Perception Score, A Learned Metric for Open-ended Text Generation Evaluation

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Abstract

Automatic evaluation for open-ended natural language generation tasks remains a challenge. Existing metrics such as BLEU show a low correlation with human judgment. We propose a novel and powerful learning-based evaluation metric: PERCEPTION SCORE. The method measures the overall quality of the generation and scores holistically instead of only focusing on one evaluation criteria, such as word overlapping. Moreover, it also shows the amount of uncertainty about its evaluation result. By connecting the uncertainty, PERCEPTION SCORE gives a more accurate evaluation for the generation system. PERCEPTION SCORE provides state-of-the-art results on two conditional generation tasks and two unconditional generation tasks.

Introduction

With the recent advances in natural language generation (NLG) tasks, automatic evaluation has drawn more attention from the research community. However, the evaluation of an advanced generation model faces obstacles with the shortcomings of existing metrics, especially in open-ended text generation tasks.

Existing metrics such as BLEU and BLEURT have been proved useful in various text generations evaluation tasks. Usually, these metrics measure the similarity between the reference and the candidate in different standards. However, when it comes to open-ended tasks, these metrics will become less effective.

N-gram overlapping based metrics such as BLEU [Papineni et al. 2002] and ROUGE [Lin 2004] could be the most widely used ones across different NLG tasks. These metrics only consider word-form variation and often fail to capture the real semantic meaning which the reference or the candidate conveys. A candidate sentence that shares similar semantic meaning with the reference will be scored unfairly low under n-gram matching. As a result, these metrics inevitably show poor correlation with human judgment [Liu et al. 2016; Novikova et al. 2017; Chaganty, Mussmann, and Liang 2018].

Recently, different neural network-based metrics are also proposed towards text generation evaluation. BERTSCORE [Zhang* et al. 2020] replace the hard n-gram matching with a soft similarity of context embedding. MOVERSCORE [Zhao et al. 2019] word embeddings of a pre-trained model to find the semantic similarity via Word Mover’s Distance. Both methods utilize prior knowledge in a large pre-trained neural model. However, the semantic meaning of generation and reference could be context-dependent, especially in open-ended generation task. Furthermore, for those metrics which claim to capture the semantic meaning, can they really measure the quality of a sentence? For example, how do they measure a story that is enchanting but also reasonable, or how do they understand a poem is striking but also rhyming? It requires more than the surface of words to recognize and comprehend in open-ended generation tasks. To truly fathom the quality of generations, we need to transcend the limits of using the superficial understanding of a language.

In the creed of building a universal and straightforward evaluation metric for open-ended text generation tasks, we propose PERCEPTION SCORE, a system-level automated evaluation metric that diffuses evaluation onto the multi-dimensional space and assigns a single holistic score based on its overall quality to system-generated text with the reference as goal standard. This gives us the most direct observation of the quality through the comparisons of the reference and the generated text. By using a large pre-training model, PERCEPTION SCORE learns to measures the difference between the generations and the distribution of references. Moreover, PERCEPTION SCORE also shows data uncertainty estimation and model uncertainty estimation when scoring generated text. PERCEPTION SCORE provides a more accurate overall evaluation for a generation system by focusing more on the generation that is scored with confidence. We validate PERCEPTION SCORE with extensive experiments on four tasks, including two conditional generation tasks, i.e., ROCStories and Large Movie Review Conditional, and two unconditional tasks, i.e., Large Movie Review Unconditional and COCO Image Captions. PERCEPTION SCORE shows stronger correlation with human judgement than other metrics including BLEU, PERPLEXITY, BERTSCORE and BLEURT. Besides, it show more robustness than other metrics under several adversarial attacks.
Related Works

Evaluation is an essential topic in natural language generation. While human evaluation is probably the most accurate metric for generation evaluation (Celikyilmaz, Clark, and Gao 2020), it is usually time-consuming and expensive. Researchers have proposed different types of automated evaluation metrics to replace human evaluation.

$n$-gram matching is the most used evaluation method in the natural language generation task. In the machine translation task, BLEU is a common metric to evaluate the similarity between candidates and references in word surface level. METEOR is also an automatic metric for machine translation evaluation which considers surface forms, stemmed forms and meanings. ROUGE (Lin 2004) is commonly used in summarization evaluation task. The performance of $n$-gram matching metric only considers similarity in word surface.

PERPLEXITY is another commonly used metric in open-ended generation tasks such as chit-chat tasks. It has been proven to be a proper measurement of the quality of a language model but can not directly reflect the generation sentence quality.

Recently, context embedding in the large pre-trained model is also used for evaluation. BERTSCORE utilizes semantic embeddings in large pre-trained neural models for each token, then applies cosine similarity and greedy matching to maximize the similarity score between references and candidates. MOVERSSCORE combines the contextual embeddings from a pre-trained model and Word Mover’s Distance to evaluate text generation. These metric utilizes large pre-trained models to could evaluate the semantic similarity between the references and candidates. However, in an open-ended generation, a generated text of high quality could have a different meaning with the reference.

Recently, various learned metrics are also proposed. Blend (Ma et al. 2017) uses an SVM model to combine different existing evaluation metrics. RUSE (Shimanaka, Kajiwara, and Komachi 2018) evaluates machine translation by training sentence embeddings on data obtained in other tasks. Cui et al. (2018) trains a neural network conditioning on image to distinguish between human and machine-generated captions. BLEURT utilizes a BERT model fine-tuned on various automated metrics to evaluate the quality of the generated text. Zhou and Xue (2020) propose to evaluate NLG models by learning to compare a pair of generated sentences by fine-tuning BERT.

Since human evaluation remains the gold standard for almost all NLG tasks, another popular research topic is to train an augmented metric based on human evaluation. To calibrate human judgments and automatic evaluation metrics, model-based approaches that use human judgments as attributes or labels have been proposed. HUSE (Hashimoto, Komachi 2018) evaluates machine translation by training a neural network conditioning on image and risk poor generalization to new domains. Meanwhile, the human evaluation to evaluate summarization and chit-chat contribute or labels have been proposed. HUSE (Hashimoto, Komachi 2018) evaluates machine translation by training a neural network conditioning on image and risk poor generalization to new domains.

We define Perception Score as a function $\delta$ that measures the realness of the generation with the reference as the goal standard. Since realness is a relative measure, in contrast to the static evaluation metrics, PERCEPTION SCORE is a learning-based metric and should be parameterized to fit various evaluation tasks.

We define this realness by aggregating the inter-distances between every pair of samples in the reference set and generation sets. In mathematics terms, such realness measure is defined as:

$$\delta_{\theta} = \arg \max_{\theta} \mathbb{E}_{\hat{x} \sim P_G, x \sim P_R} [\delta_{\theta}(\hat{x}, x)]$$

Since in many NLG tasks, the semantic meaning of the generation is context-dependent, we further incorporate context information into $G$ and $R$ to get comprehensive understanding in evaluation process. We now have $G = \{(c_1, \hat{x}_1), \ldots, (c_n, \hat{x}_n)\}$, and have $R$ as $\{(c_1, x_1), \ldots, (c_n, x_n)\}$, where $c_i$ is the context of $i$-th sample in the dataset.

Eq[1]can be viewed as one form of Earth Mover’s Distance (EMD). EMD is a measure of the distance between two probability distributions. The goal is to compute a reasonable and efficient approximation of EMD.

Apply the Earth-Movers’ Distance or Wassertein-1, we have

$$W(P_G, P_R) = \inf_{\gamma \in \Pi(P_G, P_R)} \mathbb{E}_{(x, \hat{x}) \sim \gamma} [||x - \hat{x}||]$$

where $\Pi(P_G, P_R)$ denotes the set of all joints distributions. $\gamma$ indicates how much “mass” must be transported from $\hat{x}$ to $x$ in order to transform the distribution $P_G$ to the distribution $P_R$. The EM distance is the optimal transport plan.

The formulaFollowing (Arjovsky, Chintala, and Bottou 2017), we convert the formula by using the supremum over the 1-Lipschitz functions.

$$W(P_G, P_R) = \sup_{||f||_1 \leq 1} \mathbb{E}_{\hat{x} \sim P_G} [f(\hat{x})] - \mathbb{E}_{x \sim P_R} [f(x)]$$

Method

In this section, we first present our proposed metric PERCEPTION SCORE and uncertainty estimation, then we introduce the overall evaluation process.

PERCEPTION SCORE

For a generation system to be evaluated, denote its generation on the dataset as $G = \{\hat{x}_1, \ldots, \hat{x}_n\}$, where $\hat{x}_i$ is the generation for $i$-th sample in the dataset, and denote the corresponding reference as $R = \{x_1, \ldots, x_n\}$. An automated metric evaluates the quality of the generation system by scoring $G$ with $R$ as the goal standard.

Different metrics usually focus on a different aspect in the scoring process. For example, BLEU focuses on word surface overlapping, and BERTSCORE focuses on token-level semantic similarity. A qualified generation usually meets various criteria and high performance in one aspect does not guarantee quality, especially in open-ended natural language generation tasks.

In this section, we first present our proposed metric PERCEPTION SCORE and uncertainty estimation, then we introduce the overall evaluation process.
When we use a neural network to find the solution, it is equivalent to optimize the following problem:

\[ W(P_G, P_R) = \max_\theta \mathbb{E}_{\hat{x} \sim P_G, x \sim P_R}[f_\theta(\hat{x}) - f_\theta(x)] \] (4)

with a gradient penalty loss to fulfill the Lipschitz constraint:

\[ GP = \mathbb{E}_{\hat{x} \sim P_G, x \sim P_R}[(\|\nabla_{\hat{x}, x} D(\hat{x}, x)\|_2 - 1)^2] \] (5)

However, one problem is that in text space, the elements are all discrete. Sequences can also have various lengths, unlike images where the resolution is fixed at the beginning. Then there exists a much larger space for fake sequences than the real sequences. To resolve this problem, we bound the maximum earth-mover distance to be 1. Otherwise, the original distance measure diverges quickly in text space. Thus, instead of directly using the output from Perception Model as the \textsc{Perception Score}, we normalize the output with softmax. We denote the output of the Perception model of reference sample and generation sample as \( f'_\theta(x) \) and \( f'_\theta(y) \), then we have:

\[ P_{\text{generated}} = f_\theta(x) = \frac{e^{f'_\theta(x)}}{e^{f'_\theta(x)} + e^{f'_\theta(y)}} \] (6)

and

\[ P_{\text{reference}} = f_\theta(y) = \frac{e^{f'_\theta(y)}}{e^{f'_\theta(x)} + e^{f'_\theta(y)}} \] (7)

Then we get the final optimization object for neural network:

\[ \arg\max_\theta \mathbb{E}_{x \sim P_r, y \sim P_g} \log P_{\text{reference}} \] (8)

**Uncertainty**

Uncertainty comes with judgment. For example, when we consider a story to be good, we also know how confident we are to the judgment. When evaluating a generation system in NLG tasks, weighing the generation that could be scored with high confidence more leads to a better evaluation of the system overall. Since \textsc{Perception Score} is based on neural networks, we could use the feature of neural networks to measure the uncertainty. Uncertainty in the neural network includes data uncertainty and model uncertainty (Gal 2016). We utilize both of them for a more accurate evaluation result. Gal and Ghahramani (2016) proposes using dropout to measure model uncertainty. During the evaluation process, different random dropout settings are used to get different results from the neural network. Then the variance of those results is a measure of the model uncertainty. We adapt that idea and use dropout to measure the model uncertainty of
**Perception Score.** When $m = 1$, Perception Score is sure that its scoring is correct.

$$m = 1 - \text{Var}(P_{\text{generated}})$$  \hfill (9)

As for data uncertainty, following DeVries and Taylor (2018), we use additional fully-connected layers and sigmoid function.

$$c = f_0(x, y), \quad x \in \mathbb{P}_g, y \in \mathbb{P}_r$$  \hfill (10)

Then the optimize object is adjusted by interpolating between the original Perception Score and the data uncertainty:

$$p' = c \cdot P_{\text{reference}} + (1 - c).$$  \hfill (11)

And instead of optimizing $P_{\text{reference}}$, we optimize $p'$:

$$L_t = - \sum_{i=1}^{M} \log(p'_i).$$  \hfill (12)

As suggested by DeVries and Taylor (2018), we utilize an extra regularizer serving as a loss to prevent the network from minimizing the loss by always choosing data uncertainty as 0.

$$L_c = - \log(c).$$  \hfill (13)

The final loss is the weighted sum of the losses we mentioned:

$$\mathcal{L} = L_t + \lambda L_c + \beta \mathcal{GP}.$$  \hfill (14)

**Evaluation Process**

Now we introduce how to use Perception Score in NLG tasks. The overall using process is similar to the general neural network training process. The dataset is the concatenation of $G$ and $R$. $G$ is generated by the generation system that we want to evaluate. A Perception Model such as RoBERTa learns to grasp the criteria of a high quality generation and to find the difference between the references and the candidates. Then the Perception Score is the result of the test dataset.

Unlike a general classification task, where a more powerful model usually leads to higher accuracy, in our evaluation process, a powerful model leads to a more close approximation of the EMD between $G$ and $R$. In other words, the highest possible Perception Score is only related to the difference between $G$ and $R$.

During the test time, as introduced before, we weigh each generation with its corresponding uncertainty. Then the Perception Score for $G$ is:

$$P_{sys} = \sum_{i=1}^{n} w_i \cdot P_{\text{generated}}$$  \hfill (15)

where $w$ is calculated by model uncertainty $m$ and data uncertainty $c$.

$$w_i = \frac{1/(c_i + m_i)}{\sum_{k=1}^{n} 1/(c_k + m_k)}$$  \hfill (16)

Higher $P_{sys}$ means higher system generation quality. A system whose generation is of the same quality of the reference should get $P_{sys}$ around 0.5, meaning the Perception Model can not distinguish them by text quality.

**Experiment Setting**

A qualified metric should provide similar results with human judgments. We evaluate Perception Score in both open-ended conditional generation and open-ended unconditional generation. The Perception Model could be any neural networks with a strong understanding ability. We use RoBERTa in this paper. We choose the state-of-the-art generation model GPT-2 with different architectures and training hyperparameter choices as the system to be evaluated by Perception Score. We test our proposed metric on four open-ended natural language generation tasks, including two conditional generation tasks and two unconditional generation tasks. Refer Appendix for detail about the datasets.

**Conditional Generation**

In an open-ended conditional generation, a system needs to generate text based on a given context. We first evaluate Perception Score on ROCStoriesCompletion task (Mostafazadeh et al. 2016). The purpose of this task is to generate an open-ended ending for a four-sentence short story. Then we evaluate our method on Large Movie Review Conditional (Maas et al. 2011). The purpose of this dataset is to finish the review based on a movie review context. Since both are open-ended generation tasks, the generation from the language system could share little semantic similarity with the given reference in the dataset.

**Unconditional Generation**

We also evaluate Perception Score on two unconditional generation tasks Large Movie Review Unconditional (Maas et al. 2011) and COCO Image Captions (Chen et al. 2015). The purpose of Large Movie Review Unconditional is to generate an original and high-quality movie, and the purpose of COCO Image Captions is to generate high-quality image caption unconditionally. Unlike in conditional generation, there is no fixed reference for a system generation. Other metrics such as BLEU need to set all text in the dataset as references. However, since Perception Score scores based on how much the generation fits the task and is not limited to word-surface or semantic level similarity, a few references would be enough for Perception Score to measure a generation. In the experiment, we use four references for each generation and take the average Perception Score.

**Result**

**Correlation with Human Judgement**

The performance of an evaluated metric is usually measured by its correlation with the human judgment (Celikyilmaz, Clark, and Gao 2020). Following previous work (Zhang et al. 2020, Zhao et al. 2019), we use Turing score M1 as the human judgment. Turing score M1 is the percentage of a model’s generations that are evaluated as better or equal to the references. We compare with various popular metrics including: BLEU, PERPLEXITY, BERTSCORE, MOVERSCORE, BLEURT. Following BERTScore, we compute the Pearson correlation with Turing score M1.

As is shown in Table 1, Perception Score has the highest correlation with human judgment among all metrics.
Table 1: Correlation with human judgement. R is short for ROCStories dataset. LMRC is short for Large Movie Review Conditional dataset; CIC is short COCO Image Captions dataset; LMRU is short for Large Movie Review Unconditional dataset. Perception Score outperforms other metrics by a large margin in all four tasks.

| Metrics                  | R  | LMRC | CIC  | LMRU |
|--------------------------|----|------|------|------|
| BLEU-1                   | 0.195 | 0.386 | 0.504 | 0.119 |
| BLEU-2                   | 0.491 | 0.316 | 0.0933 | 0.0908 |
| BLEU-3                   | 0.432 | -0.485 | 0.116 | 0.152 |
| BLEU-4                   | 0.355 | -0.390 | 0.0523 | 0.173 |
| PERPLEXITY               | 0.638 | 0.419 | 0.4948 | 0.128 |
| BERTSCORE (base)         | 0.290 | 0.454 | -    | -    |
| BERTSCORE (large)        | 0.282 | 0.474 | -    | -    |
| MOVERSCORE (base)        | 0.313 | 0.467 | -    | -    |
| MOVERSCORE (large)       | 0.328 | 0.487 | -    | -    |
| BLEURT (base)            | 0.513 | 0.467 | -    | -    |
| BLEURT (large)           | 0.529 | 0.491 | -    | -    |
| PERCEPTION SCORE (base)  | 0.671 | 0.488 | 0.563 | 0.231 |
| PERCEPTION SCORE (large) | 0.692 | 0.494 | 0.578 | 0.249 |

Table 2: Ablation study on uncertainty. R is short for ROCStories dataset. LMRC is short for Large Movie Review Conditional; CIC is short COCO Image Captions.

We conduct an ablation study on ROCStories and COCO Image Captions to study the influence of uncertainty. Table 2 presents the experiments results. We found that data uncertainty contributes more to the evaluation performance than the model uncertainty. Note PERCEPTION SCORE still outperforms other metrics without using uncertainty to re-weigh each generation.

Robustness Analysis

We also tested the robustness of PERCEPTION SCORE. After a Perception Model is trained, it also learns the standard of good generation. For example, when it is trained to find the realness of real stories, it also learns what qualifies a good story instead of overfitting the dataset. We first created four kinds of story endings on the test set of ROCStories dataset, and then evaluate these endings with various generation metrics. The created endings types are as following: 1) Human written ending (HWE). Given the story context, turkers created a reasonable story ending. This is used to test metric performance for high quality generation. 2) Lexical different human written ending (LDHWE). Given the story context and the story ending, turkers created a reasonable story ending while avoiding using words from the original reference. 3) Human writing ending with better quality (HWEBQ). Given the story context and the story ending reference, turkers created a reasonable story ending that is of of better quality than the original reference. To reduce the bias, another group of turkers will make sure the created endings is of better quality than the original ones. 4) Adversarial endings (AE). Given the context and the reference, turkers modify the original reference as little as possible to create an unreasonable story ending. We randomly selected 100 stories from the test set of ROCStoriesand ask workers on Amazon Mechanical Turk (also known as Turkers) to create these four kinds of endings.

The evaluation result is shown in Table 3. We also show the various metric scores on the generated ending (GE). Since BERTSCORE has a small scale between 0.8 1.0, MOVERSCORE could give a negative score, and BLEURT scores ranges from negative number to more than 1.0, so we rescale them to 0.0 1.0. The scaling does not affect the ranking

Table 3: Correlation with human judgement. R is short for ROCStories dataset. LMRC is short for Large Movie Review Conditional dataset; CIC is short COCO Image Captions dataset; LMRU is short for Large Movie Review Unconditional dataset. Perception Score outperforms other metrics by a large margin in all four tasks.

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| BLEU-3                   | 0.432 | -0.485 | 0.116 | 0.152 |
| BLEU-4                   | 0.355 | -0.390 | 0.0523 | 0.173 |
| PERPLEXITY               | 0.638 | 0.419 | 0.4948 | 0.128 |
| BERTSCORE (base)         | 0.290 | 0.454 | -    | -    |
| BERTSCORE (large)        | 0.282 | 0.474 | -    | -    |
| MOVERSCORE (base)        | 0.313 | 0.467 | -    | -    |
| MOVERSCORE (large)       | 0.328 | 0.487 | -    | -    |
| BLEURT (base)            | 0.513 | 0.467 | -    | -    |
| BLEURT (large)           | 0.529 | 0.491 | -    | -    |
| PERCEPTION SCORE (base)  | 0.671 | 0.488 | 0.563 | 0.231 |
| PERCEPTION SCORE (large) | 0.692 | 0.494 | 0.578 | 0.249 |
Table 3: Robustness analysis results on ROCStories dataset. MGE is short for model generated ending; HWE is short for Human written ending; LDHWE is short for lexical different human written ending; HWEBQ is short for human writing ending with better quality; AE is short for Adversarial endings.

| Metric   | MGE | HWE | LDHWE | HWEBQ | AE |
|----------|-----|-----|-------|-------|----|
| BLEU-1   | 0.1551 | 0.1348 | 0.1406 | 0.1612 | 0.6816 |
| BLEU-2   | 0.0468 | 0.0359 | 0.0309 | 0.0514 | 0.5809 |
| BLEU-3   | 0.0142 | 0.0125 | 0.0104 | 0.0168 | 0.4411 |
| BLEU-4   | 0.0052 | 0.0054 | 0.0038 | 0.0074 | 0.3014 |
| BERTSCORE| 0.4223 | 0.3631 | 0.3742 | 0.3974 | 0.7586 |
| MOVERSCORE| 0.2439 | 0.2220 | 0.2359 | 0.2510 | 0.5935 |
| BLEURT   | 0.4785 | 0.4847 | 0.4768 | 0.5007 | 0.6458 |
| PERCEPTION SCORE | 0.1115 | 0.4817 | 0.6001 | 0.7845 | 0.3650 |

Figure 3: Created ending example used in robustness analysis.

and the Relationship between data, but only increases readability. The second column is the performance on the original dataset and shows the quality of generated story ending.

As is shown in the third column, we found that all the baseline metrics has a difficulty in recognizing the quality of the good story endings. Since all other metrics are measuring similarity in in word or semantic level, it will fail to judge a good generation that has little similarity with the given reference fairly, which is a common scenario in open-ended generation tasks. In the LDHWE column, we get similar results with the HWE column, It shows that whether the turkers are intended to write a ending that is different than the original reference, the overall wording and semantic of created ending is different than the original one. It matches the common sense that there could be many ground truth text in open-ended task, and using similarity based metric on limited reference will inevitably leads to quality misjudgment. In the HWEBQ column, each metrics show the superiority to the generated ending in quality by presenting a higher score than its corresponding one for the generated endings. However, there is a huge gap between the real quality difference and the quality difference shown by these baseline metrics. For example, BLEU-1 only increases 0.0061. Meanwhile, our PERCEPTION SCORE successfully reflects the quality difference. It does not suggest that PERCEPTION SCORE could be used to judge whether a generation is of higher quality than the given reference, but a reflection of the generalizability of PERCEPTION SCORE. In the last column, we can see that all other base shows a significant boost and gives a high score for a unreasonable ending. Since PERCEPTION SCORE scores much less than 0.5, showing PERCEPTION SCORE scores not solely on the lexical or semantic feature, but also consider the appropriateness under the related context. It shows the necessity of taking context into consideration in open-ended generation tasks.

Conclusion

We propose a learned metric PERCEPTION SCORE for text generation tasks. PERCEPTION SCORE evaluates the semantic difference between generations and references and consider the context information. PERCEPTION SCORE show superiority than various metrics with extensive experiments.
Four different datasets are used. For conditional generation task, we use ROCStories dataset (Mostafazadeh et al. 2016) and IMDB review conditional dataset. ROCStories is to generate an open-ended ending for a four-sentence story. Unlike unconditional or other more constrained text generation tasks, remembering the training set will not lead to good performance in this task, as every story is unique. IMDB review conditional dataset came from Large Movie Review Dataset v1.0. For each review in the Large Movie Review Dataset, we set the context before the last sentence as context and set the last sentence as a review ending. For unconditional generation task, we use COCO Image Captions dataset (Chen et al. 2015) and IMDB review unconditional dataset. IMDB review came from Large Movie Review Dataset v1.0.

| Dataset Name        | Train Tokens | Dev Tokens | Test Tokens |
|---------------------|--------------|------------|-------------|
| ROCStories          | 98,162       | 1,871      | 1,871       |
| IMDB conditional    | 21,730       | 10,854     | 10,854      |
| COCO Image Caption  | 10,000       | -          | 10,000      |
| IMDB unconditional  | 22,146       | 11,063     | 11,062      |

Table 4: Dataset statistics.