# Text Similarity as An Evaluation Measure of Machine Translation

## GitHubCode

## Overleaf

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## Abstract

This paper is aimed at benchmarking the correlation of some existing metrics with human scores, in the context of Machine Translation related tasks.
Do to so, we focus on untrained measures, in particular BLEU (string-based), InfoLM, TER, DepthScore, METEOR, and BaryScore (embedding-based, text as probability distributions) introduced in [Colombo et al., 2021b].
The data used for this task comes from the Tenth Workshop on Machine Translation (WMT15) and includes pairwise generated sentences and reference sentences associated with human annotation.
To assess the relevance of each aforementioned evaluation metrics, we rely on it closeness to the human annotation in terms of correlation: Spearman, Pearson and Kendall.
The main conclusion to be drawn from our numerical results is that Baryscore is the most correlated with human annotation.

## 1 Introduction

Natural Language Processing (NLP) computer programs are getting more and more used in real life. From translating text from one language to another, through responding to spoken commands to summarizing large volumes of text rapidly, their application occur in several fields. Although its importance and usefulness, the quality of natural language generation systems must be evaluated using objective and precise criteria in order to have confidence in their results.
This paper is aimed at focusing on the Machine Translation task in order to benchmark some existing criteria to evaluate the accuracy or similitude of a natural language generation system to a human annotation or gold-reference. Indeed, due to both high annotation costs and time, researchers tend to rely on automatic evaluation to compare the outputs of such systems. Regarding how the used metric is obtained, two categories are distinguished: pre-trained metrics and untrained metrics. This work focuses on the later which is split into three subgroups [Colombo et al., 2021b]: (1) string matching; (2) edit based and (3) embedding based metrics. For each of them, we propose at least one type of metric that can be used to assess the evaluation criteria. In particular, we describe three particular exemples of each type of metrics : BLEU (for string-based), BaryScore (for embedding based metrics), TER (edit based) and infoLM (for a mix) metrics. The remainder of the paper is structured as follows. Section 2 presents the general and theoretical framework of the Machine Translation task and provides the main findings of the related literature. Section 3 focuses on the chosen metrics and introduces core theoretical considerations and the main steps for the computation tasks. Section 3 presents and discusses the numerical results of such metrics applied on data.

Contributions : (1) we introduce brief summaries and explanations of the existing metrics in order that the intuition of this metrics could be understood by non-experts ; (2) we benchmark the correlation of existing metrics with human scores for the data2text generation task.

## 2 Problem Framing and State of the Art

Although we decide to focus on Machine Translation[Colombo et al., 2021b], benchamarking existing metrics could also be done in several tasks, e.g., Data2Text generation([Colombo et al., 2021a]; ) or story generation as in [Chhun et al., 2022]. Regardless, the task one is interested in, the general framework is set as following:

### 2.1 Problem Framing

Given a dataset $\mathcal{D} = \{r_i, \{c_i^s, h(r_i, c_i^s)\}_{s=1}^S\}_{i=1}^N$, where:

- $r_i = (r_1, \ldots, r_M)$ is the $i$-th reference text composed of M tokens (e.g., words or subwords);
- $c_i^s = (c_1, \ldots, c_L)$ is the $i$-th candidate text composed of L tokens generated by the $s$-th NLG (Natural Language Generation) system;
- $h(r_i, c_i^s) \in \mathbb{R}^+$ is the score associated by a human annotation to the candidate text compared to the reference one,

the main goal is then to define an evaluator metric such that $f(r_i, c_i^s) \in \mathbb{R}^+$ which ideally should be correlated to the human annotation $h(r_i, c_i^s)$. This correlation is measured by correlation coefficients such as the Pearson, Spearman or Kendhal coefficients.

### 2.2 Data

The data we use in this paper are part of the resources provided for the Tenth Workshop on Machine Translation (WMT15) and include pairwise generated English sentences and reference sentences associated with human annotation. TrueSkill [Sakaguchi et al., 2014], originally developed by Microsoft Research for the Xbox Live gaming community, was adapted to Machine Translation Evaluation task and used as the human evaluation ranking for all translation shared tasks in this workshop.

### 2.3 State of the Art

As precised above, this paper focuses in the particular task of Machine Translation. In the literature, several papers, departing from the framework described above with specific applications such as Data2Text or story generation in addition to Machine Translation, are published in order to shed light on how different metrics perform compared to human annotation task which is indeed time consuming. As Machine Translation task, for instance, [Colombo et al., 2021b] and [Leusch et al., 2003] use respectively BaryScore metric and a string-to-string distance measure to evaluate how well a Machine Translator perform. [Perez-Beltrachini et al., 2016], and again [Colombo et al., 2021b] focus on Data2Text task to evaluate, regarding correlation metric, to evaluate metrics compared to human annotation. From the story generator point of view, [Xu et al., 2018] propose skeleton-based model to promote the coherence of generated stories. In the same sense, [Chhun et al., 2022] introduce a set of 6 orthogonal and comprehensive human criteria, carefully motivated by the social sciences literature, which could serve as a guideline for evaluating metrics.

## 3 Presentation of the metrics

### 3.1 BLEU Score

We will introduce first a string-based metric : BLEU[Papineni et al., 2002]. This metric is language-independent, and can be then used to evaluate a lot of models.

BLEU is computed as follows : $BLEU_N = Bp * exp(\sum_{n=1}^{N} w_n * log(p_n))$

where $Bp$ is the Brevity Penalty, $p_n$ the n-gram clipped precision, $w_n$ the weight associated to the n-gram clipped precision and N the bound of the set of integers m over which we want the geometric mean of the m-gram clipped precisions to be calculated, a n-gram being a set of 'n' consecutive words, taken in order.

The clipped precision is a way to solve the problem of repetitions in the predicted sentence : for example, "The the the the", prediction of "The apple is red", has a precision 1-gram of 1 if the precision is equal to the number of correct predicted words (1-gram) over the number of total predicted words (as "The" is in the list of 1-gram of the sentence of the reference text). Here, the number of correct predicted n-grams is the number of n-grams from the predicted sentence that matches with all of the reference text ; however, the count for each correct n-gram is limited to the maximum number of times that a n-gram occurs in the reference text.

Nevertheless, if "the" is the prediction of "The apple is red", the clipped precision will be 1. To have a significant metric, we need a penalty for too short predictions. The Brevity penalty is a mean to solve this issue. Brevity penalty either is equal to 1 if the number of words in the predicted sentence is strictly superior to the number of words in the sentence of the reference text, or to $exp(\frac{1 - nb_p}{1 - nb_r})$, if the number of words in the predicted sentence ($nb_p$) is inferior or equal to the number of words in the sentence of the reference text ($nb_r$).

However, this metric has some drawbacks : The main issue is that this score doesn't take into account synonyms. What is more, the importance of words is ignored (incorrect words like "to" have

the same weight as words that contributes significantly to the meaning), and finally it does not take into account the order of words (mainly for $BLEU_1$).

### 3.2 TER

We will introduce second an edit based metric : TER[Snover et al., 2006]. The TER score measures the minimum number of edits required to modify a hypothesis so that it exactly matches one of the references. This is then normalized by the average length of the references. The TER score is specifically focused on determining the minimum number of edits needed to modify the hypothesis to match with the closest reference.

$$TER = \frac{number\ of\ edits}{average\ length\ of\ the\ setence}$$

The TER score takes into account 4 types of edits that can be made to a hypothesis in order to match a reference. These edits are : the insertion, the deletion, the substitution of individual words and the shifting of word sequences within the hypothesis. It is important to note that all edits, including shifts of any length and distance count as the same value, so that they are considered equally in calculating the TER score. Furthermore, punctuation tokens are treated as normal words, and any mistakes in capitalization are also counted as edits.

### 3.3 Baryscore

The BaryScore introduced in [Colombo et al., 2021b] is based on deep contextualized embeddings (e.g., BERT, Roberta, ELMo) and mostly relies on Wasserstein barycentric distributions[1] of contextual encoder layers for $x_i$ and $y_i^s$. The metric can be summarized in two steps: (1)-compute the Wasserstein barycentric distributions [Agueh and Carlier, 2011] of contextual encoder layers for $x_i$ and $y_i^s$; (2)-Evaluate these barycentric distributions using the Wasserstein distance $\mathcal{W}$. In brief, the algorithm (the notation is adapted to our framework described above) proposed by [Colombo et al., 2021b] to compute the BaryScore is as following:

**INPUT:** $r_i$, $c_i^s$, $(\phi_k, \ldots, \phi_K)$ pre-trained layers from BERT or ELMo:

For k from 1 to K:

1. compute layers embeddings: $\phi_k(r_i)$ and $\phi_k(c_i^s)$;
2. compute $\hat{\mu}_{r_i,k} = \sum_{m=1}^{M} \alpha_m \delta_{\phi_k(r_m)}$ and $\hat{\mu}_{c_i^s,k} = \sum_{l=1}^{L} \beta_l \delta_{\phi_k(c_l)}$, where: $\alpha_m$ and $\beta_l$ are repectively the inverse document frequencies of each token $r_m$ and $c_l$ and $\delta_{(.)}$ the Dirac's measure.
3. Compute the two Wasserstein barycenters: $\hat{\mu}_{r_i} = \arg\min_{\hat{u}} \sum_{k=1}^{K} \mathcal{W}(\hat{\mu}_{r_i,k}, \hat{u})$ and $\hat{\mu}_{c_i^s} = \arg\min_{\hat{u}} \sum_{k=1}^{K} \mathcal{W}(\hat{\mu}_{c_i,k}, \hat{u})$

**OUTPUT**: Compute the Wasserstein distance of these two barycenters which correponds to the Baryscore: $\mathcal{W}(\hat{\mu}_{r_i}, \hat{\mu}_{c_i^s})$

### 3.4 InfoLM

For this metric, we rely on the work of COLOMBO [Colombo et al., 2021a]. For tha calculation of the infoLM, we need two different elements.

First this metric uses a pretrained language model (PLM). The PLM processes a given input sentence $x$, with a masked position i ($[x]^i$), and generates a discrete probability distribution ($p_\Omega(.|[x]^i)$) across the vocabulary ($\Omega$).

Additionally, this metric uses an information measure ($J : [0;1]^{=|\Omega|} \times [0;1]^{=|\Omega|}$) determines the similarity between the accumulated distributions. The information measure can be a divergence measure ($\alpha$ divergence,$\gamma$ divergence, AB Divergence) or a distance measure (L1 distance, L2 distance, L$\infty$ distance, Fisher-Rao distance)

The calculation of InfoLM involves three critical steps: first, compute the individual distributions for both the candidate C and reference R. Second, aggregate these individual distributions using a weighted sum : $p_\Omega(.|x) = \sum_{i=1}^{N} \gamma_i \times p_\Omega(.|[x]^i)$ where $\gamma_i$ is the importance of the i-th token in the sentence. Finally, the similarity between the aggregated distributions is determined using $J$.

## 4 Numerical results

We will compute the correlation between human annotations and automatic metrics. We put us in the framework of Colombo et al.[Colombo et al.,

[1] See [Colombo et al., 2021b], for details.

2021a]. We take human annotation into account because it is agreed that measuring how well an automatic metric correlates with human judgment is crucial. There is an ongoing discussion about which type of correlation (such as Pearson, Spearman, or Kendall) is the most useful for evaluating automated metrics. Two main strategies are often used for evaluation: (1) text-level correlation and (2) system-level correlation. In this case, we will use the text-level correlation approach as we evaluate the WMT15 model [Bojar et al., 2015]

Formally, the text level correlation $C_{t,f}$ is computed as follows:

$$C_{t,f} = \frac{1}{N} \sum_{i=1}^{N} K(F_i, H_i) \quad (1)$$

where $F_i = [f(c_i, r_i^1), ..., f(c_i, r_i^S)]$ and $H_i = [h(c_i, r_i^1), ..., h(c_i, r_i^S)]$ are the vectors composed of scores provided respectively by the automatic metric f and the human annotation h. $K : R^N \times R^N \rightarrow [-1, 1]$ is the chosen correlation measure.

The different correlation measure are : Pearson [Leusch et al., 2003], Spearman [Melamed et al., 2003] and Kendall [KENDALL, 1938]. We compute the correlations between human annotation and automatic metrics. Further more, we compute the correlation between several automatic metrics. The results are in Figure 1. As we are mainly interested in the Spearman correlations between human annotation and automatic metrics, the values can be found in the first columns. We observe that the best correlation achieved is 0.76 by Baryscore. METEOR has a correlation superior to 0.5, but all the other metrics are below this threshold. All the p-values associated to these correlations are below the usual significance thresholds (cf. Table 1).

We remark that the correlations between human annotation and automatic metrics are similar to the correlations of automatic metrics between themselves.

## 5 Discussion/Conclusion

We computed the correlations between human annotation and automatic metrics. We observe that the best correlation achieved is 0.76 by Baryscore. METEOR has a correlation superior to 0.5, but all the other metrics are below this threshold. All the p-values associated to these correlations are below the usual significance thresholds.

Our results are plausible. Indeed, we have correlation between human metrics and automatic

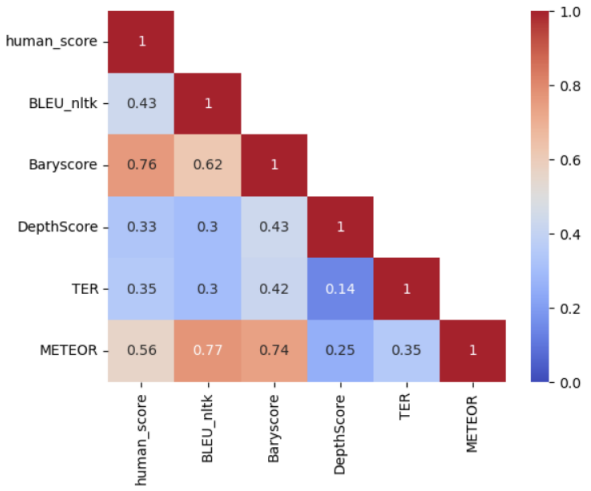


Figure 1: Matrix of the Spearman correlations between human annotation and automatic metrics

Table 1: Matrix of the Spearman p values between annotations and automatic metrics

| human_score | BLEU_nltk | Baryscore | DepthScore | TER | METEOR |
|---|---|---|---|---|---|
| 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

metrics similar to other work that study it, e.g. Moramarco [Moramarco et al., 2022] Shimorina [Shimorina, 2021]. It could be either due to our data (ML translation) or to the quantity of data studied.

A limitation to our work is that we have only look for correlation between human metrics and automatic metrics. However, another important point is the complementarity between human metrics and automatic metrics. It will be a way to see if "automatic metrics are similar to each other much more than they are to human metric", therefore the new automatic metrics should look for both correlation with human ones and complementary with existing metrics. The lack of complementarity between existing metrics and human metrics has be shown in Colombo et al. [Colombo et al., 2022].

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Table 2: Matrix of the Pearson p values between human annotation and automatic metrics

| human_score | BLEU_nltk | Baryscore | DepthScore | TER | METEOR |
|---|---|---|---|---|---|
| 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

# Appendix

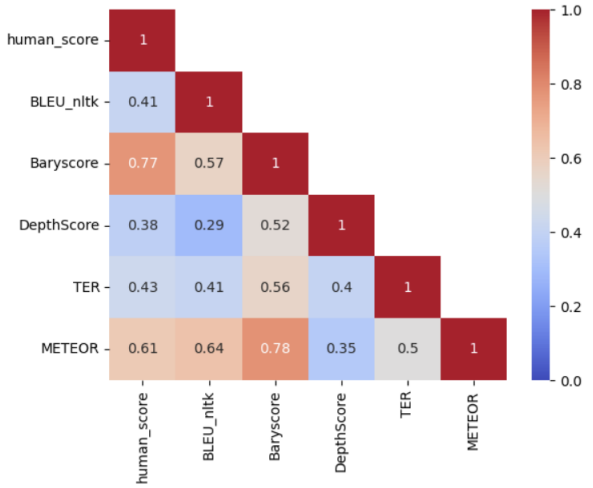


Figure 2: Matrix of the Pearson correlations between human annotation and automatic metrics

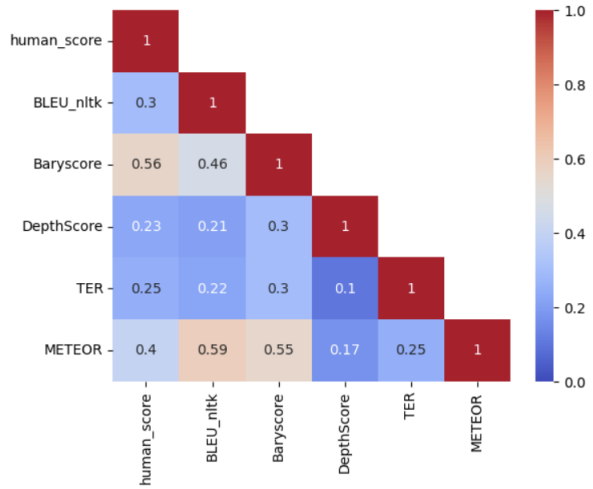


Figure 3: Matrix of the Kendall correlations between human annotation and automatic metrics

Table 3: Matrix of the Kendall p values between human annotation and automatic metrics

| human_score | BLEU_nltk | Baryscore | DepthScore | TER | METEOR |
|---|---|---|---|---|---|
| 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |