Social Biases in Automatic Evaluation Metrics for NLG

Mingqi Gao, Xiaojun Wan
Wangxuan Institute of Computer Technology, Peking University
The MOE Key Laboratory of Computational Linguistics, Peking University
{gaomingqi,wanxiaojun}@pku.edu.cn

Abstract

Many studies have revealed that word embeddings, language models, and models for specific downstream tasks in NLP are prone to social biases, especially gender bias. Recently these techniques have been gradually applied to automatic evaluation metrics for text generation. In the paper, we propose an evaluation method based on Word Embeddings Association Test (WEAT) and Sentence Embeddings Association Test (SEAT) to quantify social biases in evaluation metrics and discover that social biases are also widely present in some model-based automatic evaluation metrics. Moreover, we construct gender-swapped meta-evaluation datasets to explore the potential impact of gender bias in image caption and text summarization tasks. Results show that given gender-neutral references in the evaluation, model-based evaluation metrics may show a preference for the male hypothesis, and the performance of them, i.e., the correlation between evaluation metrics and human judgments, usually has more significant variation after gender swapping.

1 Introduction

In text generation, automatic evaluation metrics, as proxies for manual evaluation, often play an indispensable role in a variety of tasks. Metrics based on n-gram matching were proposed early and used widely, such as BLEU (Papineni et al., 2002) and ROUGE (Lin, 2004). They are simple to use, but have been criticized for a long time for their low correlation to human judgments on a number of tasks or aspects, such as text simplification (Sulem et al., 2018), text summarization (Liu and Liu, 2008; Fabbri et al., 2021), and factual consistency evaluation (Maynez et al., 2020; Honovich et al., 2021). Later, metrics based on word embeddings, pre-trained language models and other approaches were proposed one after another, such as BERTScore (Zhang* et al., 2020) and BARTScore (Yuan et al., 2021). They correlate significantly better than n-gram based metrics on many tasks. Nevertheless, their interpretability is poor and the reasons for their high correlation with manual evaluation has not been clarified, which also limits their usability (Leiter et al., 2022).

Previous studies have revealed that static word embeddings (Bolukbasi et al., 2016), contextualized word embeddings (Zhao et al., 2019a), language models (Nadeem et al., 2021), and models for specific downstream tasks in NLP (Rudinger et al., 2018; Stanovsky et al., 2019; Dinan et al., 2020) are prone to social biases, which may have a negative impact on their performance and the social effect when applied in reality (Costa-jussà and de Jorge, 2020; Hutchinson et al., 2020). Biases in them come from the data, the annotation process, the model architecture, etc. (Hovy and Prabhumoye, 2021). Noticing some of the automatic evaluation metrics are created through pre-training, e.g., BLEURT (Sellam et al., 2020), and some utilize word embeddings or language models that are biased, e.g., BERTScore, it is reasonable to suspect that similar biases also exist in them. To the best of our knowledge, no work has been done to discuss this issue.

Exploring the biases present in automatic evaluation metrics can help us better understand these recently proposed evaluation metrics that are not simply rule-based (we call them model-based evaluation metrics) from a unique perspective. On the one hand, we can examine the impact of social biases in metrics on evaluation and better understand their correlation to human judgments to improve them. Whether it conforms to social stereotypes or not should not be a factor affecting the quality of the text. To give a simple example, there should be no difference in fluency between "He is a doctor." and "He is a nurse.". We argue that more complex aspects, such as the relevance of the summary to the source document, may also be influenced by
bias in the evaluation metrics. On the other hand, we have new considerations when we use these evaluation metrics in areas other than evaluation, such as model training and text matching.

Our contribution consists of two main parts: 1) We propose an evaluation methodology to measure the biases in reference-based metrics comprehensively, and confirm the bias in the model-based evaluation metrics. 2) We investigate the impact of gender bias on evaluation by constructing gender-swapped data on several tasks, and find the preference for male hypotheses in the model-based evaluation metrics and more significant variation in their performance after gender swapping.

2 Related Work

Analysis of automatic evaluation metrics There are many studies comparing the correlation between different evaluation metrics and human judgments on quite a few tasks, such as machine translation (Ma et al., 2019; Mathur et al., 2020), text summarization (Bhandari et al., 2020; Fabbri et al., 2021), image caption (Kilickaya et al., 2017). Apart from that, Durmus et al. (2022) find that spurious correlation exists in the meta-evaluation for reference-free metrics. Xiang et al. (2022) observe that the performance of metrics varied across datasets of different years. Sai et al. (2021) and Chen et al. (2021) discover the unreliability of metrics for perturbation. They are not about social biases.

Measuring social biases in NLP Caliskan et al. (2017) propose Word Embeddings Association Test (WEAT) to measure biases in word embeddings by using Implicit Association Test. Manzini et al. (2019) extend WEAT to multiclass settings, such as religion and race. With the appearance of models such as BERT (Devlin et al., 2019), Guo and Caliskan (2021) adapt WEAT to contextualized embeddings. May et al. (2019) propose Sentence Embeddings Association Test (SEAT), which uses simple sentences instead of words. Nadeem et al. (2021) adopt Context Association Tests (CATs) to measure stereotypical bias in pre-trained language models. Sharma et al. (2021) construct a challenge task to investigate gender bias in models for Natural Language Inference. They do not involve evaluation metrics or text matching models.

3 Evaluation Metrics

The inputs to the evaluation metrics may have 3 parts: source documents, hypotheses and references. Evaluation metrics with hypotheses and references as inputs are the most numerous and are most widely used in a variety of text generation tasks. We choose them as the subjects of our study.

We select the following model-based evaluation metrics, covering a variety of types: BERTScore (Zhang* et al., 2020), MoverScore (Zhao et al., 2019b), BLEURT (Sellam et al., 2020), BARTScore (Yuan et al., 2021), WMD (Kusner et al., 2015), Embedding average (Landauer and Dumais, 1997), Vector extrema (Forgues et al., 2014), Greedy matching (Rus and Lintean, 2012). More details can be found in appendix A.

For comparison with the model-based metrics above, we choose BLEU¹ (Papineni et al., 2002), ROUGE (Lin, 2004)², METEOR (Banerjee and Lavie, 2005), TER, CIDEr³ (Vedantam et al., 2015), SPICE (Anderson et al., 2016), due to their widespread use.

4 Bias Measurement

Greenwald et al. (1998) propose the Implicit Association Test (IAT) to study social biases in human, and they find differences in the reaction latencies of people given different pairs of targets concepts (e.g. insects or flowers) and attributes (e.g. pleasant or unpleasant). Similarly, we use the matching scores from the output of evaluation metrics, analogous to the reaction time, between different pairs of targets and attributes to study the social biases in them. Table 1 shows an example for targets and attributes we use in this work.

4.1 Measuring Method

We establish a method for measuring the association between target concepts and attributes in reference-based evaluation metrics based on WEAT and SEAT. We define a reference-based metric as $M$, and $M(x, y)$ denotes the output score when the hypothesis is $x$ and the reference is $y$. We view it as a text matching model. Considering that $x$ and $y$ are not interchangeable in some evaluation metrics,

¹Using MultiEval (Clark et al., 2011), also for METEOR and TER.
²https://github.com/Diego999/py-rouge, and RELEASE-1.5.5.pl script for ROUGE-SU4
³https://github.com/wangleihits/CaptionMetrics, also for SPICE
i.e. \( M(x, y) \neq M(y, x) \), here we use the average of the two to indicate the matching score.

\[
S(x, y) = \frac{1}{2}(M(x, y) + M(y, x))
\]

Assuming there are two sets of target concepts, denoted as \( A \) and \( B \), and two sets of attributes, denoted as \( X \) and \( Y \). We want to estimate the extent to which \( X \) is close to \( A \) and \( Y \) is close to \( B \) under an evaluation metric \( M \). Differential association between two sets of targets and attributes for an evaluation metric is formulated as follows:

\[
s(X, Y, A, B) = \sum_{x \in X} r(x, A, B) - \sum_{y \in Y} r(y, A, B)
\]

\[
r(t, A, B) = \frac{1}{|A|} \sum_{a \in A} S(t, a) - \frac{1}{|B|} \sum_{b \in B} S(t, b)
\]

Note that test sets ensure \(|X| = |Y|\), then the permutation test is used to compute the statistical significance over the equal-size partitions \((X_i, Y_i)\) of \( X \cup Y \) obtained by random sampling. Here we follow the practice of May et al. (2019): If there are more than 100000 partitions, we sample another 99999 partitions uniformly with replacement. Otherwise, we use all the partitions.

\[
p = \Pr[s(X_i, Y_i, A, B) \geq s(X, Y, A, B)]
\]

The effect size is the same as WEAT:

\[
d = \frac{\text{mean}_{x \in X} r(x, A, B) - \text{mean}_{y \in Y} r(y, A, B)}{\text{std}_t \text{dev}_{t \in X \cup Y} t'}
\]

### 4.2 Test Sets

**Caliskan Test** includes 10 sets of tests used in WEAT (Caliskan et al., 2017). Some of them are for humans, covering gender, region, etc. and others are towards plants, animals and diseases. The number of targets and attributes at word level is usually in the tens.

**Angry Black Woman Stereotype** is a test for the intersection of racism and gender, introduced by May et al. (2019). Black women are often perceived to have different stereotypes from white women, such as loud and argumentative.

Both of the above tests consist of two levels: word level and sentence level. The sentence-level test is an extension of the word-level test, in which the structure of the sentences is very simple and little other information is added, e.g., "This is <word>.", "They are <word>." In addition, we follow the improvements of May et al. (2019) to make some tests contain two versions: using the name (e.g. Amy) and using the term (e.g. girl) to represent the targets or attributes.

**Double Binds** (May et al., 2019) is designed for the dual dilemma women face: if they do not achieve clear success, such as "Amy is an engineer.", they are easily considered incompetent; if they do achieve clear success, such as "Amy is an engineer with great skills.", they are easily considered unlikeable. These tests contain the same word level and sentence level as the previous tests, with an additional level: using sentences containing more information as described above, denoted as semantically unbleached, as a comparison.

### 4.3 Results

Table 2 contains the targets and attributes of some of these tests and Table 3 shows the results. We do not use C9 because in its sentence-level test, there are differences introduced by different pronouns that would not have existed in different targets and attributes.

The results suggest that the model-based evaluation metrics also suffer from similar biases as word embeddings and language models, especially in Angry Black Woman Stereotype and Caliskan Test. In particular, the bias of BARTScore, BLEURT and BERTScore are more significant on sentence-level...
| Targets                        | Attributes                     |
|-------------------------------|-------------------------------|
| ABW White-Female vs Black-Female Terms | Antonyms vs ABW Stereotype |
| DB:C Male vs Female Names     | Competent vs Incompetent      |
| DB:L Male vs Female Names     | Likable vs Unlikable          |
| C1 Flowers vs insects        | Pleasant vs Unpleasant        |
| C2 Instruments vs weapons    | Pleasant vs Unpleasant        |
| C3, C4 and C5 Eur.-American vs Afr.-American | Pleasant vs Unpleasant |
| C6 Male vs Female Career vs Family |                    |
| C7 Math vs Arts              | Male vs Female                |
| C8 Science vs Arts           | Male vs Female                |
| C10 Young vs Old people’s Names | Pleasant vs Unpleasant |

Table 2: The categories of targets and attributes of the tests.

tests than word level. It is worth noting that the results of Word Mover Distance based on static word embedding on some sentence-level tests such as ABW and C7 are more significant than the word-level results. The results for Vector Extrema and Greedy matching are very similar to Embedding average, so we do not put them in the table. Other than those, the data does not show an obvious pattern. C3, C4 and C5 have the same category of targets, attributes, only different in specific names or descriptive words, but there are also some differences in their results. The effect of using names or terms of a target group on test results varies by the type of the metrics. For Double Binds test, the influence of whether the sentence describing the targets is semantically bleached is also uncertain.

Almost all n-gram based evaluation metrics such as BLEU and ROUGE have p-values and effect sizes very close to 0 on these tests, which is shown in Table 8 (in Appendix). According to their matching algorithm, this is to be expected. METEOR, due to its use of synonymy and morphological information, exhibits a larger effect size compared to them.

5 Impact on NLG Evaluation

We select gender bias to explore its impact on the evaluation of NLG tasks. Specifically, we focus on whether gender-related factors have an impact on the preference of evaluation metrics for different hypotheses (preference analysis) and the correlation of evaluation metrics with human judgments at example level and system level (performance analysis) on the meta-evaluation dataset of image caption and text summarization.

5.1 Datasets

We choose Flickr8k (Hodosh et al., 2013) and Composite for image caption. There are example-level human judgments in them. For text summarization, we choose REALSumm (Bhandari et al., 2020) and SummEval (Fabbri et al., 2021), which contain summaries generated by different systems for the same source documents and the corresponding manual human judgments. For a source image or document, some of these meta-evaluation datasets contain one or more references, and manual evaluations may be overall scores or scores of several dimensions. See appendix B for more details.

5.2 Gender Swapping

Given a meta-evaluation dataset, we do gender swapping on all the hypotheses and references, assuming this transformation does not affect human judgements. In theory, we also need to change the source documents or images, and since we only study reference-based metrics, we do not need to do this. Specifically, we replace male-related words in a sentence, including but not limited to nouns, pronouns, and possessives, with their female counterparts, and vice versa. As POS is involved, the process is automated with the aid of some toolkits. The gender-related word list in WinoBias (Zhao et al., 2018) is used and finally we manually check and correct additional changes. There is an example in Table 4.

For preference analysis, in order to eliminate the interference of gender factors in references, we choose examples in which all references do not contain gender-related words to compare the preference of different evaluation metrics for male hypothesis and female hypothesis. In these exam-
| Test | Context | BARTS  | BLEURT | BERTS  | MoverS  | WMD   | EmbAvg  | METEOR |
|------|---------|--------|--------|--------|---------|-------|---------|--------|
| ABW-T | word   | 1.03   | -0.03  | -0.44  | 1.34    | 1.45  | 0.29    | 0.00   |
| ABW-T | sent   | 1.38*  | 0.79*  | 0.28   | 0.82*   | 1.35* | 0.83*   | 0.00   |
| ABW-N | word   | 0.61   | 1.22*  | 1.70*  | 1.23*   | -0.31 | 0.00    | 0.00   |
| ABW-N | sent   | 0.18   | 0.44*  | 0.71*  | -0.19   | -0.38 | 0.00    | 0.00   |
| DB:C  | sent (u)| 0.50   | 1.72*  | 0.80   | 0.61    | 0.91  | 0.00    | 0.00   |
| DB:C  | sent   | 0.73*  | 0.86*  | 0.23   | 0.15    | 0.67* | 0.00    | 0.00   |
| DB:C  | word   | 0.62   | -1.09  | 0.05   | 0.75    | 0.89  | 0.00    | 0.00   |
| DB:L  | sent (u)| 0.98   | 1.65*  | 0.30   | 0.48    | 1.46* | 0.00    | 0.00   |
| DB:L  | sent   | 0.52*  | -0.12  | -0.07  | -0.17   | 1.43* | 0.00    | 0.00   |
| DB:L  | word   | 0.20   | -1.25  | 0.27   | -0.45   | 1.60* | 0.00    | 0.00   |
| C1    | word   | 1.19*  | 0.60   | -0.33  | 0.92*   | 1.42* | 1.32*   | 0.00   |
| C1    | sent   | 1.64*  | 1.36*  | 1.05*  | 1.26*   | 1.51* | 0.86*   | -0.06  |
| C2    | word   | 1.18*  | 0.54   | -0.90  | 0.42    | 1.57* | 1.44*   | 0.00   |
| C2    | sent   | 1.41*  | 1.14*  | 0.58*  | 1.12*   | 1.52* | 1.06*   | 0.03   |
| C3-T  | word   | 0.24   | 1.10*  | 0.26   | -0.28   | -0.81 | 0.00    | 0.00   |
| C3-T  | sent   | 0.68*  | -0.39  | 0.30*  | -0.09   | -0.73 | 0.01    | 0.06   |
| C3-N  | word   | 0.15   | 0.30   | 1.54*  | 1.30*   | 0.95* | 0.00    | 0.00   |
| C3-N  | sent   | 0.04   | 0.68*  | 0.11   | -0.08   | 0.70* | 0.00    | 0.07   |
| C4-N  | word   | 0.39   | 0.96*  | 1.73*  | 1.41*   | 0.69  | 0.00    | 0.00   |
| C4-N  | sent   | 0.32*  | 0.54*  | 0.09   | -0.11   | 0.54* | 0.00    | 0.00   |
| C5-T  | word   | -0.35  | -0.16  | -0.79  | 0.35    | 0.52  | 0.66    | 0.00   |
| C5-T  | sent   | 0.50*  | -0.28  | -0.07  | 0.21    | 0.03  | -0.00   | -0.04  |
| C5-N  | word   | -0.08  | 0.38   | 1.47*  | 0.20    | -0.53 | 0.00    | 0.00   |
| C5-N  | sent   | 0.81*  | 0.47*  | 0.19   | 0.07    | 0.51* | 0.00    | 0.00   |
| C6-T  | word   | 0.52   | 0.83   | 0.47   | 0.12    | 0.06  | 0.76    | -0.93  |
| C6-T  | sent   | 0.05   | 0.27   | 0.10   | 0.17    | 0.08  | 0.41*   | -0.62  |
| C6-N  | word   | 1.06   | -0.82  | -0.17  | 1.60*   | 1.55* | 0.00    | 0.00   |
| C6-N  | sent   | 0.96*  | 1.23*  | 0.37   | 1.17*   | 1.59* | 0.00    | 0.00   |
| C7-T  | word   | 0.73   | 0.27   | 0.19   | 1.33*   | 1.01  | 1.13*   | 0.00   |
| C7-T  | sent   | 0.92*  | 0.81*  | 0.10   | 0.03    | 0.95* | 0.89*   | 0.16   |
| C7-N  | word   | 1.42*  | -0.23  | 0.12   | -0.13   | 0.98  | 0.00    | 0.00   |
| C7-N  | sent   | 1.69*  | 1.30*  | 0.91*  | 1.08*   | 0.45* | 0.00    | 0.00   |
| C8-T  | word   | 0.39   | -0.03  | 0.69   | 0.42    | 1.30* | 0.31    | 0.00   |
| C8-T  | sent   | 0.82*  | 0.35   | 0.35   | 0.61*   | 1.07* | 0.71*   | 0.21   |
| C8-N  | word   | 1.19*  | -0.53  | 0.56   | 0.40    | -0.06 | 0.00    | 0.00   |
| C8-N  | sent   | 1.51*  | 0.74*  | 0.58*  | 1.07*   | -0.19 | 0.00    | 0.00   |
| C10   | word   | -0.26  | 0.94   | 1.08   | 0.49    | -0.45 | 0.00    | 0.00   |
| C10   | sent   | 0.70*  | 1.14*  | 0.09   | 0.17    | 0.35  | 0.00    | 0.00   |

Table 3: Effect sizes for tests we select. *=significant for $p \leq 0.01$. Each test includes word level and sentence level. In Double Binds test, there is an additional unbleached sentence level. Tests with -T means using terms to represent targets or attributes, and -N means using names. Tests starting with C are tests in Caliskan Test.
Table 4: An example of gender swapping in Flickr8k. There are 5 references in total, and all of them are transformed.

| Hypothesis | Reference |
|------------|-----------|
| origin     | A woman in a red shirt with her arm raised. | Two girls walking down the street. |
| swap       | A man in a red shirt with his arm raised. | Two boys walking down the street. |

Table 5: Output scores of evaluation metrics on examples where all references do not contain gender-related words and the original hypothesis contains male-related words and does not contain female-related words. Column "male" denotes the average of the scores given by evaluation metrics on these examples, and column "female" denotes the swapped results. ">", "<" and "=" refer to the proportion of these pairs of the original and the gender-swapped examples in which the male hypothesis score is greater than, less than or equal to the female hypothesis score, respectively.

For performance analysis, we compute example-level or system-level correlations on the original and gender-swapped dataset. Because of the limited number of examples affected by gender swapping in the entire dataset, when we compare example-level correlations before and after the gender swapping on Flickr8k and Composite, we calculate the results not only on the entire dataset, but also on the examples that contain only male-related words in the original hypothesis, i.e. only female-related words in the swapped hypothesis. This selection leaves about 1/3 of the data for both datasets. For REALSumm and SummEval, we do not make the selection because it may be unfair to ignore some of the outputs of a system when calculating system-level correlations.

5.3 Results

Model-based evaluation metrics show a clear preference for male hypotheses, which is shown in Table 5. For the same gender-neutral references, BLEURT scores the male hypothesis significantly higher than the female sample both in the overall average and in the comparison of each pair. MoverScore and BERTScore treat the male and female hypotheses with little difference in average scores, but still differ in the comparison of each pair.

The example-level correlation between model-based evaluation metrics and human judgments varies more after the gender swapping, especially for BLEURT and BARTScore, which is shown in Table 6 and Table 9 (in Appendix), and metrics show more variation on Flickr8k than Composite. Compared with the previous measurements in Section 4.3, while some of the model-based evaluation
| Metrics       | Flickr8k ($N = 1685$) | Composite/MSCOCO ($N = 2462$) | Correctness | Thoroughness |
|---------------|------------------------|--------------------------------|--------------|--------------|
|               | Overall                |                                |              |              |
| BLEURT-max    | 0.590                  | 0.740                          | 0.609        | 0.591        |
| BLEURT-mean   | 0.586                  | 0.722                          | 0.569        | 0.560        |
| MoverS        | 0.516                  | 0.695                          | 0.579        | 0.576        |
| BARTS-max     | 0.530                  | 0.714                          | 0.599        | 0.595        |
| BARTS-mean    | 0.528                  | 0.649                          | 0.514        | 0.503        |
| BLEU          | 0.446                  | 0.659                          | 0.559        | 0.559        |
| METEOR        | 0.530                  | 0.699                          | 0.595        | 0.592        |
| TER           | -0.251                 | -0.627                         | -0.551       | -0.551       |
| ROUGE-SU4     | 0.408                  | 0.672                          | 0.576        | 0.576        |
| BARTS-f1      | 0.496                  | 0.692                          | 0.596        | 0.599        |
| WMD-max       | 0.539                  | 0.729                          | 0.606        | 0.605        |
| WMD-mean      | 0.516                  | 0.719                          | 0.599        | 0.598        |
| EmbAvg        | 0.402                  | 0.670                          | 0.565        | 0.563        |
| VecExt        | 0.511                  | 0.720                          | 0.596        | 0.594        |
| GreedyMatch   | 0.525                  | 0.711                          | 0.587        | 0.587        |

Table 6: Example-level Spearman’s correlation between automatic evaluation and human judgments on image caption datasets. Examples that do not meet the condition that the original hypothesis contains male-related words and does not contain female-related words are removed. All the results satisfy $p \leq 0.01$. If the metric does not explicitly specify the aggregation method for multiple reference settings, we take the maximum value and the average value. "-max" indicates the metric takes the maximum value of multiple references, and "-mean" refers to the average value.

| REALSumm | SummEval |
|----------|----------|
| Coverage | Coherence | Consistency | Fluency | Relevance |
| Metrics  | origin    | swap       | origin    | swap       | origin    | swap       |
| BLEURT   | 0.722*    | 0.685*     | -0.118    | -0.218     | 0.479     | 0.397      | 0.090     | 0.072      | -0.012    | -0.082    |
| MoverS   | 0.310     | 0.313      | 0.024     | 0.027      | 0.050     | 0.038      | 0.185     | 0.168      | 0.265     | 0.274     |
| BARTS    | 0.883*    | 0.889*     | 0.256     | 0.221      | 0.685*    | 0.662*     | 0.578     | 0.537      | 0.515     | 0.477     |
| BLEU     | 0.054     | 0.054      | 0.574     | 0.574      | -0.018    | -0.018     | 0.350     | 0.350      | 0.527     | 0.527     |
| METEOR   | 0.714*    | 0.713*     | 0.474     | 0.474      | 0.732*    | 0.732*     | 0.649*    | 0.649*     | 0.624*    | 0.624*    |
| ROUGE-1  | 0.474     | 0.474      | 0.547     | 0.509      | 0.653*    | 0.644*     | 0.693*    | 0.670*     | 0.753*    | 0.718*    |
| ROUGE-2  | 0.411     | 0.410      | 0.335     | 0.335      | 0.779*    | 0.779*     | 0.690*    | 0.690*     | 0.621     | 0.621     |
| ROUGE-L  | 0.226     | 0.230      | 0.591     | 0.574      | 0.565     | 0.559      | 0.704*    | 0.701*     | 0.788*    | 0.771*    |
| BARTS-f1 | 0.257     | 0.264      | 0.750*    | 0.718*     | -0.024    | -0.059     | 0.284     | 0.246      | 0.494     | 0.469     |
| WMD      | 0.565*    | 0.573*     | 0.212     | 0.212      | 0.668*    | 0.668*     | 0.522     | 0.522      | 0.509     | 0.509     |
| EmbAvg   | 0.511*    | 0.530      | 0.159     | 0.144      | 0.679*    | 0.682*     | 0.408     | 0.390      | 0.359     | 0.347     |
| VecExt   | 0.190     | 0.182      | 0.200     | 0.312      | -0.291    | -0.300     | -0.191    | -0.146     | -0.056    | 0.059     |
| GreedyMatch | 0.730*    | 0.731*     | 0.524     | 0.538      | 0.418     | 0.406      | 0.344     | 0.350      | 0.347     | 0.362     |

Table 7: System-level Spearman’s correlation between automatic evaluation and human judgments on text summarization datasets. *=significant for $p \leq 0.01$. For metrics does not explicitly specify the aggregation method for multiple reference settings, their results in the table are all averaged.
metrics are more correlated with human judgments, the correlation may carry bias. Furthermore, it can be seen that keeping only single gender-related examples can make this trend more obvious on both datasets by comparing Table 6 and Table 9.

Similar findings can be observed in system-level correlation, illustrated in Table 7, but the evidence is less solid than example level. On REALSumm, only BLEURT shows a significant change. But as the number of top systems changes, such variation can also be detected, which is shown in Figure 1. On SummEval, while BLEURT, BARTScore, MoverScore, and BERTScore show quite significant variation in the four dimensions, some of the n-gram based metrics such as ROUGE-1 also show sizable variation in performance. For this counter-intuitive phenomenon, we examine those instances where the ROUGE values change after gender swapping and find that this is due to the fact that some of the words do not have one-to-one correspondence between males and females, e.g., the counterparts of both "his" and "him" are "her". This reminds us that the variation in the performance of an evaluation metric on the gender-swapped meta-evaluation dataset may, in addition to the effect of bias, be partly due to the problem of its own robustness.

6 Conclusion

We illustrate that model-based evaluation metrics have similar biases to those of word embeddings and language models through association tests. In particular for gender bias, given gender-neutral references in the evaluation, they show a preference for the male hypothesis. However, due to the complexity of the texts in the actual evaluation, it is difficult to say whether a hypothesis or reference is biased or conforms to some stereotypes simply, so it remains not completely clear how these biases affect the performance of the evaluation metrics. But they still influence the evaluation in a very subtle way. By doing gender-swapping on the meta-evaluation datasets, it is possible to find a greater variation in correlation between model-based evaluation metrics and human judgments under certain conditions. This at least suggests that there are problems with the reliability of these evaluation metrics under gender swapping, which differs from the gender-related errors in text generation, such as unilaterally changing gender-related words in hypothetical or reference texts in Sai et al. (2021). For future research, it is worth considering explora-
ing the impact of removing bias from model-based evaluation metrics on their performance.

**Limitations**

Similar to WEAT and SEAT, our measurements for bias can not prove that there is no bias in an evaluation metric. In addition, measuring bias in the evaluation metrics requires more computational resources and is more time-consuming because the calculation of the distance between word embeddings in WEAT cannot be followed. We use GeForce GTX 1080 Ti for acceleration.

**Ethics Statement**

Our work examines social biases in automatic evaluation metrics. Automatic evaluation metrics are important tools in text generation, and in many cases social bias should not be a factor for evaluating text quality. In addition, when evaluation metrics are used beyond evaluation, such as text matching, bias in these evaluation metrics is something to be aware of.

**References**

Peter Anderson, Basura Fernando, Mark Johnson, and Stephen Gould. 2016. Spice: Semantic propositional image caption evaluation. In *ECCV*.

Satanjeev Banerjee and Alon Lavie. 2005. **METEOR**: An automatic metric for MT evaluation with improved correlation with human judgments. In *Proceedings of the ACL Workshop on Intrinsic and Extrinsic Evaluation Measures for Machine Translation and/or Summarization*, pages 65–72, Ann Arbor, Michigan. Association for Computational Linguistics.

Manik Bhandari, Pranav Narayan Gour, Atabak Ashfaq, Pengfei Liu, and Graham Neubig. 2020. Re-evaluating evaluation in text summarization. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 9347–9359, Online. Association for Computational Linguistics.

Tolga Bolukbasi, Kai-Wei Chang, James Y Zou, Venkatesh Saligrama, and Adam T Kalai. 2016. Man is to computer programmer as woman is to homemaker? debiasing word embeddings. In *Advances in Neural Information Processing Systems*, volume 29, Curran Associates, Inc.

Aylin Caliskan, Joanna J. Bryson, and Arvind Narayanan. 2017. Semantics derived automatically from language corpora contain human-like biases. *Science*, 356(6334):183–186.

Yiran Chen, Pengfei Liu, and Xipeng Qiu. 2021. Are factuality checkers reliable? adversarial meta-evaluation of factuality in summarization. In *Findings of the Association for Computational Linguistics: EMNLP 2021*, pages 2082–2095, Punta Cana, Dominican Republic. Association for Computational Linguistics.

Jonathan H. Clark, Chris Dyer, Alon Lavie, and Noah A. Smith. 2011. Better hypothesis testing for statistical machine translation: Controlling for optimizer instability. In *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies*, pages 176–181, Portland, Oregon, USA. Association for Computational Linguistics.

Marta R. Costa-jussà and Adrià de Jorge. 2020. Fine-tuning neural machine translation on gender-balanced datasets. In *Proceedings of the Second Workshop on Gender Bias in Natural Language Processing*, pages 26–34, Barcelona, Spain (Online). Association for Computational Linguistics.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. **BERT**: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

Emily Dinan, Angela Fan, Adina Williams, Jack Urbanek, Douwe Kiela, and Jason Weston. 2020. Queens are powerful too: Mitigating gender bias in dialogue generation. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 8173–8188, Online. Association for Computational Linguistics.

Esin Durmus, Faisal Ladhak, and Tatsunori Hashimoto. 2022. Spurious correlations in reference-free evaluation of text generation. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1443–1454, Dublin, Ireland. Association for Computational Linguistics.

Desmond Elliott and Frank Keller. 2014. Comparing automatic evaluation measures for image description. In *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 452–457, Baltimore, Maryland. Association for Computational Linguistics.

Alexander R. Fabbri, Wojciech Kryściński, Bryan McCann, Caiming Xiong, Richard Socher, and Dragomir Radev. 2021. **SummEval**: Re-evaluating summarization evaluation. *Transactions of the Association for Computational Linguistics*, 9:391–409.
Gabriel Forgues, Joelle Pineau, Jean-Marie Larchevêque, and Réal Tremblay. 2014. Bootstrapping dialog systems with word embeddings. In Nips, modern machine learning and natural language processing workshop, volume 2.

Anthony G Greenwald, Debbie E. McGhee, and Jordan L. K. Schwartz. 1998. Measuring individual differences in implicit cognition: the implicit association test. Journal of personality and social psychology, 74 6:1464–80.

Wei Guo and Aylin Caliskan. 2021. Detecting Emergent Intersectional Biases: Contextualized Word Embeddings Contain a Distribution of Human-like Biases, page 122–133. Association for Computing Machinery, New York, NY, USA.

Karl Moritz Hermann, Tomas Kocisky, Edward Grefenstette, Lasse Espeholt, Will Kay, Mustafa Suleyman, and Phil Blunsom. 2015. Teaching machines to read and comprehend. Advances in neural information processing systems, 28:1693–1701.

Micah Hodosh, Peter Young, and Julia Hockenmaier. 2013. Framing image description as a ranking task: Data, models and evaluation metrics. J. Artif. Int. Res., 47(1):853–899.

Or Honovich, Leshem Choshen, Roee Aharoni, Ella Neeman, Idan Szpektor, and Omri Abend. 2021. \(q^2\): Evaluating factual consistency in knowledge-grounded dialogues via question generation and question answering. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, pages 7856–7870, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Dirk Hovy and Shrimai Prabhunoye. 2021. Five sources of bias in natural language processing. Language and Linguistics Compass, 15(8):e12432.

Ben Hutchinson, Vinodkumar Prabhakaran, Emily Denton, Kellie Webster, Yu Zhong, and Stephen Denuy. 2020. Social biases in NLP models as barriers for persons with disabilities. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 5491–5501, Online. Association for Computational Linguistics.

Mert Kilickaya, Aykut Erdem, Nazli Ikizler-Cinbis, and Erkut Erdem. 2017. Re-evaluating automatic metrics for image captioning. In Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 1, Long Papers, pages 199–209, Valencia, Spain. Association for Computational Linguistics.

Matt Kusner, Yu Sun, Nicholas Kolkin, and Kilian Weinberger. 2015. From word embeddings to document distances. In Proceedings of the 32nd International Conference on Machine Learning, volume 37 of Proceedings of Machine Learning Research, pages 957–966, Lille, France. PMLR.

Thomas K Landauer and Susan T. Dumais. 1997. A solution to plato’s problem: the latent semantic analysis theory of acquisition, induction and representation of knowledge. Psychological Review, pages 211–240.

Christoph Leiter, Piyawat Lertvittayakumjorn, Marina Fomicheva, Wei Zhao, Yang Gao, and Steffen Eger. 2022. Towards explainable evaluation metrics for natural language generation. Computing Research Repository, arXiv:2203.11131.

Chin-Yew Lin. 2004. ROUGE: A package for automatic evaluation of summaries. In Text Summarization Branches Out, pages 74–81, Barcelona, Spain. Association for Computational Linguistics.

Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollar, and Larry Zitnick. 2014. Microsoft coco: Common objects in context. In ECCV. European Conference on Computer Vision.

FeiFei Liu and Yang Liu. 2008. Correlation between ROUGE and human evaluation of extractive meeting summaries. In Proceedings of ACL-08: HLT, Short Papers, pages 201–204, Columbus, Ohio. Association for Computational Linguistics.

Qingsong Ma, Johnny Wei, Ondřej Bojar, and Yvette Graham. 2019. Results of the WMT19 metrics shared task: Segment-level and strong MT systems pose big challenges. In Proceedings of the Fourth Conference on Machine Translation (Volume 2: Shared Task Papers, Day 1), pages 62–90, Florence, Italy. Association for Computational Linguistics.

Thomas Manzini, Lim Yao Chong, Alan W Black, and Yulia Tsvetkov. 2019. Black is to criminal as caucasian is to police: Detecting and removing multiclass bias in word embeddings. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 615–621, Minneapolis, Minnesota. Association for Computational Linguistics.

Nitika Mathur, Johnny Wei, Markus Freitag, Qingsong Ma, and Ondřej Bojar. 2020. Results of the WMT20 metrics shared task. In Proceedings of the Fifth Conference on Machine Translation, pages 688–725, Online. Association for Computational Linguistics.

Chandler May, Alex Wang, Shikha Bordia, Samuel R. Bowman, and Rachel Rudinger. 2019. On measuring social biases in sentence encoders. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 622–628, Minneapolis, Minnesota. Association for Computational Linguistics.
References

Peter Anderson, Basura Fernando, Mark Johnson, and Stephen Gould. 2016. Spice: Semantic propositional image caption evaluation. In ECCV.

Satanjeev Banerjee and Alon Lavie. 2005. METEOR: An automatic metric for MT evaluation with improved correlation with human judgments. In Proceedings of the ACL Workshop on Intrinsic and Extrinsic Evaluation Measures for Machine Translation and/or Summarization, pages 65–72, Ann Arbor, Michigan. Association for Computational Linguistics.

Manik Bhandari, Pranav Narayan Gour, Atabak Ashfaq, Pengfei Liu, and Graham Neubig. 2020. Re-evaluating evaluation in text summarization. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 9347–9359, Online. Association for Computational Linguistics.

Tolga Bolukbasi, Kai-Wei Chang, James Y Zou, Venkatesh Saligrama, and Adam T Kalai. 2016. Man is to computer programmer as woman is to homemaker? debiasing word embeddings. In Advances in Neural Information Processing Systems, volume 29. Curran Associates, Inc.

Aylin Caliskan, Joanna J. Bryson, and Arvind Narayanan. 2017. Semantics derived automatically from language corpora contain human-like biases. Science, 356(6334):183–186.

Yiran Chen, Pengfei Liu, and Xipeng Qiu. 2021. Are factuality checkers reliable? adversarial meta-evaluation of factuality in summarization. In Findings of the Association for Computational Linguistics: EMNLP 2021, pages 2082–2095, Punta Cana, Dominican Republic. Association for Computational Linguistics.

Jonathan H. Clark, Chris Dyer, Alon Lavie, and Noah A. Smith. 2011. Better hypothesis testing for statistical machine translation: Controlling for optimizer instability. In Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies, pages 176–181, Portland, Oregon, USA. Association for Computational Linguistics.

Marta R. Costa-jussà and Adrià de Jorge. 2020. Fine-tuning neural machine translation on gender-balanced datasets. In Proceedings of the Second Workshop on Gender Bias in Natural Language Processing, pages 26–34, Barcelona, Spain (Online). Association for Computational Linguistics.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

Emily Dinan, Angela Fan, Adina Williams, Jack Urbanek, Douwe Kiela, and Jason Weston. 2020. Queens are powerful too: Mitigating gender bias in dialogue generation. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 8173–8188, Online. Association for Computational Linguistics.

Esin Durmus, Faisal Ladhak, and Tatsunori Hashimoto. 2022. Spurious correlations in reference-free evaluation of text generation. In Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1443–1454, Dublin, Ireland. Association for Computational Linguistics.

Desmond Elliott and Frank Keller. 2014. Comparing automatic evaluation measures for image description. In Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers), pages 452–457, Baltimore, Maryland. Association for Computational Linguistics.

Alexander R. Fabbri, Wojciech Kryściński, Bryan McCann, Caiming Xiong, Richard Socher, and Dragomir Radev. 2021. SummEval: Re-evaluating summarization evaluation. Transactions of the Association for Computational Linguistics, 9:391–409.

Gabriel Forgues, Joelle Pineau, Jean-Marie Larchevêque, and Réal Tremblay. 2014. Bootstrapping dialog systems with word embeddings. In Nips, modern machine learning and natural language processing workshop, volume 2.

Anthony G Greenwald, Debbie E. McGhee, and Jordan L. K. Schwartz. 1998. Measuring individual differences in implicit cognition: the implicit association test. Journal of personality and social psychology, 74 6:1464–80.

Wei Guo and Aylin Caliskan. 2021. Detecting Emergent Intersectional Biases: Contextualized Word
Embeddings Contain a Distribution of Human-like Biases, page 122–133. Association for Computing Machinery, New York, NY, USA.

Karl Moritz Hermann, Tomas Kocisky, Edward Grefenstette, Lasse Espeholt, Will Kay, Mustafa Suleyman, and Phil Blunsom. 2015. Teaching machines to read and comprehend. Advances in neural information processing systems, 28:1693–1701.

Micah Hodosh, Peter Young, and Julia Hockenmaier. 2013. Framing image description as a ranking task: Data, models and evaluation metrics. J. Artif. Int. Res., 47(1):853–899.

Or Honovich, Leshem Choshen, Roeo Aharoni, Ella Neeman, Idan Szpektor, and Omri Abend. 2021. $q^2$: Evaluating factual consistency in knowledge-grounded dialogues via question generation and question answering. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, pages 7856–7870, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Dirk Hovy and Shrimai Prabhumoye. 2021. Five sources of bias in natural language processing. Language and Linguistics Compass, 15(8):e12432.

Ben Hutchinson, Vinodkumar Prabhakaran, Emily Denton, Kellie Webster, Yu Zhong, and Stephen Dennyu. 2020. Social biases in NLP models as barriers for persons with disabilities. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 5491–5501, Online. Association for Computational Linguistics.

Mert Kilickaya, Aykut Erdem, Nazli Ikizler-Cinbis, and Erkut Erdem. 2017. Re-evaluating automatic metrics for image captioning. In Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 1, Long Papers, pages 199–209, Valencia, Spain. Association for Computational Linguistics.

Matt Kusner, Yu Sun, Nicholas Kolkin, and Kilian Weinberger. 2015. From word embeddings to document distances. In Proceedings of the 32nd International Conference on Machine Learning, volume 37 of Proceedings of Machine Learning Research, pages 957–966, Lille, France. PMLR.

Thomas K Landauer and Susan T. Dumais. 1997. A solution to plato’s problem: the latent semantic analysis theory of acquisition, induction and representation of knowledge. Psychological Review, pages 211–240.

Christoph Leiter, Piyawat Lertvittayakumjorn, Marina Fomicheva, Wei Zhao, Yang Gao, and Steffen Eger. 2022. Towards explainable evaluation metrics for natural language generation. Computing Research Repository, arXiv:2203.11131.

Chin-Yew Lin. 2004. ROUGE: A package for automatic evaluation of summaries. In Text Summarization Branches Out, pages 74–81, Barcelona, Spain. Association for Computational Linguistics.

Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollar, and Larry Zitnick. 2014. Microsoft coco: Common objects in context. In ECCV. European Conference on Computer Vision.

Feifan Liu and Yang Liu. 2008. Correlation between ROUGE and human evaluation of extractive meeting summaries. In Proceedings of ACL-08: HLT, Short Papers, pages 201–204, Columbus, Ohio. Association for Computational Linguistics.

Qingsong Ma, Johnny Wei, Ondřej Bojar, and Yvette Graham. 2019. Results of the WMT19 metrics shared task: Segment-level and strong MT systems pose big challenges. In Proceedings of the Fourth Conference on Machine Translation (Volume 2: Shared Task Papers, Day 1), pages 62–90, Florence, Italy. Association for Computational Linguistics.

Nitika Mathur, Johnny Wei, Markus Freitag, Qingsong Ma, and Ondřej Bojar. 2020. Results of the WMT20 metrics shared task. In Proceedings of the Fifth Conference on Machine Translation, pages 688–725, Online. Association for Computational Linguistics.

Chandler May, Alex Wang, Shikha Bordia, Samuel R. Bowman, and Rachel Rudinger. 2019. On measuring social biases in sentence encoders. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 615–621, Minneapolis, Minnesota. Association for Computational Linguistics.

Thomas Manzini, Lim Yao Chong, Alan W Black, and Yulia Tsvetkov. 2019. Black is to criminal as caucasian is to police: Detecting and removing multiclass bias in word embeddings. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 622–628, Minneapolis, Minnesota. Association for Computational Linguistics.

Joshua Maynez, Shashi Narayan, Bernd Bohnet, and Ryan McDonald. 2020. On faithfulness and factuality in abstractive summarization. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 1906–1919, Online. Association for Computational Linguistics.

Moin Nadeem, Anna Bethke, and Siva Reddy. 2021. StereoSet: Measuring stereotypical bias in pretrained language models. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Learning.
Conference on Natural Language Processing (Volume 1: Long Papers), pages 5356–5371, Online. Association for Computational Linguistics.

Ani Nenkova and Rebecca Passonneau. 2004. Evaluating content selection in summarization: The pyramid method. In Proceedings of the Human Language Technology Conference of the North American Chapter of the Association for Computational Linguistics: HLT-NAACL 2004, pages 145–152, Boston, Massachusetts, USA. Association for Computational Linguistics.

Shanya Sharma, Manan Dey, and Koustuv Sinha. 2021. Evaluating gender bias in natural language inference. Computing Research Repository, arXiv:2105.05541.

Shikhar Sharma, Layla El Asri, Hannes Schulz, and Jeremie Zumer. 2017. Relevance of unsupervised metrics in task-oriented dialogue for evaluating natural language generation. CoRR, abs/1706.09799.

Gabriel Stanovsky, Noah A. Smith, and Luke Zettlemoyer. 2019. Evaluating gender bias in machine translation. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 1679–1684, Florence, Italy. Association for Computational Linguistics.

Elior Sulem, Omri Abend, and Ari Rappoport. 2018. BLEU is not suitable for the evaluation of text simplification. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 738–744, Brussels, Belgium. Association for Computational Linguistics.

Ramakrishna Vedantam, C. Lawrence Zitnick, and Devi Parikh. 2015. Cider: Consensus-based image description evaluation. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR).

Jiannan Xiang, Huayang Li, Yahui Liu, Lemaor Liu, Guoping Huang, Defu Lian, and Shuming Shi. 2022. Investigating data variance in evaluations of automatic machine translation metrics. In Findings of the Association for Computational Linguistics: ACL 2022, pages 150–157, Dublin, Ireland. Association for Computational Linguistics.

Peter Young, Alice Lai, Micah Hodosh, and Julia Hockenmaier. 2014. From image descriptions to visual denotations: New similarity metrics for semantic inference over event descriptions. Transactions of the Association for Computational Linguistics, 2:67–78.

Wei Zhang*, Varsha Kishore*, Felix Wu*, Kilian Q. Weinberger, and Yoav Artzi. 2020. Bartscore: Evaluating text generation with bert. In International Conference on Learning Representations.
A Introduction for evaluation metrics

BERTScore (Zhang* et al., 2020) computes cosine similarity between tokens in two texts using contextual embeddings from BERT as representations. We adopt its F1 value in this work.

MoverScore (Zhao et al., 2019b) applies word mover’s distance at the basis of BERTScore. And it uses embeddings pooled from BERT to represent n-gram.

BLEURT (Sellam et al., 2020) treats evaluation as a kind of text matching. It is designed specifically for evaluation with pre-training objectives and can be fine-tuned on task-specific human judgments.

BARTScore (Yuan et al., 2021) regards evaluation as a kind of text generation. It is like perplexity for a conditional language model using hypotheses as inputs to generate references in the reference-based mode.

WMD, word mover’s distance (Kusner et al., 2015), uses minimum distance matching to compute the matching score between two sentences, represented by static embeddings of the words in them.

There are three metrics based on static word embedding, which are mainly used together in the evaluation for dialogue response generation.

Embedding average (Landauer and Dumais, 1997) computes the cosine similarity between two texts. Each text is represented by the average embeddings of the words in them.

Vector extrema (Forgues et al., 2014) is similar to Embedding average. It uses the most extreme value of the embeddings of the words in the text for each dimension of the embedding to represent the text.

Greedy matching (Rus and Lintean, 2012) directly compares the words in the two texts using a greedy matching algorithm. It uses cosine similarity to compute matching scores between two words represented by embeddings.

B Meta-evaluation datasets

Flickr8k is an image caption dataset with human judgments of the hypothesis captions of 5822 images in the test set (Hodosh et al., 2013). These hypotheses are from retrieval based models with 5 references per image. The score for the overall quality of each instance is given by three experts separately as an integer from 1 to 4. For this dataset, we follow the way (Elliott and Keller, 2014) to calculate the correlation coefficient.

Composite contains human judgments for images in three image caption datasets: Flickr8k (Hodosh et al., 2013), Flicker30k (Young et al., 2014), and MSCOCO (Lin et al., 2014). We use the part of MSCOCO because the other two parts have a smaller size. The human judgments of each example is given by an annotator on the Amazon Mechanical Turk and contains two dimensions, correctness and thoroughness, with an integer score from 1 to 5. There are 5 reference captions for an image.

REALSumm (Bhandari et al., 2020) is a meta-evaluation for text summarization, including coverage scores for the summaries generated by 25 systems on 100 source documents from the CNN/DailyMail test set (Hermann et al., 2015), annotated using the pyramid method (Nenkova and Passonneau, 2004). Only one reference summary is used for a source document.

SummEval (Fabbri et al., 2021) is another data resource for summarization evaluation similar to REALSumm, with the outputs of 16 systems. The difference is that its manual evaluation is performed through 4 dimensions: fluency, relevance, factuality, and coherence. For each example, we use the average of human judgments from the three experts. 11 references are used for a document in evaluation.

---

https://github.com/Tiiiger/bert_score
https://github.com/AIPHES/emnlp19-moverscore
https://github.com/google-research/bleurt
https://github.com/neulab/BARTScore
We refer to the code at https://github.com/elliottd/compareImageDescriptionMeasures
We use code at https://github.com/Maluuba/nlg-eval, provided by Sharma et al. (2017)

https://github.com/elliottd/compareImageDescriptionMeasures
https://www.mturk.com
https://imagesdg.wordpress.com/image-to-scene-description-graph/
https://github.com/neulab/REALSumm
https://github.com/Yale-LILY/SummEval
| Test  | Context | BLEU-4 | CIDEr | SPICE | ROUGE-1 | ROUGE-2 | ROUGE-L |
|-------|---------|--------|-------|-------|---------|---------|---------|
| ABW-T | word    | 0.00   | 0.00  | 0.00  | 0.00    | 0.00    | 0.00    |
| ABW-T | sent    | 0.00   | 0.02  | 0.00  | 0.00    | 0.00    | 0.00    |
| ABW-N | word    | 0.00   | 0.00  | 0.00  | 0.00    | 0.00    | 0.00    |
| ABW-N | sent    | 0.00   | 0.00  | 0.20  | 0.00    | 0.00    | 0.00    |
| DB:C  | sent (u)| 0.00   | 0.00  | 0.00  | 0.00    | 0.00    | 0.00    |
| DB:C  | sent    | 0.00   | 0.00  | 0.00  | 0.00    | 0.00    | 0.00    |
| DB:C  | word    | 0.00   | 0.00  | 0.00  | 0.00    | 0.00    | 0.00    |
| DB:L  | sent (u)| 0.00   | 0.00  | 0.00  | 0.00    | 0.00    | 0.00    |
| DB:L  | sent    | 0.00   | 0.00  | 0.25  | 0.00    | 0.00    | 0.00    |
| DB:L  | word    | 0.00   | 0.00  | 0.00  | 0.00    | 0.00    | 0.00    |
| C1    | word    | 0.00   | 0.00  | 0.00  | 0.00    | 0.00    | 0.00    |
| C1    | sent    | -0.02  | -0.03 | 0.09  | -0.08   | -0.12   | -0.06   |
| C2    | word    | 0.00   | 0.00  | 0.00  | 0.00    | 0.00    | 0.00    |
| C2    | sent    | 0.02   | 0.02  | 0.17  | 0.00    | 0.03    | -0.00   |
| C3-T  | word    | 0.00   | 0.00  | 0.00  | 0.00    | 0.00    | 0.00    |
| C3-T  | word    | 0.01   | 0.04  | -0.14 | 0.07    | 0.08    | 0.05    |
| C3-N  | word    | 0.00   | 0.00  | 0.00  | 0.00    | 0.00    | 0.00    |
| C3-N  | sent    | 0.00   | 0.00  | 0.12  | 0.00    | 0.00    | 0.00    |
| C4    | word    | 0.00   | 0.00  | 0.00  | 0.00    | 0.00    | 0.00    |
| C4    | sent    | 0.00   | 0.00  | 0.06  | 0.00    | 0.00    | 0.00    |
| C5    | word    | 0.00   | 0.00  | 0.00  | 0.00    | 0.00    | 0.00    |
| C5    | sent    | 0.05   | 0.06  | -0.05 | -0.02   | -0.07   | -0.01   |
| C5    | word    | 0.00   | 0.00  | 0.00  | 0.00    | 0.00    | 0.00    |
| C5    | sent    | 0.00   | 0.00  | 0.02  | 0.00    | 0.00    | 0.00    |
| C6-T  | word    | 0.00   | 0.00  | 0.00  | 0.00    | 0.00    | 0.00    |
| C6-T  | sent    | 0.00   | 0.00  | 0.00  | 0.00    | 0.00    | 0.00    |
| C6-N  | word    | 0.00   | 0.00  | 0.00  | 0.00    | 0.00    | 0.00    |
| C6-N  | sent    | 0.00   | 0.00  | 0.00  | 0.00    | 0.00    | 0.00    |
| C7-T  | word    | 0.00   | 0.00  | 0.00  | 0.00    | 0.00    | 0.00    |
| C7-T  | sent    | 0.15   | 0.18  | 0.42  | 0.00    | 0.00    | 0.00    |
| C7-N  | word    | 0.00   | 0.00  | 0.00  | 0.00    | 0.00    | 0.00    |
| C7-N  | sent    | 0.10   | 0.12  | -0.34 | 0.00    | 0.00    | 0.00    |
| C8-T  | word    | 0.00   | 0.00  | 0.00  | 0.00    | 0.00    | 0.00    |
| C8-T  | sent    | -0.11  | 0.02  | 0.56* | 0.00    | 0.00    | 0.00    |
| C8-N  | word    | 0.00   | 0.00  | 0.00  | 0.00    | 0.00    | 0.00    |
| C8-N  | sent    | -0.00  | -0.07 | -0.28 | 0.00    | 0.00    | 0.00    |
| C10   | word    | 0.00   | 0.00  | 0.00  | 0.00    | 0.00    | 0.00    |
| C10   | sent    | 0.00   | 0.00  | 0.04  | 0.00    | 0.00    | 0.00    |

Table 8: Effect sizes for test we select. *=significant for $p \leq 0.01$. Each test includes word level and sentence level. In Double Binds test, there is an additional unbleached sentence level. Tests with "-T" means using terms to represent targets or attributes, and "-N" means using names. Tests starting with "C" are tests used in WEAT (Caliskan et al., 2017).
### Table 9: Example-level Spearman’s correlation between automatic evaluation and human judgments on image caption datasets, regardless of whether the example contains gender-related words. The entire dataset is swapped. All the results satisfy $p \leq 0.01$. -max indicates the metric takes the maximum value of multiple references, and -mean refers to the average value.

| Metrics       | Flickr8k ($N = 5822$) | Composite/MSCOCO ($N = 8020$) |
|---------------|------------------------|-------------------------------|
|               | Overall                | Correctness                  | Thoroughness                 |
|               | origin | swap | origin | swap | origin | swap | origin | swap |
| BLEURT-max    | 0.621  | 0.615 | 0.675  | 0.674 | 0.559  | 0.557 |
| BLEURT-mean   | 0.608  | 0.599 | 0.648  | 0.642 | 0.524  | 0.521 |
| MoverS        | 0.532  | 0.526 | 0.617  | 0.615 | 0.516  | 0.515 |
| BARTS-max     | 0.571  | 0.569 | 0.662  | 0.660 | 0.557  | 0.554 |
| BARTS-mean    | 0.572  | 0.569 | 0.615  | 0.610 | 0.495  | 0.491 |
| BLEU          | 0.441  | 0.441 | 0.623  | 0.623 | 0.530  | 0.530 |
| METEOR        | 0.533  | 0.529 | 0.639  | 0.641 | 0.542  | 0.542 |
| TER           | -0.283 | -0.282 | -0.604 | -0.604 | -0.522 | -0.522 |
| ROUGE-SU4     | 0.439  | 0.438 | 0.626  | 0.626 | 0.534  | 0.534 |
| BERTS-f1      | 0.535  | 0.533 | 0.624  | 0.625 | 0.530  | 0.530 |
| WMD-max       | 0.592  | 0.591 | 0.669  | 0.669 | 0.560  | 0.560 |
| WMD-mean      | 0.579  | 0.576 | 0.661  | 0.660 | 0.552  | 0.552 |
| EmbAvg        | 0.415  | 0.409 | 0.618  | 0.618 | 0.526  | 0.526 |
| VecExt        | 0.571  | 0.567 | 0.671  | 0.671 | 0.558  | 0.556 |
| GreedyMatch   | 0.556  | 0.554 | 0.649  | 0.649 | 0.542  | 0.542 |