. $\downarrow$ indicates the lower, the better; $\uparrow$ indicates the higher, the better. Generally, our BBScore achieves the best performance in the robustness check.

cipal purposes of paraphrase generation.

BBScore should be used alongside human evaluation. BBScore was created to facilitate the development and tuning of paraphrase models. As such, BBScore can be used for model selection and hyperparameter tuning. Besides, please note that BBScore is specifically designed for paraphrase generation and may not work with other text generation tasks, which will not be discussed here.

8 Conclusion

This paper first reviews the reliability of existing metrics for paraphrasing evaluation and investigate how well they correlate with human judgment. Then based on such empirical evidence, we present two conclusions that contradict the conventional wisdom in paraphrasing evaluation: (1) existing paraphrasing evaluation metrics terribly correlate with human judgment, so fail to reflect the paraphrase's quality. (2) reference is not indispensable when evaluating a paraphrase candidate's quality. To this end, we propose a metric called BBScore, a reference-free, simple, and unsupervised metric for paraphrase evaluation. After comprehensive experiments, the results validate that BBScore significantly outperforms existing metrics.

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