Abstract

In text summarization and simplification, system outputs must be evaluated along multiple dimensions such as relevance, factual consistency, fluency, and grammaticality, and a wide range of possible outputs could be of high quality. These properties make the development of an adaptable, reference-less evaluation metric both necessary and challenging. We introduce MaskEval, a reference-less metric for text summarization and simplification that operates by performing masked language modeling (MLM) on the concatenation of the candidate and the source texts. It features an attention-like weighting mechanism to modulate the relative importance of each MLM step, which crucially allows it to be adapted to evaluate different quality dimensions. We demonstrate its effectiveness on English summarization and simplification in terms of correlations with human judgments, and explore transfer scenarios between the two tasks.

1 Introduction

Automatic evaluation metrics are central to measuring progress in natural language generation (NLG) (Callison-Burch et al., 2006; Graham, 2015; Martin et al., 2018). Particularly challenging is the development of metrics for tasks such as summarization and text simplification. Compared to machine translation (MT), where good outputs are limited to those that reproduce all input information, there is a wider range of good summaries/simplifications because the degree of succinctness/simplicity of the output can vary greatly. A further complication is that multiple qualities of the output text must be evaluated, such as factual consistency or fluency.

For such tasks, traditional reference-based metrics such as ROUGE (Lin, 2004) and BLEU (Papineni et al., 2002) can therefore be limited by the diversity of the available references. Indeed, previous work has shown their limited correlation with human quality judgments (Callison-Burch et al., 2006; Novikova et al., 2017; Sulem et al., 2018).

A promising alternative is reference-less metrics which score a candidate text given only the source text. One such approach makes use of neural language models (LM) (Devlin et al., 2019; Lewis et al., 2020; Zhang et al., 2020; Rei et al., 2020; Yuan et al., 2021). For example, BARTScore (Yuan et al., 2021) uses a LM to autoregressively score one text (e.g. a candidate) given another (e.g. the source or the reference). This provides the means to exploit the LM for the task for which it was trained. A second approach consists of question-based metrics (Wang et al., 2020; Durmus et al., 2020; Scialom et al., 2021a), which carry out automatic question generation and answering (QG/QA) based on the candidate and the source text. Typically, answers are assumed to be nouns which are extracted from the text.

Both approaches have achieved state-of-the-art correlation scores with human judgments, depending on the specific dataset and dimension of evaluation. However, there has been limited prior work in either paradigm on adapting a reference-less evaluation metric to multiple evaluation dimensions, tasks, and languages.

In this work, we propose MaskEval, an adaptable reference-less LM-based metric which draws on the strengths of both approaches above. Like prior LM-based approaches, it can exploit in-domain data for fine-tuning. However, it shares a key assumption of question-based metrics that not all tokens should be equally important for evaluating the output. In fact, we propose to learn this importance to further improve performance.

1 Multiple references, including automatically generated ones (Bawden et al., 2020), can improve this scenario, but cannot cover all possibilities and are also costly to produce.

2 We do not evaluate in the multilingual setting due to current lack of evaluation data.
**Figure 1:** Illustration of the MaskEval framework, which consists of two steps: (i) masked language modeling (MLM) and (ii) score aggregation. More details are provided in Section 3.

MaskEval can be characterized by the following: (i) it features a masked language modeling task (MLM) over both the candidate and source text, inspired by the translation modeling objective (TLM) (Lample and Conneau, 2019), and (ii) learned weights that allow MaskEval to vary the importance given to words. We use this second feature to analyze the contribution of certain classes of words, and to selectively mask inputs to reduce computational cost.

Our contributions can be summarized as follows:

- **We introduce MaskEval**, a reference-less metric for text transformation tasks based on a modified MLM framework and a novel learned weighter of words;\(^3\)
- **We evaluate MaskEval** on English summarization, surpassing the best previous question-based metric (Scialom et al., 2021a) in three out of four dimensions, and the best previous LM-based metric (Yuan et al., 2021) in factual consistency and fluency;
- **We show that MaskEval** trained on summarization data transfers well to simplification, and vice versa. We also show that weighters trained on summarization can improve the metric’s performance on simplification.

## 2 Related Work

While n-gram-based reference-based metrics such as ROUGE (Lin, 2004) and BLEU (Papineni et al., 2002) are perhaps the most established in NLG, two more recent approaches have been shown to provide better correlations with human judgments of quality while being reference-less: those based on pre-trained neural LMs and those based on QG/QA.

**LM-based metrics** Pretrained LMs have been used in different ways: (i) by comparing aligned token-level embeddings between the candidate and reference text, as with BERTScore (Zhang et al., 2020), (ii) by fine-tuning them either to directly reproduce human quality judgments (Sellam et al., 2020) or to rerank pairs of candidate texts (Rei et al., 2020), and (iii) by exploiting text-to-text pre-trained LMs to score the candidate and source texts, as with BARTScore (Yuan et al., 2021), in a similar way to PRISM (Thompson and Post, 2020), which relies on multilingual paraphrasing as opposed to an LM. BERTScore has been shown to be poorly adapted to summarization (Scialom and Hill, 2021).

Both BARTScore and PRISM formulate the evaluation task as text generation, where the score is based on the log probability of the candidate being auto-regressively generated given the source text. While BARTScore achieves good correlations with human judgments for English summarization, it has a few potential disadvantages with respect to the way in which one text is scored based on the other: (i) the model is auto-regressive, and therefore, while the text being scored is conditioned on the entirety of the other text, it is only conditioned on the left context of itself and (ii) it uses a uni-
form weighting scheme, assigning an equal importance to each generation step (alternative weighting schemes were reported to give lower results).

We seek to solve both of these disadvantages with MaskEval, by (i) replacing auto-regressive generation with successive masked language modeling (MLM), with prediction conditioned on both the candidate text and the source text, inspired by the translation language modeling (TLM) objective of XLM (Lample and Conneau, 2019) and (ii) learning a weighter to attribute varying importance to different words in the texts.

**Question-based metrics** A parallel direction is the development of question-based metrics (Eyal et al., 2019; Scialom et al., 2019a; Durmus et al., 2020; Wang et al., 2020; Scialom et al., 2021a), where the idea is to automatically generate and then answer questions based on the candidate and the source text. The answers to the questions are nouns extracted from the texts. Different versions exist depending on which texts the questions/answers are conditioned on: Scialom et al. (2019a) generate questions by using the source document while Wang et al. (2020) and Durmus et al. (2020) do so using the candidate text. QuestEval unified both approaches, enabling further improvement. Most of the proposed metrics based on question-answering have targeted summarization.

One of the major advantages of question-based metrics is their interpretability, producing human-readable questions and answers, which can offer insights into how a candidate text is either good or bad. However, they are limited by the necessity to have good systems for question generation and answering. This requires large-scale and high-quality data, which are not available in many languages other than English (Riabi et al., 2021).

3 **MaskEval Framework**

MaskEval scores a candidate text with respect to its source text by weighting word-level scores (from both the candidate and source text) in a two-step process (illustrated in Figure 1).

1. **Successive MLM:** We perform successive MLM on the words of both the candidate and source text, comparing each prediction to the ground truth to produce one score per word.

2. **Weighted Score Aggregation:** We aggregate the scores using a learned weighter (optimized to different quality dimensions) in order to vary the importance given to each word.

3.1 **Word-level Segmentation in MLM**

In both steps, we choose to assign scores (respectively weights) to linguistically meaningful tokens (words as defined by a language-specific word-level tokenizer,\(^4\)) with the aim of making the method more interpretable and allowing us to perform linguistic analysis on learned weighters. In order to ensure that word-level segmentation is consistent with the existing segmentation of the pretrained MLMs we use (i.e. masking these linguistically defined units does not result in unnatural subword tokenization), we propose a method to reconcile the two by taking the intersection of their segmentation boundaries. An example of this method is shown in Figure 2. We refer to each text segment resulting from this scheme as a “word”.

- ![Figure 2](image-url) — Figure 2: The proposed text segmentation (3) is the intersection of the boundaries between (1) linguistically motivated tokenization produced by spaCy (Honnibal and Montani, 2017) and (2) learned subword tokenization produced by WordPiece (Johnson et al., 2017).

Given candidate text \(x = (x_1, \ldots, x_N)\) containing \(N\) words and source text \(y = (y_1, \ldots, y_M)\) containing \(M\) words, the aim is to produce \(N + M\) scores. For model-internal subword segmentation, we refer to the tokenized candidate text as \(x = (t_x^{(1)}, \ldots, t_x^{(n)})\) and the tokenized source text as \(y = (t_y^{(1)}, \ldots, t_y^{(m)})\), where \(n\) and \(m\) are the number of subword tokens in the candidate and source texts respectively \((N \leq n \text{ and } M \leq m)\). We will use the notation \(t_x^{(k)} \in x_i\) to represent the fact that token \(t_x^{(k)}\) is part of word \(x_i\).

3.2 **Masked Language Modeling**

The goal of this step is to produce a list of scores, each corresponding to an MLM step (i.e. a word). Intuitively, each score evaluates how well a trained model can predict the word when it is masked, given the other words in its text and the other text.

**Masking and prediction** We first create a sequence by concatenating \(x = (x_1, x_2, \ldots, x_N)\) and

\(^4\)We use spaCy tokenisers (Honnibal and Montani, 2017).
$y = (y_1, y_2, ..., y_M)$, placing a special separator mono-token word `<sep>` to denote the boundary between the two. In this respect, our MLM resembles the translation language modeling objective introduced in XLM (Lample and Conneau, 2019). Next, for each word position $i$ in the $x$ part of the sequence, we replace it with the mask token, thus creating masked sequence $m_{x_i}$. We take the original word $x_i$ as the ground-truth corresponding to this masked sequence. We do the same with each word position $j$ in the $y$ part of the sequence, resulting in masked sequence $m_{y_j}$ with ground-truth $y_j$. This results in $N + M$ masked sequences, each paired with its ground-truth word. The masked sequences are inputs to our MLM. We predict the masked words in the masked sequences $m_{x_i}$’s and $m_{y_j}$’s, denoting the predictions as:

$$
\hat{x}_i = \text{MLM}(m_{x_i}) \quad (1)
$$

$$
\hat{y}_j = \text{MLM}(m_{y_j}) \quad (2)
$$

Scoring  We score predictions $\hat{x}_i$ and $\hat{y}_j$ by computing their exact-match score against their corresponding ground-truth words $x_i$ and $y_j$. We give the score of 1 if the prediction and the ground-truth word are exactly the same and 0 otherwise. We denote the scores by:

$$
s_{x_i} = \text{Exact-Match}(x_i, \hat{x}_i) \quad (3)
$$

$$
s_{y_j} = \text{Exact-Match}(y_j, \hat{y}_j) \quad (4)
$$

MLM Training  When fine-tuning our MLM (we fine-tune pre-trained MLMs), we create examples using the above procedure on existing datasets of document pairs. The only difference is that for each pair, we first randomly choose which text to mask (candidate or source text), and then randomly select one word position within the chosen document. This creates one masked sequence per pair of texts. We train using cross-entropy loss between the predicted word and the ground-truth word.

3.3 Aggregation of Scores

In order to produce a single quality score (which can be adjusted for different dimensions), we aggregate the scores from the previous step by computing a weighted sum as follows:

$$
\text{MaskEval}(x, y) = c \sum_{i=1}^{N} w_{x_i}s_{x_i} + (1 - c) \sum_{j=1}^{M} w_{y_j}s_{y_j},
$$

(5)

where $w_{x_i}$ (resp. $w_{y_j}$) denotes the weight attributed to each word $x_i$ (resp. $y_j$) of the candidate text $x$ (resp. $y$), learned as described below and normalized such that $\sum_{i=1}^{N} w_{x_i} = 1$ and $\sum_{j=1}^{M} w_{y_j} = 1$. $c$ denotes the learned weight (between 0 and 1) attributed to the candidate text. The final MaskEval score is between 0 and 1.

![Figure 3: MaskEval’s word weighter. We (i) extract contextual embeddings of the candidate and source texts, (ii) apply a linear layer $W$ over the token embeddings, (iii) apply a softmax over tokens for each text and (iv) regroup token scores to form word scores (a word’s weight is the sum of its tokens’ weights).](image)

3.3.1 Learned weights

The weights $w_x$ and $w_y$ are learned using a separate attention-like module such that greater attention weights to words of interest, varying the importance given to each MLM step depending on their utility for the final score.

As for the MLM step (Section 3.2), the input to the weighter is the concatenation of the tokenized candidate and source texts: $(t_x^{(1)}, ..., t_x^{(n)}, <sep>, t_y^{(1)}, ..., t_y^{(m)})$. We encode this input with a pretrained language model, resulting in contextual embeddings $e_x^{(k)}$ (resp. $e_y^{(k')}$) for each token in $x$ (resp. $y$). We then apply an attention-like mechanism over these embeddings, in the form of a linear layer $W$ followed by a separate softmax function for $x$ and for $y$, such that the

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5We considered other scoring functions: i) computing the BERTScore between the prediction and the ground truth; ii) the perplexity score of the predicted word, and iii) the perplexity score of the ground-truth word. These scoring functions result in slightly worse performance than exact-match.

6Both the prediction and the ground-truth word are lowercased before making the comparison.
We evaluate with the T5 base model (Raffel et al., 2020), and the weighter’s loss function is the mean squared error between the mask evaluation score and the human score for the candidate in the dimension we are optimizing for, we compute the MaskEval score (Equation 5) using the weights in Equation 7. The weighter’s loss function is the mean squared error between the MaskEval score and the human evaluation score.

**Baseline weighting schemes** As a baseline, we consider MaskEval with uniform weights, a setup where \( w_{x_i} = \frac{1}{n} \) for all words \( x_i \) in \( x \), \( w_{y_j} = \frac{1}{M} \) for all words \( y_j \) in \( y \), and \( c = 1/2 \). Since some quality of a candidate text (e.g. its fluency) should not be influenced by the source text, we also consider candidate-only MaskEval, a setup where \( w_{x_i} = \frac{1}{n} \) for all words \( x_i \) in \( x \), and \( c = 1 \).

## 4 Experiments

### 4.1 Experimental Details

We evaluate MaskEval on English summarization and simplification. See Appendix A for additional training details.

**MLMs** We train two MLMs: one for summarization and one for simplification. Both are initialized with the T5 base model (Raffel et al., 2020), and then fine-tuned using the data described in Section 4.2, following the process described in Section 3. To be consistent with T5’s training, we continue to use their masking format: the masked word is replaced with the token \(<\text{extra_id}_0>\), and when fine-tuning we format the ground-truth output by placing it between the tokens \(<\text{extra_id}_0>\) and \(<\text{extra_id}_1>\).

To keep the MLM steps reasonably memory-efficient, we use a maximum sequence length of 512 tokens. Each sequence, at both training time and inference time, is modified as follows: a sliding window is applied on the text being masked so that each masked token has a maximum of 24 tokens on each side. Then, the other text is truncated at the token level to respect the sequence length limit.

**Attention Weight Module** The weighter takes as input contextual embeddings from the T5 base model. We train two sets of weighters using human-annotated data described in Section 4.2: one for summarization and one for simplification. The data has annotations of quality across different dimensions, and we train a weighter for each quality dimension, using the average score given by human annotators in said dimension as the ground-truth value (scaled to range from 0 to 1).

### 4.2 Data

**Summarization** Our MLM for summarization (MaskEval\textsubscript{sum}) is trained on the train set of CNN/Dailymail (Hermann et al., 2015; See et al., 2017) (~287K documents and their summaries).

To train the weighters for summarization and to evaluate our metric on summarization, we use SummEval (Fabbri et al., 2021), one of the largest human-annotated datasets for English summarization. The collection comprises 100 news articles, randomly selected from the test set of CNN/Dailymail (Hermann et al., 2015). It contains 1,600 summary-article pairs, each pair scored by three annotators with respect to four dimensions: consistency (con), coherence (coh), fluency (flu), and relevance (rel).

We evaluate MaskEval\textsubscript{sum} with uniform weights on the whole of SummEval, allowing us to compare its performance with existing metrics (listed in Section 4.4). To train the weighters, we use a subset of SummEval (700 randomly selected examples), and then test its performance on the remaining 900 examples. We also evaluate the model with uniform weights on this same test subset to enable a fair comparison.

**Simplification** We train our MLM for simplification, MaskEval\textsubscript{simpl}, on WikiLarge’s train set (Zhang and Lapata, 2017) (~296K simplifications).

To train the weighters and to evaluate our metric, we use human simplification judgments provided
in ASSET (Alva-Manchego et al., 2020). This data is composed of randomly selected sentences from TurkCorpus (Xu et al., 2016a), with simplifications generated automatically (162 examples). Each simplification was scored with respect to three dimensions: fluency (flu), simplicity (sim) and meaning preservation (mea).

We evaluate MaskEval\textsubscript{Simpl} with uniform weights on the whole test set, allowing us to compare to existing metrics (listed in Section 4.4). We train the weighters on a subset of ASSET (62 randomly selected examples), and then test on the remaining 100 examples. We also evaluate the model with uniform weights on this same test subset to enable a fair comparison.

4.3 Task Transfer

To explore transfer between summarization and simplification tasks, we evaluate MaskEval\textsubscript{Simpl} trained for one task on the other task, both with uniform weights and with the set of weighters trained for the other task.

4.4 Comparison to Existing Metrics

As baseline metrics, we first consider the length and the perplexity of the hypothesis summary, as they are reported to perform as well as some evaluation metrics (Durmus et al., 2022).

Reference-based We also consider three reference-based metrics: ROUGE (Lin, 2004) and BLEU (Papineni et al., 2002), and BERTScore (Zhang et al., 2020). They compare a hypothesis text to one or more manually produced ground-truth texts, contrarily to MaskEval, which is reference-less. For simplification, we additionally report SARI (Xu et al., 2016b), a standard n-gram-based metric standard simplification.

QA-Based We consider three QA-based metrics for summarization: SummaQA (Scialom et al., 2019b), QAGS (Lee et al., 2021), and QuestEval (Scialom et al., 2021a). For simplification, we report QuestEval only since it is the only one, to the best of our knowledge, to have been adapted to evaluate simplification (Scialom et al., 2021b).

LM-based We compare to the two LM-based metrics closest to ours, in their reference-less variants: PRISM (Thompson and Post, 2020) and BARTScore (Yuan et al., 2021).\footnote{The performance of both metrics on SummEval (Pearson correlation) are computed using outputted scores made available by at https://github.com/neulab/BARTScore/tree/main/SUM/SummEval. We report BARTScore, with the BART model finetuned with CNN/Dailymail (Hermann et al., 2015; See et al., 2017) and with prompt-tuning.}

| SummEval, with reference(s) | #refs | con | coh | flu | rel | Ave. |
|-----------------------------|-------|-----|-----|-----|-----|------|
| ROUGE-I                     | 11    | 18.1| 20.1| 14.9| 35.6| 22.2 |
| ROUGE-L                     | 11    | 15.7| 15.6| 13.8| 33.4| 19.6 |
| BLEU                        | 11    | 17.5| 22.0| 13.7| 35.6| 22.2 |
| BERTScore-f                 | 11    | 20.3| 18.5| 21.6| 31.9| 23.1 |
| ROUGE-I                     | 1     | 11.0| 9.8 | 7.5 | 18.9| 11.8 |
| ROUGE-L                     | 1     | 8.2 | 7.3 | 5.7 | 13.5| 8.7  |
| BLEU                        | 1     | 8.9 | 3.9 | 4.0 | 12.7| 7.4  |
| BERTScore-f                 | 1     | 8.7 | 9.8 | 10.6| 17.9| 11.8 |

| SummEval, reference-less    |       |     | con | coh | flu | rel | Ave. |
|-----------------------------|-------|-----|-----|-----|-----|-----|------|
| Perplexity                  |       | -3.1| 15.7| 8.9 | 19.8| 10.3|
| Length                      |       | 8.1 | 8.6 | 2.9 | 26.6| 10.1|
| BARTScore                   |       | 37.1| 41.3| 33.1| 44.8| 39.1|
| PRISM                       |       | 29.7| 28.1| 24.8| 29.7| 28.1|
| SummaQA                     |       | 8.3 | 8.0 | 2.9 | 26.2| 9.9 |
| QAGS                        |       | 20.4| 7.7 | 16.8| 9.1 | 13.7|
| QuestEval                   |       | 42.0| 24.0| 28.4| 39.2| 33.5|
| MaskEval\textsubscript{Summ} uniform | 44.6 | 27.6| 40.6| 35.6| 37.1|
| MaskEval\textsubscript{Summ} candidate | 50.7 | 25.9| 45.9| 28.6| 37.8|
| MaskEval\textsubscript{Simpl} uniform | 44.6 | 29.4| 37.6| 35.2| 36.7|
| MaskEval\textsubscript{Simpl} candidate | 41.2 | 24.5| 34.5| 32.6| 33.2|
| MaskEval\textsubscript{Simpl} opt | 40.6 | 24.9| 34.5| 32.2| 33.1|
| MaskEval\textsubscript{Simpl} opt | 41.5 | 25.2| 34.8| 32.3| 33.5|

Table 1: English summarization results on the SummEval dataset (Pearson correlation). Unless indicated otherwise, the results are on the full SummEval test set. Baseline non-QA metrics results are as reported in (Fabbri et al., 2021); QA-based metrics results are as reported in (Scialom et al., 2021a).

5 Results

5.1 Summarization

We report the Pearson correlation between MaskEval scores and human judgments on the SummEval dataset in Table 1.

MaskEval\textsubscript{Summ} achieves good scores on average, the candidate-only variant surpassing QuestEval by 4.3 points, although remaining below BARTscore by 1.3 points. The slightly lower average score for MaskEval\textsubscript{Summ} than BARTscore is mainly due to the lower score for coherence, which could be explained by the use of an MLM rather than auto-regressive decoding. However, it per-
Table 2: English simplification results on the ASSET dataset (Pearson correlation). Unless indicated otherwise, the results are on the full ASSET test set.

|                        | ASSET, with reference(s) | ASSET, reference-less |
|------------------------|--------------------------|-----------------------|
|                        | #refs | flu | sim | mea | flu | sim | mea |
| ROUGE-1                | 10    | 42.0 | 42.4 | 61.8 | 33.7 | 31.2 | 47.9 |
| ROUGE-L                | 10    | 40.9 | 41.0 | 59.4 | 31.8 | 28.5 | 43.0 |
| BLEU                   | 10    | 28.9 | 29.5 | 47.6 | 25.6 | 23.5 | 29.9 |
| BERTScore-f            | 10    | 58.0 | 54.7 | 73.4 | 48.5 | 46.8 | 61.4 |
| SARI                   | 10    | 34.4 | 29.9 | 51.9 | 30.1 | 25.2 | 33.4 |
| Perplexity             |       | 22.9 | 20.4 | 23.1 |       |       |     |
| Length                 |       | 2.5  | -0.8 | 19.4 |       |       |     |
| BARTScore              |       | 57.5 | 52.0 | 70.6 |       |       |     |
| PRISM                  |       | 56.8 | 45.1 | 71.0 |       |       |     |
| QuestEval              |       | 33.9 | 32.7 | 63.4 |       |       |     |
| MaskEvalSimpl uniform  |       | 50.5 | 43.6 | 67.5 |       |       |     |
| MaskEvalSimpl candidate|       | 53.6 | 50.3 | 63.6 |       |       |     |
| MaskEvalSumm uniform   |       | 48.6 | 40.3 | 66.7 |       |       |     |
| MaskEvalSumm candidate |       | 49.8 | 42.8 | 61.0 |       |       |     |
| MaskEvalSumm uniform   |       | 39.6 | 31.1 | 61.9 |       |       |     |
| MaskEvalSumm candidate |       | 58.7 | 51.8 | 56.9 |       |       |     |
| MaskEvalSimpl          |       | 44.0 | 34.1 | 65.0 |       |       |     |
| MaskEvalSumm           |       | 49.5 | 46.3 | 68.8 |       |       |     |
| MaskEvalSimpl learned  |       | 39.7 | 32.9 | 58.7 |       |       |     |

Table 2: English simplification results on the ASSET dataset (Pearson correlation). Unless indicated otherwise, the results are on the full ASSET test set.

forms better than all previous metrics on two out of four dimensions, outperforming both BARTScore and QuestEval for consistency and fluency. The dimension that benefits most from our approach with respect to the previous best score is fluency (45.9<33.1).

With learned weights, MaskEvalSumm is able to improve its performance in all four dimensions with respect to uniform weighting, with relevance being improved the most (+18%).

5.2 Simplification

We report the Pearson correlation between MaskEval scores and human judgments on the simplification evaluation set in Table 2. Without considering the transfer scenario, the highest performing metric is the reference-based BERTScore, when it has access to 10 references. The best reference-less metric is BARTScore, although PRISM is best for meaning preservation.

MaskEvalSimpl with uniform weighting has good correlations, behind both BARTscore and PRISM, but outperforming QuestEval. Given the very small number of examples that could be used to train the weighters, MaskEvalSimpl with learned weights is unable to improve its performance in any of the dimensions in ASSET. We nevertheless report these figures for completeness.

5.3 Transfer Between Tasks

We also report scores for transfer between the tasks in Tables 1 and 2. MaskEval with uniform weights trained for the task performs similarly to its counterpart trained for the other task. This shows that transfer is possible between the tasks.

For the weighted versions of the metrics, MaskEvalSimpl does not provide improvements when transferring, which is not unexpected given its poor performance on simplification. However positive results can be seen when transferring from the weighted version of MaskEvalSumm to simplification. In particular, with weights optimized for summarization fluency, MaskEvalSumm obtains state-of-the-art result on fluency, and greatly improves simplicity. Whilst it is expected that optimizing for summarization fluency improved simplification fluency, the improvements in the simplicity dimension are more surprising, and show the judgments for fluency are easily influenced by other evaluation dimensions. However, these results do show the potential to be able to transfer across dimensions from different tasks, which could be interesting when there are few annotations available.

6 Discussion

We choose to analyze our highest performing set of weighters, those optimized for summarization dimensions. In the following sections, the learned weight of a word $x_i$ (resp. $y_j$) includes the candidate weight, thus equaling $c \cdot w_{x_i}$ (resp. $1 - c \cdot w_{y_j}$).

6.1 Analysis of the Weighting Function

Figure 4 shows the average weight distribution across parts of speech on summary-source pairs from the test set of SummEval. We can see that by using weights optimized for fluency, MaskEval primarily uses MLM steps masking adpositions, determinants, and other POS tags (i.e. conjunctions, numbers, etc.) in the summary. This is expected since the fluency of a summary does not involve the source document. This equally applies to simplifi-
culation, which could explain the great performance we obtain during task transfer.

Some weights behave in an unexpected way: the weights optimized for factual consistency gives more importance to determiners than to nouns, which goes against the assumption commonly held by existing question-based metrics that nouns contain the most salient information.

6.2 Sparsity: Towards Selective Masking

An important factor for an automatic metric to be widely adopted is computational efficiency. This was one of the important concerns with question-based metrics. We propose to use our weighters to selectively mask the input texts, only calculating scores based on the highest weighted MLM steps, in order to reduce the number of masked predictions while best maintaining performance.

In Figure 5, we report the Pearson correlation on the test subset of SummEval when only some weighted MLM steps are used in the computation of the MaskEval score (i.e we apply the weighter before the MLM step). We sort them by their weight, and only keep the top MLM steps whose learned weights sum up to a set threshold, computing the MaskEval score using the retained MLM steps only. We can see that a threshold of $\sim 0.70$ to preserve over 90% of MaskEval’s original performance, and to match the performance of MaskEval with uniform weights. This threshold corresponds to only considering (on average) 25 to 130 MLM steps of a total of 480. This suggests that with learned weights, the number of MLM steps necessary can be greatly reduced without compromising the performance.

7 Conclusion

We have proposed MaskEval, a metric for summarization and simplification that scores words in source and candidate texts using a MLM, then applies a learned weighting function over those scores, optimized to the task and evaluation dimension. Our analysis shows that different weights are applied depending on the dimension and that some parts of speech such as adpositions are more important than previously suspected. Our weighting function also allows us to produce a light-weight version of the metric, which uses only $\sim 20\%$ of the words to reach comparable correlation performance to using uniform weighting over all words.

In future work, we plan to test the approach for other text generation tasks (e.g. MT) and for languages other than English, depending on the availability of such data.
Limitations

Our LM-based metric can be easily adapted to a multilingual setting by finetuning a multilingual LM instead of the English one used in this paper. However, due to the lack of human annotations in multilingual summarization and simplification, we have not yet tested this capability. The capability of our metric to provide a good evaluation for texts from other tasks, other text generation systems, and other data distributions is also left to future work. Note that We considered using the Multi-SummEval dataset (Koto et al., 2021) to test the multilingual capacity of our metric. However, we decided against this, due to potential problems we identified in the human annotation scheme employed in Multi-SummEval. Notably, (i) annotators did not have access to source documents and annotated on the basis of a single reference text and (ii) automatic evaluation metrics reported having a higher performance than human annotators.

We measure the performance of our proposed metric by computing the correlation of its output scores with that given by human annotators. Our results are therefore reliant on the quality of evaluation datasets. For SummEval, for example, we have employed scores given by experts (annotators who have written academic papers on the topic of summarization). The expertise of these annotators may introduce a bias in the evaluation set as their judgments might differ from that of regular users of summarization systems.

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A Implementation Details

A.1 Training Details

MLMs Both MLMs are fine-tuned for three epochs, with a batch size of 8 and the AdamW optimizer (Loshchilov and Hutter, 2017), used with a constant learning rate of 1e-5. We trained using an NVIDIA QUADRO RTX 8000, with 48GB GPU memory. 20% of the assigned training set is held-out during training to act as the validation set. We select the best checkpoint as being the one with the lowest validation loss.

Attention Weight Module The weighter is trained over 100 epochs, using Adam optimizer (Kingma and Ba, 2015) with a constant learning rate of 1e-5. 20% of the assigned training set is held-out during training to act as the validation set. Our final weighting function is produced by the checkpoint with the lowest validation loss. We randomly initialize weight vector $W$ (from Equation 6) and initialize candidate weight $c$ (from Equation 5) to 0.5.