

# Pre-gen metrics: Predicting caption quality metrics without generating captions

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**Abstract.** Image caption generation systems are typically evaluated against reference outputs. We show that it is possible to predict output quality without generating the captions, based on the probability assigned by the neural model to the reference captions. Such pre-gen metrics are strongly correlated to standard evaluation metrics.

**Keywords:** Image captioning; Neural architectures; Evaluation metrics

## 1 Introduction

Automatic metrics for image description generation (IDG) compare  $c$ , a generated caption, to a set of reference sentences,  $R_1 \dots R_n$ . We therefore refer to these as **post-gen**(eration) metrics. In most neural IDG architectures generation is performed by an algorithm such as beam search that samples the vocabulary at every timestep, selecting a likely next word after a given sentence prefix (according to the neural network) and attaching it to the end of the prefix, and repeating this procedure until the entire caption is produced. Given that the output thus generated is evaluated against a gold standard, post-gen metrics actually evaluate the neural network’s ability to predict the words in the reference captions given an image. Unfortunately, generating sentences is a time consuming process due to the fact that every word in a sentence requires its own forward pass through the neural network. This means that generating a 20-word sentence requires calling the neural network 20 times. As an indicative example, it takes 20.8 minutes to generate captions for every image in the MSCOCO test set on a standard hardware setup (GeForce GTX 760) using a beam width of just 1.

Our question is whether a system’s performance can be assessed *prior* to the generation step, by exploiting the fact that the output is ultimately based on this core sampling mechanism. We envisage a scenario in which a neural caption generator is evaluated based on the extent to which its estimated softmax probabilities over the vocabulary maximise the probability of the words in the reference sentences  $R_1 \dots R_n$ . We refer to this as a **pre-gen**(eration) evaluation metric, as it can be computed prior to generating any captions. A well-known example of a pre-gen metric is language model perplexity although, as we show below, this metric is not the best pre-gen candidate in terms of its correlation to standard evaluation measures for IDG systems.

From a development perspective, the advantage of a pre-gen metric lies in that all the word probabilities in a sentence are immediately available to the network in one forward pass, whereas a post-gen metric can only be computed following a relatively expensive process of word-by-word generation requiring repeated calls to a neural network. To return to the earlier example, on the same hardware setup it only takes 28 seconds to compute model perplexity.

Thus, if pre-gen metrics can be shown to correlate strongly with established post-gen metrics, they could serve as a proxy for such metrics. This would speed up processes requiring repeated caption quality measurement such as during hyperparameter tuning.

Finally, from a theoretical and empirical perspective, if caption quality, as measured by one or more post-gen metric(s), can be predicted prior to generation, this would shed further light on the underlying reasons for the observed correlations of such metrics [14].

All code used in these experiments is publicly available.<sup>1</sup>

The rest of this paper is organised as follows; background on metrics is covered in section 2, the methodology and experimental setup in section 3, and the results are given in section 4; the paper is concluded in section 5.

## 2 Background: *Post-gen* metrics for image captioning

In IDG, automatic metrics originally developed for Machine Translation or Summarisation, such as BLEU [21], ROUGE [18], and METEOR [2], were initially adopted, followed by metrics specifically designed for image description, notably CIDEr [24] and SPICE [1]. Lately, Word Mover’s Distance (WMD) [17], originally from the document similarity community, has also been suggested for IDG [14]. Like BLEU, ROUGE and METEOR, CIDEr makes use of n-gram similarities, while WMD measures the semantic distance between texts on the basis of word2vec [20] embeddings. All of these metrics are purely linguistically informed. By contrast, SPICE computes similarity between sentences from scene graphs [13], obtained by parsing reference sentences. This method is also linguistically informed; however the intuition behind it is that the human authored sentences should be an accurate reflection of image content.

A typical IDG experiment reports several post-gen metrics. One reason is that the metrics correlate differently with human judgments, depending on task and dataset [3], echoing similar findings in other areas of NLP [7, 5, 6, 22, 4, 11, 10, 26]. Thus, BLEU, METEOR, and ROUGE correlate weakly [16, 12, 15] and yield different system rankings compared to human judgments [25]. METEOR has a reportedly higher correlation than BLEU/ROUGE [8, 9], with stronger relationships reported for CIDEr [24] and SPICE [1]. Meta-evaluation of the ability of metrics to discriminate between captions have also been somewhat inconsistent [24, 14].

The extent to which post-gen metrics correlate with each other also varies, with stronger relationships among those based on n-grams on the one hand, and

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<sup>1</sup> See: <https://github.com/mtanti/pregen-metrics>

more semantically-oriented ones on the other [14], suggesting that these groups assess complementary aspects of quality, and partially explaining their variable relationship to human judgments in addition to variations due to dataset.

For neural IDG architectures, post-gen metrics have one fundamental property in common: they compare reference outputs to generated sentences which are based on sampling at each time-step from a probability distribution. Our hypothesis is that it is possible to exploit this, using the probability distribution itself to directly estimate the quality of captions, prior to generation.

### 3 Pre-gen Metrics

Given a prefix, a neural caption generator predicts the next word by sampling from the softmax’s probabilities estimated over the vocabulary. Let  $R$  be a reference caption of length  $m$ . Given a prefix  $R^{0\dots k}$  (where  $R^0$  is the start token),  $k \leq m$ , a neural caption generator can be used to estimate the probability of the next word (or the end token) in the reference caption,  $R^{k+1}$ . The intuition underlying pre-gen metrics is that the higher the estimated probability of  $R^{k+1}$ , for all  $k \leq m$ , the more likely it is that the generator will approximate the reference caption. Note that the idea is to estimate the probability of *reference* captions based on a trained IDG model.

Pre-gen metrics produce a score by aggregating the word probabilities predicted by the generator for all reference captions (combined with their respective image) over prefixes of different lengths. To find the best way to do this, we define a search space by setting options at four different algorithmic steps which we call ‘tiers’. Each tier represents a function and the composition of all four tiers together constitutes a pre-gen function. We try several different options for each tier in order to find the best pre-gen function. Figure 1 shows an example of how tiers form a pre-gen function.

Given a set of images with their corresponding reference captions, the process starts by computing each reference caption’s the individual word probabilities (given the image) according to the model. Note that the model may not predict every word in a reference caption as the most likely in the vocabulary.

The first tier is a filter that selects which predicted word probabilities should be considered in the next tier. We consider three possible filters: (a) the filter *none* passes all probabilities; (b) *filter0* filters out the word probabilities that are not ranked as most probable in the vocabulary by the model, i.e are not predicted to be maximally probable continuations of the current prefix; and (c) *prefix0* selects the longest prefix of the caption such that the model predicts all words in the prefix as being the most likely in the vocabulary.

At the second tier, we aggregate the selected word probabilities in each reference sentence into a single score for each sentence. We define four possible functions: (a) *prob* multiplies all probabilities; (b) *pplx* computes the perplexity; (c) *count* counts the number of word probabilities that were selected in the first tier; and (d) *normcount* normalises *count* by the total number of words in the reference sentence.

Ground truth sentences for each image	image 1	• a dog nipping at the feet of a cow <END> • a dog pounces on the grass <END>
	image 2	• a dog eating a pine cone <END> • a dog plays with a pine cone <END>
Find probabilities of each word according to caption generator (probabilities in bold are maximum in vocabulary)	image 1	• <b>0.975 0.566 0.246 0.938 0.913 0.486 0.940 0.925 0.142 0.928</b> • <b>0.975 0.566 0.244 0.918 0.938 0.483 0.926</b>
	image 2	• <b>0.975 0.566 0.245 0.918 0.283 0.960 0.958</b> • <b>0.975 0.566 0.245 0.928 0.908 0.283 0.96 0.958</b>
Tier 1: Take longest prefix of maximal probabilities	image 1	• <b>0.975 0.566 0.246 0.938 0.913 0.486 0.940 0.925</b> • <b>0.975 0.566</b>
	image 2	• <b>0.975 0.566</b> • <b>0.975 0.566</b>
Tier 2: Calculate the length of each sequence divided by original length	image 1	• $8/10 = 0.800$ • $2/7 = 0.286$
	image 2	• $2/7 = 0.286$ • $2/8 = 0.250$
Tier 3: Calculate the maximum of each image's normalized length	image 1	0.800
	image 2	0.286
Tier 4: Calculate the mean of the image scores		0.543

Fig. 1: An example illustrating how tiers work. This illustration shows the best pre-gen metric found: *mean\_max\_normcount\_prefix0*.

The third tier aggregates the scores obtained for all reference sentences into a single score for each image. We explore six possibilities: (a) *sum*; (b) *mean*; (c) *median*; (d) *geomean*, the geometric mean; (e) *max*; and (f) *min*. We also consider (g) *join*, whereby all the image-sentence scores are joined into a single list without aggregation so that they are all aggregated together in the next tier.

The fourth tier aggregates the image scores into a single dataset score, which is the final pre-gen score of the caption generator. For this aggregation, we use the same six functions as in the previous tier (excluding *join*).

The above possibilities result in 504 unique combinations. In what follows, we adopt the convention of denoting a pre-gen metric by the sequence of function names that compose it, starting from tier four e.g. *mean\_max\_normcount\_prefix0*. In our experiments, we compute all of these different combinations and compare their predictions to standard post-gen metrics, namely METEOR, CIDEr, SPICE, and WMD. All metrics except WMD were computed using the MSCOCO Evaluation toolkit<sup>2</sup>. Since the toolkit does not include WMD, we created a fork of the repository that includes it.<sup>3</sup>

<sup>2</sup> See: <https://github.com/tylin/coco-caption>

<sup>3</sup> See: <https://github.com/mtanti/coco-caption>

### 3.1 Experimental Setup

For our experiments, we used a variety of pre-trained neural caption generators (36 in all) from [23].<sup>4</sup> These models are based on four different caption generator architectures. Each was trained and tested over three runs on Flickr8k [12], Flickr30k [27], and MSCOCO [19]. The four architectures differ in terms of how the CNN image encoder is combined with the RNN: **init** architectures use the image vector as the initial hidden state of the RNN decoder; **pre** architectures treat the image vector as the first word of a caption; **par** architectures are trained on captions where each word is coupled with an image vector at each time-step; and **merge** architectures keep the image out of the the RNN entirely, merging the image vector with the RNN hidden state in a final feedforward layer, prior to prediction.

Since only the final trained versions of the models are available, there is a bias towards good quality post-gen metric results. This renders the values of the post-gen metrics rather similar and concentrated in a small range. A pre-gen metric is useful if it makes good predictions on models of any quality not just good ones. Rather than re-training all the models and saving the parameters at different intervals during training, we opted to stratify the dataset on the basis of how well each individual image is rated by the CIDEr metric.

We grouped images into the best and worst halves on the basis of the CIDEr score (since CIDEr is the post-gen metric that best correlates with the other post-gen metrics [14]) of their sentences as generated by a model. This creates two datasets, one where the model performs well and one where the model performs badly. We stratified the dataset into different numbers of equal parts and not just two, namely: 1 (whole), 2, 3, 4 and 5, resulting in a 15-fold increase over the original 36 averaged results and more importantly, over a wide dynamic range in CIDEr scores, which we required to study the correlation in between pre- and post-gen metrics.

## 4 Results

We evaluate the correlation between pre- and post-gen metrics using the Coefficient of Determination, or  $R^2$ , defined as the square of the Pearson correlation coefficient. The reason for this is twofold. First,  $R^2$  reflects the magnitude of a correlation, irrespective of whether it is positive or negative (the pre-gen metrics based on perplexity would be expected to be negatively correlated with post-gen metrics). Second, given a linear model in which a pre-gen metric is used to predict the value on a post-gen metric,  $R^2$  indicates the proportion of the variance in the latter that the pre-gen metric predicts.

As a baseline, we show the scatter plot for the relationship between language model perplexity and the post-gen metrics in Figure 2. In terms of the description in the previous section, perplexity is defined as *geomean-join-pplx-none*. As can be seen, perplexity performs somewhat poorly on low scoring captions. Our question is whether a better pre-gen metric can be found.

<sup>4</sup> See: <https://github.com/mtanti/where-image2>

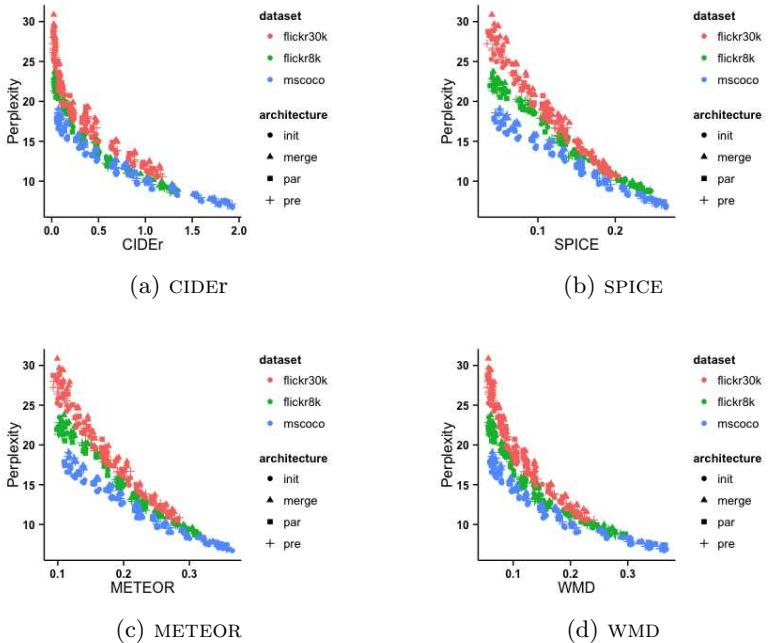


Fig. 2: Relationship between perplexity and post-gen metrics by dataset and architecture. The overall correlation has an  $R^2$  of 0.76. (Best viewed in colour.)

For each of the 4 post-gen metrics, we identified the top 5 best correlated pre-gen metrics, based on the  $R^2$  value computed over all the data (i.e. aggregating scores across architectures and datasets). The top 4 pre-gen metrics were the same for all post-gen metrics, namely:

1. *mean\_max\_normcount\_prefix0*;
2. *mean\_mean\_normcount\_prefix0*;
3. *mean\_join\_normcount\_prefix0*;
4. *mean\_sum\_normcount\_prefix0*

Note that all the best performing metrics are based on the variable *prefix0*. This is not surprising since when generating a sentence, it is probably the word with the maximum probability in the vocabulary which gets selected as a next word in a prefix. On the other hand, the fifth most highly correlated pre-gen metric differed for each post-gen metric, as follows:

- CIDEr: *mean\_min\_count\_filter0*;
- METEOR: *mean\_mean\_count\_prefix0*;
- SPICE: *geomean\_min\_pplx\_filter0*;
- WMD: *mean\_join\_count\_prefix0*

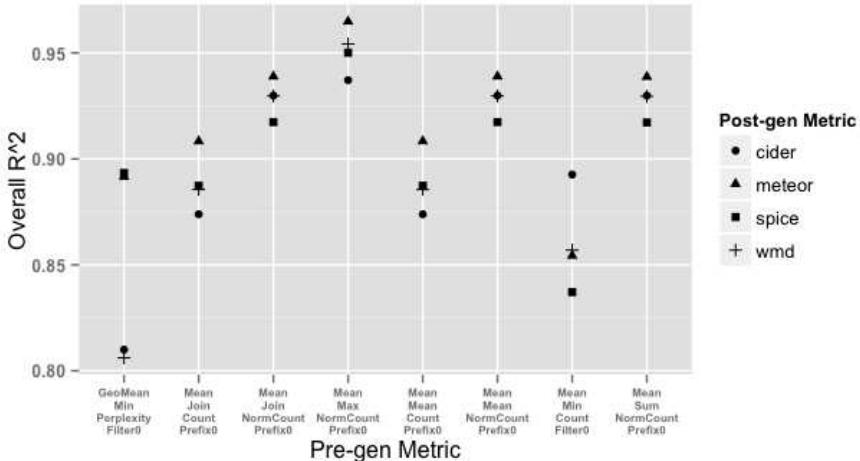


Fig. 3: Overall  $R^2$  between the 4 post-gen metrics and their 5 most highly correlated pre-gen metrics. Scores average over architectures and datasets.

Figure 3 displays the relationship between these pre-gen metrics and the post-gen scores. Note that all  $R^2$  scores are above 0.8, indicating a very strong correlation.<sup>5</sup> The top 4 scores have  $R^2 \geq 0.9$ .

To investigate the relationship between pre- and post-gen metrics more closely, we focus on the best pre-gen metric (that is, *mean\_max\_normcount\_prefix0*) and consider its relationship to each post-gen metric individually. This is shown in Figure 4. Irrespective of architecture and/or dataset, we observe a broadly linear relationship, despite some evidence of non-linearity at the lower ends of the scale, especially for CIDEr and WMD. This supports the hypothesis made at the outset, namely, that it is possible to predict the quality of captions, as measured by a standard metric, by considering the probability of the reference captions in the test set, without the need to generate the captions themselves.

## 5 Discussion and conclusion

We have introduced and defined the concept of pre-gen metrics and described a methodology to search for useful variants of these metrics. Our results show that pre-gen metrics closely approximate a variety of standard evaluation measures.

These results can be attributed to the fact that neural captioning models share core assumptions about the sampling mechanisms that underlie generation, and that standard evaluation metrics ultimately assess the output of this sampling process. Thus, it is possible to predict the quality of the output, as measured by a post-gen metric, using the probability distribution that a trained

<sup>5</sup> All correlations are significant at  $p < 0.001$ .

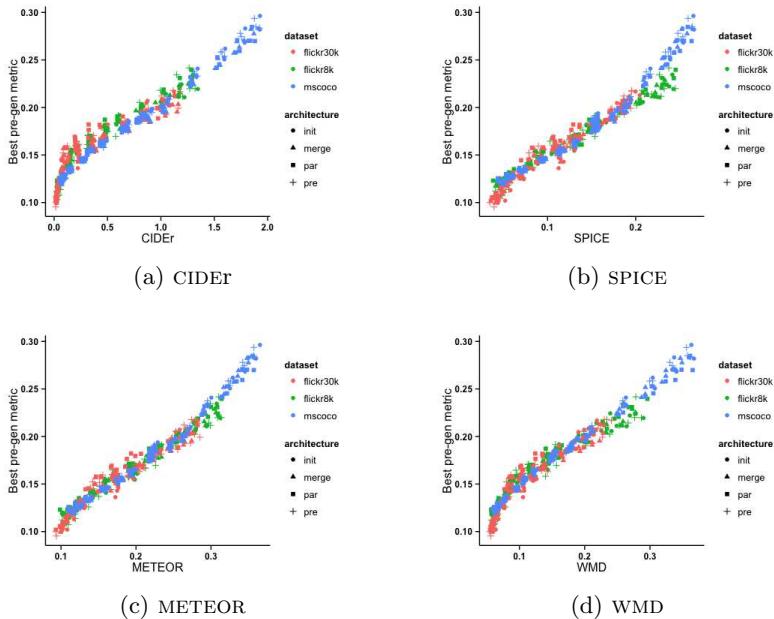


Fig. 4: Best pre-gen metric (`mean_max_normcount_prefix0`) vs post-gen metrics. The overall correlation has an  $R^2$  of 0.94. (Best viewed in colour.)

model predicts over prefixes of varying length in the reference captions. The practical implication is that pre-gen metrics can act as quick and efficient evaluation proxies during development. The theoretical implication is that the correlations among standard evaluation metrics reported in the literature are due, at least in part, to core sampling mechanisms shared by most neural generation architectures.

In future work, we plan to experiment with tuning captioning models using pre-gen metrics. We also wish to compare pre-gen metrics directly to human judgments.

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