Cluster-based Evaluation of Automatically Generated Text

Tiago Pimentel∗1, Clara Meister∗2, Ryan Cotterell2
1 University of Cambridge, 2 ETH Zürich
tp472@cam.ac.uk, clara.meister@inf.ethz.ch, ryan.cotterell@inf.ethz.ch

Abstract

While probabilistic language generators have improved dramatically over the last few years, the automatic evaluation metrics used to assess them have not kept pace with this progress. In the domain of language generation, a good metric must correlate highly with human judgements. Yet, with few exceptions, there is a lack of such metrics in the literature. In this work, we analyse the general paradigm of language generator evaluation. We first discuss the computational and qualitative issues with using automatic evaluation metrics that operate on probability distributions over strings, the backbone of most language generators. We then propose the use of distributions over clusters instead, where we cluster strings based on their text embeddings (obtained from a pretrained language model). While we find the biases introduced by this substitution to be quite strong, we observe that, empirically, this methodology leads to metric estimators with higher correlation with human judgements, while simultaneously reducing estimator variance. We finish the paper with a probing analysis, which leads us to conclude that—by encoding syntactic- and coherence-level features of text, while ignoring surface-level features—these clusters may simply be better equipped to evaluate state-of-the-art language models.

1 Introduction

Probabilistic text generators have improved greatly in quality over the last years, with models producing increasingly human-like text (Yang et al., 2019; Brown et al., 2020; Raffel et al., 2020; Rae et al., 2021; Hoffmann et al., 2022). As the gap between human and model-generated text closes, the quality of our evaluation metrics becomes ever more important for differentiating between the top systems. In this context, human evaluations currently serve as the gold standard. These human evaluations, however, are costly (in both time and money), leading researchers to rely on automatic metrics—i.e., metrics that can be measured by a computer—at least for preliminary experiments.

Many such automatic metrics are based on the comparison of two probability distributions; specifically, comparing the distributions over strings defined by: (1) a language generation model2 and (2) the natural language itself. In fact, this includes some of the most widely used language evaluation metrics:3 cross-entropy (Shannon, 1948), perplexity (Jelinek et al., 1977), and more recently, MAUVE (Pillutla et al., 2021). As typically applied, however, these metrics are inherently ill-suited to evaluate

∗Equal contribution

2We define a language generator as a probability distribution qw over strings w. Specifically, and contra prior work, we consider this distribution as used for sampling, i.e. if a model is augmented with nucleus sampling, we consider the final probability distribution where every sentence not in the nucleus is assigned a probability of zero.

3A number of the measurements considered in this work are not metrics in the strict sense. E.g., cross-entropy is not symmetric. Nonetheless, we use the term “metric” for text evaluation measurements out of convention.
language generation. First, it is difficult (if not impossible) to get tight estimates for them, due to their dependence on the unknown distribution over natural language strings. Second, any generator that assigns zero probability to a valid string—as is the case with systems that use nucleus or top- \( k \) sampling (Fan et al., 2018; Holtzman et al., 2020)—will have both infinite perplexity and cross-entropy with respect to the natural language distribution.

Inspired by Pillutla et al. (2021), we show that these shortcomings can be overcome by using a different class of metrics. Specifically, we do not directly compare our original two distributions over strings. Instead, we first cluster these strings in the embedding space of a pre-trained language model; we then compare the multinomial distributions over these clusters instead. While this substitution leads to quite biased metrics (with respect to the original string-based divergences), it also leads to metrics with much lower variance. Further, these cluster-based evaluations present stronger correlations with human judgements. Specifically, we find that all divergence measures analysed here correlate more strongly with human judgements when cluster-based distributions are used in place of the original string-based ones.

Finally, in order to understand the root of the effectiveness of these cluster-based metrics, we probe the clusters themselves. We find that word order has a strong influence on cluster assignment. Further, sentence-level permutations suggest that these cluster-based metrics are susceptible to coherence-level features of the input text. On the other hand, basic manipulations that render text unhuman-like, such as removing all articles from the input text, do not seem to affect these divergences significantly. Together, these results lead us to conjecture that our clusters might be more useful than raw strings when estimating the qualities of state-of-the-art (SOTA) language models, as SOTA models are known to (at least typically) produce grammatical text. Explicitly, by ignoring surface-level features of text—while emphasising syntactic- and coherence-level ones—clustered embeddings may simply be more easily leveraged for the evaluation of the top language generation systems.

### 2 Comparing Distributions

When evaluating language generation systems, we will first assume the existence of an unknown ground-truth distribution \( p_w \). This distribution is defined over strings \( w \) and its domain spans \( \mathcal{W} \equiv \Sigma^* \), where \( \Sigma \) is an alphabet of words and \( \Sigma^* \) is its Kleene closure. Second, we are given a probabilistic text generator \( q_w \), which is also a distribution over \( \mathcal{W} \). An evaluation metric for a language generator \( q_w \) can now be defined as a measure of its “distance” from \( p_w \):

\[
\Delta(p_w, q_w)
\]

In short, this function \( \Delta(\cdot, \cdot) \) should return high values if \( q_w \) is a bad approximation to \( p_w \), and it should return low values if it is good.

#### 2.1 Divergences as Quality Evaluators

Notably, it is not clear whether \( q_w \) being a good approximation to \( p_w \) guarantees it to be a good language generator. Indeed, models that perform well in terms of standard metrics, such as perplexity, have often been observed to produce poor quality text (Holtzman et al., 2020). In order to choose a good metric \( \Delta(\cdot, \cdot) \), we must assess the quality of the metric itself; typically, this is determined by the metric’s correlation with human judgements.

More formally, we define human quality judgements as a mapping \( \alpha(q_w) \) from a language generator to a real-valued score. For fixed \( p_w \), a good metric \( \Delta(p_w, \cdot) \) is one whose scores for a language generator \( q_w \) correlate highly with the scores assigned to this generator by humans. This notion can be operationalised as follows. Assume we have \( N \) language generator models. Let us define:

\[
\delta_{\text{human}}(q_w^{(1)}, \ldots, q_w^{(N)}) = [\alpha(q_w^{(1)}), \ldots, \alpha(q_w^{(N)})]
\]

\[
\delta_{\text{metric}}(q_w^{(1)}, \ldots, q_w^{(N)}) = [\Delta(p_w, q_w^{(1)}), \ldots, \Delta(p_w, q_w^{(N)})]
\]

We then quantify a metric’s quality on a specific natural language task (and its distribution \( p_w \)) as:

\[
\text{quality}(\Delta, p_w) = |\text{corr}(\delta_{\text{human}}, \delta_{\text{metric}})|
\]
2.2 String-based Divergences

When comparing two probability distributions, it is common to use divergences—statistical “distances” between probability distributions. Here we will analyse several commonly-used divergence measures for evaluating language generators.

**Forward Divergence.** A common choice for \(\Delta(\cdot, \cdot)\) is cross-entropy, \(\Delta_{\text{H}}(p_w, q_w) \overset{\text{def}}{=} H(p_w, q_w)\), which is equivalent (up to an additive constant) to the forward Kullback–Leibler (KL) divergence:

\[\Delta_{\text{H}}(p_w, q_w) \overset{\text{def}}{=} H(p_w, q_w) - H(p_w) \overset{(1)}{=} H(p_w, q_w) = \Delta_{\text{H}}(p_w, q_w)\]  

where (1) is true since \(H(p_w)\) is constant with respect to \(q_w\). Since both Pearson and Spearman correlations are invariant to translational shifts, the cross-entropy and forward KL are equivalent under eq. (4). We will thus refer to them interchangeably (as cross-entropy metric and forward KL) during the subsequent comparison between various \(\Delta\).

**Backward Divergence.** Albeit much less common, another potential evaluation metric would be the backward (exclusive) KL divergence:

\[\Delta_{\text{B}}(p_w, q_w) \overset{\text{def}}{=} KL(q_w \mid\mid p_w)\]  \tag{6}

As opposed to the forward KL, though, this metric is not equivalent to a cross-entropy, as the entropy term in its definition (i.e. \(H(q_w)\)) is not constant across language models \(q_w\).

**Exponentiated Divergence.** By far, the most common choice of \(\Delta\) to evaluate language models is the perplexity: \(\Delta_{\text{exp}}(p_w, q_w) \overset{\text{def}}{=} e^{H(p_w, q_w)}\). Notably, perplexity is equivalent (up to a multiplicative constant) to an exponentiated Kullback–Leibler (KL) divergence between \(p_w\) and \(q_w\), which follows from the same relationship as in eq. (5). Given the property that both Pearson and Spearman correlations are invariant to a change in scale, the perplexity and exponentiated KL will thus be equivalent under eq. (4). For consistency, we will use solely the exponentiated KL in our analyses:

\[\Delta_{\text{exp}}(p_w, q_w) \overset{\text{def}}{=} e^{KL(p_w||q_w)}\]  \tag{7}

**Jensen–Shannon Divergence.** The KL divergence is non-symmetric and unbounded. Further, if a language model \(q_w\) places zero probability on any utterance \(w\) that \(p_w\) assigns probability mass to, both the forward and exponentiated KLs will be infinite. These issues motivate the use of a different measure: the Jensen–Shannon (JS) divergence. The JS divergence is defined as the average of two KLS; it is symmetric with respect to its inputs and is guaranteed to produce bounded values:

\[\Delta_{\text{JS}}(p_w, q_w) \overset{\text{def}}{=} \frac{1}{2} (KL(p_w \mid\mid r_w^5) + KL(q_w \mid\mid r_w^5)), \quad r_w^\lambda = \lambda p_w + (1 - \lambda) q_w\]  \tag{8}

**Area Under the Curve Divergence.** Finally, less conventional measures have been proposed. For instance, Pillutla et al. (2021) recently proposed measuring the area under the curve (AUC):

\[\Delta_{\text{AUC}}(p_w, q_w) = 1 - \text{AUC}\left(e^{-s \cdot KL(p_w||r_w^5)}; e^{-s \cdot KL(q_w||r_w^5)}\right)\]  \tag{9}

where the AUC is taken while varying \(\lambda\) across the interval \([0, 1]\), and \(s \in \mathbb{R}_{>0}\) is a strictly positive real-valued scaling constant. Note that we use \(1 - \text{AUC}(\cdot, \cdot)\) so that a larger value indicates a greater discrepancy with the reference corpus \(p_w\).

3 Infelicities and their Solutions

There are several issues, both computational and qualitative, with using the divergences presented in §2 to evaluate language generators. We now review these issues, along with proposals to address them.

\(^4\)By definition, divergences meet several criteria, including non-negativity and identity of indiscernibles. Here we make use of shifted divergences: a divergence measure that potentially has an additive constant, i.e., there exists a constant \(c \in \mathbb{R}\) such that \(\Delta(\cdot, \cdot) + c\) is a divergence. For our purposes, an additive constant should not affect the quality of our metrics, as the correlation in eq. (4) is invariant to translational shifts.
3.1 Necessity of Full Support

The first shortcoming of these metrics is that some are infinite in the absence of a full support. Specifically, the inclusive (forward) KL is infinite for any model $q_w$ which assigns zero probability to a string possible under $p_w$. This issue will affect two of our presented metrics—the exponentiated and forward divergences—which rely on the inclusive KL divergence between $p_w$ and $q_w$. Most neural language models cannot assign zero probability to any string $w$ due to the final softmax operation used to produce their output, in which case, the above is not an issue. However, these same models are often used with decoding strategies that prune the space $W$: e.g., both top-$k$ and nucleus sampling modify the original distribution $q_w$, such that strings which do not meet a certain criteria are reassigned zero probability. While the shift applied by top-$k$ and nucleus sampling typically leads to models with better human evaluations, these models will likely be given an infinitely bad score by both $\Delta_{\text{exp}}$ and $\Delta_\rightarrow$, which we argue is too harsh a penalty for a perhaps otherwise good language generator.

3.2 $p_w$ is Unknown

In practice, we do not have access to the true distribution $p_w$. Rather, we are typically given a corpus $\{w^p_n\}_{n=1}^N$, whose instances we assume to be sampled i.i.d. from $p_w$. This has lead NLP to favour divergences that can be easily approximated with only a corpus of such samples, i.e., divergences for which we can derive an easily-computable statistical estimator $\hat{\Delta}$. There are two common strategies for building such estimators: Monte Carlo estimation and plug-in estimation.

3.2.1 Monte Carlo Estimation

Our i.i.d. assumption w.r.t. samples $w^p \sim p_w$ allows us to derive a Monte Carlo estimator for certain divergences. We start with the forward KL divergence—present in both $\Delta_\rightarrow$ and $\Delta_{\text{exp}}$—for which we can derive a Monte Carlo estimator:

$$\hat{\KL}(p_w \mid\mid q_w) \equiv \frac{1}{N} \sum_{n=1}^N \log \frac{p_w(w^p_n)}{q_w(w^p_n)} = -\frac{1}{N} \sum_{n=1}^N \log q_w(w^p_n) + \text{const} \quad (10)$$

where const $\in \mathbb{R}$ is constant with respect to $q_w$. Given this approximation to the KL, we can estimate both $\Delta_\rightarrow$ and $\Delta_{\text{exp}}$, e.g. $\Delta_{\rightarrow}(p_w, q_w) \approx -\frac{1}{N} \sum_{n=1}^N \log q_w(w^p_n)$. Unfortunately, the backward, JS, and AUC divergences are not as straightforward to estimate. Consider a Monte Carlo estimator for the backward KL:

$$\Delta_{\leftarrow}(p_w, q_w) \approx \hat{\KL}(q_w \mid\mid p_w) = \frac{1}{N} \sum_{n=1}^N \log \frac{q_w(w^q_n)}{p_w(w^q_n)} \quad (11)$$

where $w^q_n \sim q_w$. We can easily take samples from $q_w$. However, computing eq. (11) additionally requires knowledge of $\log p_w$, which we do not have. This issue motivates the use of our next set of estimation techniques.

3.2.2 Plug-in Estimation

The second approach we can consider in this setting is plug-in estimation—where we construct a density estimator $\hat{p}_w$ and “plug it into” our formulas given in §2.\footnote{Often, plug-in and Monte Carlo estimators must be used together. Even if we are measuring the divergence between two queryable distributions, the sum over $W$ is infinite and non-decomposable, being thus uncomputable.} However, this is a bit circular: arguably, our ultimate goal in creating a language generator $q_w$ is itself to perform density estimation. Thus, if we think $q_w$ is the best estimator for $p_w$, we should logically use it in our plug-in estimator. Yet, using $q_w$ would be nonsensical—it would always lead to the lowest possible value of $\Delta$ when evaluated on the same model, e.g., $\Delta_{\rightarrow}(q_w, q_w) = 0$. If we wish to use plug-in estimation, we must therefore choose $\hat{p}_w$ from a family of density estimators $\pi$ that differs from those used to create $q_w$.

Specifically, we need a function $\pi$ which takes a corpus as input and produces a (queryable) distribution $\hat{p}_w \equiv \pi(\{w^p_n\}_{n=1}^N)$, where $\hat{p}_w$ approximates the original $p_w$. This function can be, e.g., an $n$-gram model or neural network. We can then use the following as our estimator of the backward KL, substituting our density estimator of $p_w$: $\Delta_{\leftarrow}(p_w, q_w) \approx \hat{\KL}(q_w \mid\mid \hat{p}_w)$. Such secondary models would also be necessary for estimating the JS and AUC divergences in a similar manner.
We now take a closer look at the biases introduced by our substitution of cluster distributions. To balance out such biases, we may consider using the same method to create an approximation \( \tilde{q}_w \), rather than directly querying \( q_w \). We thus consider the following plug-in estimator for the backward divergence:

\[
\Delta_b(\{w_n^p\}_{n=1}^N, q_w) \overset{\text{def}}{=} \hat{\text{KL}}(\tilde{q}_w \| \tilde{p}_w)
\]  

Plug-in estimators for \( \Delta_{\text{IS}} \) and \( \Delta_{\text{AUC}} \) are defined similarly. Further, if \( \tilde{q}_w \) is a smoothed approximation to the original \( q_w \), using it may also mitigate the issues discussed in §3.1. We thus also compute estimators for the forward/exponentiated divergences using plug-in estimators, e.g.,:

\[
\hat{\Delta}_f(\{w_n^p\}_{n=1}^N, q_w) \overset{\text{def}}{=} -\frac{1}{N} \sum_{n=1}^N \log \hat{q}_w(w_n^p)
\]

Unfortunately, for most approximation functions \( \pi \), we cannot get a good estimate of \( p_w \) using only a (typically small) corpus \( \{w_n^p\}_{n=1}^N \). Specifically, the problem here is that the best available language models are a class of \( \pi \) that are usually trained on millions (if not billions) of sentences. A typical evaluation set, however, is quite small—on the order of one to ten thousand sentences—and we cannot expect \( \pi \) to provide a good \( \tilde{p}_w \) on such a small dataset. Accordingly, depending on our choice of \( \pi \), this class of metrics may be either high variance or high bias, both of which introduce problems.

### 4 A Clustering-Based Approach

For the \( \hat{\Delta} \) above—which require density estimators for \( p_w \) and/or \( q_w \)—our choice of \( \pi \) will have a large effect on its value. We may thus wish to rethink our approximation technique altogether, and instead work with different distributions for which we can create lower variance density estimators. In this section, drawing inspiration from Pillutla et al.’s (2021) estimators, we examine the use of cluster-based distributions (in place of string-based ones). Specifically, instead of computing the above metrics on the original distributions \( p_w \) and \( q_w \), we will use the cluster-based distributions \( p_c \) and \( q_c \). Given a pretrained language model, we define these cluster-based distributions as:

\[
p_c(c) = \sum_{w \in \mathcal{W}} p_w(w) \mathbb{I}\{c = \phi(\text{PLM}(w))\}
\]

where \( \text{PLM}(\cdot) \) takes as input an utterance \( w \) and outputs an embedding \( r \in \mathbb{R}^d \), and \( \phi(\cdot) \) is a pretrained clustering function. Given these distributions, we can evaluate cluster-based versions of all the divergences above, simply by substituting the original \( p_w \) and \( q_w \) with the new \( p_c \) and \( q_c \).

#### 4.1 Analysing the Divergences

We now take a closer look at the biases introduced by our substitution of cluster distributions. Explicitly, our original divergences had the form \( \text{KL}(p_w \| q_w) \). These KLs can be decomposed as:

\[
\text{KL}(p_w \| q_w) \overset{(1)}{=} \text{KL}(p(c) \| q(c)) + \text{KL}(p(w | c) \| q(w | c)) \geq \text{KL}(p_c \| q_c)
\]

where (1) follows from the fact that \( p(c, w) = p(w) \), which is true because the cluster assignment is deterministic, i.e.: \( p(c \mid w) = \mathbb{I}\{c = \phi(\text{PLM}(w))\} \). See the full decomposition of this equation in App. A. Notably, as KL divergences are always non-negative, these cluster-based metrics are negatively biased, lower-bounding the string-based ones. Further, the actual measurement is done on the distribution over cluster assignments \( p(c) \); the distribution \( p(w \mid c) \) is completely ignored.

Assuming a reasonable number of clusters is used when defining \( p_c \), however, these cluster distributions should be easier to approximate than string distributions—due to the sheer size of the support alone. Consequently, the variance of our metrics should be lower, at the cost of the bias introduced by this substitution. Yet, it is not clear whether this bias is inherently bad when evaluating the quality of language generators: the answer to this question must be determined empirically. To this end, we now provide an empirical comparison between string and cluster-based language generation evaluation.

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\(^6\)Pillutla et al. (2021) originally proposed using clusters to estimate the AUC divergence measure \( \Delta_{\text{AUC}} \). However, they use \( p_c \) as a way to approximate \( p_w \), which we show (in §5.1) not to be a plausible assumption. Instead, we propose the use of \( p_c \) as a principled manner (in itself) to automatically evaluate language generator models.
5 Experiments

Setup. We follow the setup of Pillutla et al. in evaluating our proposed metrics. As our language generation systems, we compare 4 model architectures (all variants of GPT-2), each under two decoding strategies, giving us a total of 8 systems. Explicitly, we compare the small, medium, large, and XL versions of GPT-2, decoding strings using either ancestral or nucleus sampling. We use a nucleus probability of 0.9 for small and medium GPT-2’s, while 0.95 for large and XL GPT-2’s. As human-generated samples \( \{ w_n^w \}_{n=1}^N \), we use 5k strings taken from WebText’s test set. As model-generated text \( \{ w_n^w \}_{n=1}^N \), we sample 5k strings from each of our evaluated systems.\(^7\)

String-based Approximations \( \hat{p}_w \). To compute our string-based divergences, we require a secondary language model \( \hat{p}_w \) to estimate \( p_w \). Further, following the issues highlighted in §3, we will also rely on a secondary language model \( \hat{q}_w \) to estimate \( q_w \). We will use \( n \)-gram models for these approximations. Specifically, we use Kneser-Essen-Ney smoothed 5-gram models, as implemented in KenLM (Ney et al., 1994; Heafield, 2011). We choose \( n \)-gram models explicitly because—while they are by no means SOTA language models—they should have inductive biases which are different from the models we are trying to evaluate. We present results using LSTM-based estimators in App. D. When computing \( \Delta_{\text{AUC}} \), we use a scaling constant \( s \) of 0.2.

Cluster-based Approximations \( \hat{p}_c \). Cluster-based distributions, as presented in eq. (14), are defined by a choice of PLM(\( \cdot \)) and pre-trained clustering function \( \phi(\cdot) \). We follow Pillutla et al.’s clustering setup here. We rely on GPT-2 XL as our PLM, and use K-means as our clustering function.\(^8\) Specifically, we extract embeddings from GPT-2 XL and then use PCA to reduce their dimensionality (keeping 90% of the original variance explained). We then train K-means (with \( K = 500 \)) on a joint set of GPT-2 embeddings extracted from: the 5k human-generated strings, and 5k model-generated sentences. Finally, we compute the approximated \( \hat{p}_c \) and \( \hat{q}_c \) by counting the number of strings (among these 5k used ones) assigned to each cluster. To avoid infinite divergence measures, we estimate distributions using Laplace smoothing with \( \alpha = 1 \) (which is equivalent to imposing a Dirichlet distributed prior with \( \alpha = 1 \) over the cluster allocation). When computing \( \Delta_{\text{AUC}} \), we use a scaling constant \( s \) of 5.\(^9\)

5.1 Does \( p_c \) Approximate \( p_w \)?

Our first experiment tries to identify whether \( p_c \) and \( q_c \) provide faithful approximations of \( p_w \) and \( q_w \). To this end, we compare both \( q_w \) and \( q_c \) to the true \( q_w \), i.e., the language generator under evaluation. Explicitly, we compute the Spearman correlations between the probabilities assigned by each model to the strings in \( \{ w_n^w \}_{n=1}^N \).

Fig. 1 presents these correlations. We see that—despite being estimated on very little data—probability estimates from our \( n \)-gram models correlate strongly with the ground-truth probabilities of \( q_w \): this result holds for all four GPT-2 architectures. On the other hand, and perhaps surprisingly, our cluster-based probabilities consistently present negative correlations with \( q_w \). This result has an important implication: if cluster distributions do not correlate with \( q_w \), then \( \text{KL}(\hat{p}_c \mid \mid \hat{q}_c) \) should not be measuring the same value as \( \text{KL}(p_w \mid \mid q_w) \). Rather, it is more likely that cluster-based divergences compute something different. Yet, this is not necessarily a shortcoming, as we show in our following experiments.

5.2 \( \Delta \) as Text Evaluation Metrics

We now compare how the string- and cluster-based divergence measures correlate with human judgement scores.\(^10\) In short, Fig. 2 shows that all divergences do better when estimated with cluster distributions. These results evince that MAUVE’s (Pillutla et al., 2021) high correlations with human

\(^{7}\)We condition our models on the first 10 words of human-generated strings before sampling.

\(^{8}\)We present results using other pretrained language models (other GPT-2 architectures and BERT) in App. D.

\(^{9}\)We ran our entire pipeline (from sampling strings \( \{ w_n^w \}_{n=1}^N \) from \( q_w \) to evaluating the KLS) with 5 different seeds. The variance across seeds is depicted as error bars in Figs. 1 and 2.

\(^{10}\)Specifically, we use the human judgement scores collected by Pillutla et al. (2021).
judgements (represented here as $\hat{\Delta}_{\text{AUC}}(p_c, q_c)$ are mainly due to their use of cluster-based approximations $(p_c, q_c)$, rather than to their proposed divergence $\Delta_{\text{AUC}}$. In fact, we see slight improvements over $\Delta_{\text{AUC}}$ when using the divergences $\hat{\Delta}_{\text{JS}}$ and $\hat{\Delta}_{\text{JS}}$ instead. Furthermore, cluster-based divergences appear to be more stable, exhibiting smaller variances across random seeds. Collectively, our results suggest that cluster-based divergences may produce better metrics of text quality than string-based divergences. This motivates the following two questions, which we subsequently address. What aspects of natural language are captured by $p_c$? And what aspects are overlooked by ignoring $p(w \mid c)$?

6 Probing Clusters

To better understand the aspects of natural language that our cluster distributions encode, we must first understand how $\phi(\text{PLM}(\cdot))$ partitions the string space $\mathcal{W}$. In other words, we must understand what components of natural language—e.g., semantics, syntactic attributes, or surface features—lead to strings being assigned to similar or different clusters. To this end, we probe (Alain and Bengio, 2016) these clusters for a number of linguistic attributes—including subject matter, sentiment, prose style, word order, basic grammaticality and document length—and look at how these different attributes affect both cluster assignment and the resulting divergence scores. Notably, we probe cluster assignments directly—without relying on any diagnostic classifiers (Adi et al., 2017). Our probing analyses are thus exempt from most recent criticism against probing methodologies (Hewitt and Liang, 2019; Pimentel et al., 2020a,b; Ravichander et al., 2021; Elazar et al., 2021).

6.1 Finding Features $p_c$ Encodes

Setup. We look at texts annotated with different attributes in order to explore correlations between the presence of these attributes and cluster membership. Specifically, we analyse texts’ sentiment (using the Yelp Polarity dataset; Zhang et al., 2015), authorship (using the News Category dataset), and topic (with the 20 NewsGroup dataset). Further details on datasets are provided in App. C. For each of these classification datasets, we learn cluster–category distributions using the standard training split; all evaluations are performed on test splits. Explicitly, we first learn a partitioning $\phi(\cdot)$ of the embedding space (w.r.t a language model $\text{PLM}(\cdot)$) using examples in the training set. Each cluster is then labelled with the majority category represented in that cluster; text categories in the test set are then predicted using this labelling, depending on which of the clusters the example falls into.

For comparison’s sake, we use four language models as $\text{PLM}(\cdot)$: GPT-2 with small, medium, large, and XL architectures. Results using embeddings from BERT (Devlin et al., 2019) can be found in App. D. Further, we use two methods for learning clusters:

- $\phi(\cdot)$ Learned on WebText. We train the PCA and $K$-means functions using the same procedure as in §5.2 (again relying on WebText’s test set for our data), mimicking the setting under which our partitions of the embedding space would be learned in practice.\(^{12}\)
- $\phi(\cdot)$ Learned on Training Set. We train the PCA and $K$-means clustering functions on the analysed dataset’s training set. This setting studies the partitioning our clustering functions have the capacity to learn in an ideal setting, i.e., where the attribute in question is one of the main differentiating factors between texts.

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\(^{11}\)Such an analysis should provide a deeper insight into the actual similarity being measured by cluster-based divergences, while also revealing how such a metric might be gamed.

\(^{12}\)If no strings in the training set are assigned to a cluster, we label it with the overall majority category.
Figure 3: Accuracy when predicting different attributes of text from their cluster assignments. Assignments (i.e. $\phi(\cdot)$) are learned using text from either WebText, or the training set of the respective classification datasets. Dashed lines represent baseline accuracies, i.e., always guessing the majority class.

**Results.** In Fig. 3a, we see that, at least for large numbers of clusters, cluster assignment is indeed indicative of a text’s sentiment. Interestingly, this is the case even when clusters are trained on data that is not particularly polar in sentiment (i.e. on WebText). On the other hand, we are only able to predict author and topic (with reasonable accuracy) when clusters are learned on text data with authorship and topic as distinguishing factors. These results indicate that, while writing style and subject matter are captured by the text embeddings, they likely were not being used as distinguishing features between corpora in our cluster-based divergences. We further see that, in all classification settings, the capacity to encode these analysed attributes appears to increase with model size, perhaps suggesting the embedding spaces of larger models decomposes along higher-level features of text.

6.2 How Text Features Impact $\Delta$

We next assess how changing different features of our evaluated text impacts divergence scores. Specifically, we look at the impact of: text truncation; article removal; stopword removal; sentence-level permutations; and word-level permutations.

**Setup.** We follow a similar setup to §5. In order to create a more controlled setting, we primarily consider human-generated text (i.e. the 5k human-written articles in WebText’s test set). We take the first 2500 articles of this dataset as our reference corpus $\{w_{wpw}^{nw} \}_{n=1}^{N}$, and use the remaining 2500 reference strings as the comparison corpus, i.e., in place of the model-generated text that we would typically evaluate $\{w_{wqw}^{nw} \}_{n=1}^{N}$. In order to explore how changing specific features of text affects $\Delta$ w.r.t. the reference corpus, we compute scores when making the following modifications to the comparison corpus:

- **No modification ($p$).** This is a baseline experiment where we keep the original strings as are.
- **Text Truncation ($p_{\text{short}}$).** We truncate texts to 1/3 of their original length.
- **Article Removal ($p_{\text{no art}}$).** We remove all articles (i.e., ‘a’, ‘an’ and ‘the’).
- **Stopwords Removal ($p_{\text{no stop}}$).** We remove all stopwords (e.g., ‘that’ or ‘so’).
- **Sentence-level Permutation ($p_{\text{swap}}$).** We permute the first halves of texts (as delineated by sentences) across the entire corpus (i.e. randomly reassigning the strings’ first halves).
- **Word-level Permutation ($p_{\text{rand}}$).** We randomly permute all the words in a text.
- **GPT-2 Baseline ($q$).** As an extra baseline, we also compute the divergence score when using the first 2500 generations from GPT-2 XL.

**Results.** Fig. 4 shows that certain alterations—such as completely removing articles from the test (comparison) text—have almost no impact on the divergence between our reference and test corpora for various $\Delta$. In fact, text without any articles is judged as better than GPT-2 XL’s by most of the cluster-based divergences. Further, while this perturbation undoubtedly affects the text’s fluency, it has less of an effect on this divergence than, e.g., truncating texts. This is arguably undesirable: A metric of text quality should place more emphasis on fluency than surface statistics, such as length.

On the other hand, our metrics deem text with stopwords removed as utterly different from the reference. Permuting words within texts has a similar effect, demonstrating that, at least to some extent, the embedding space captures notions of syntax and grammaticality, rather than pure unigram

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13Stopwords are defined as common words, such as “that” or “so”, that primarily serve a syntactic function. We use the set of English stopwords defined by NLTK (Bird et al., 2009).
statistics. The drop in scores shown when performing sentence-level permutations likewise suggests that the clusters capture some notion of coherence.

These results inspire us to investigate which surface features of text are encoded in embedding clusters. Following our setup in §6.1, we look at whether clusters encode the percentage of stopwords or punctuation in texts. We use solely the WebText dataset to train our clustering functions in this setting. We then compute the average percentage of stopwords or punctuation per cluster in half of our strings. Finally, we use these pre-computed averages when predicting the percentages in the other half, computing this prediction’s $R^2$ (i.e. the percentage of explained variance).

Interestingly, Fig. 5 shows that larger PLMs—which are often claimed to provide better representations of language—do encode more information about such surface features than smaller models. This could be due to the fact that the embeddings from larger PLMs are typically of a larger dimension and, thus, have the capacity to encode additional (perhaps “less critical”) attributes of text. Further, while these attributes do not appear to be differentiating factors when partitioning the embedding space into a small number of subspaces, they become relevant when partitioning into a larger number of subspaces. Even with several clusters and large PLMs, though, the $R^2$ values we find are still quite small, at around 0.20.

These results—along with those of §6.1—suggest cluster-based divergences are more sensitive to syntax- and coherence-related properties of the target text than to its superficial features. The opposite, however, might be said of our string-based distributions. As current SOTA language models typically produce grammatical text, being invariant to surface statistics may perhaps be a feature—as opposed to a bug—when trying to assess the quality of the text they produce. We thus conjecture that this might be what drives these clusters’ effectiveness in assessing text quality. Yet, this may also reveal potential ways in which such metrics can be gamed. We leave the investigation of these divergences’ robustness to future work.

7 Conclusion

In this paper, we present a general framework for the evaluation of language generators based on divergence measures. We discuss the computational and qualitative issues of using these divergence measures when evaluating language generation models; we then propose the use of probability distributions over word-embedding clusters—instead of the traditional distributions over strings—as a method for ameliorating these issues. While this substitution introduces bias into our divergences, the use of cluster-based metrics leads to much stronger correlations with human judgements than string-based metrics. In order to better understand the nature of this improvement, we probe the clusters leveraged by our density estimators, analysing what they ignore and what they emphasise about the input text. We find that, while distributions over clusters are sensitive to syntactic- or coherence-level perturbations to the text, this is not the case for several surface-level perturbations. We thus conjecture that, by focusing on higher-level text features, cluster-based language evaluation metrics are simply better suited to rank high performing models, for which grammaticality is less of a differentiating factor.
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Checklist

The checklist follows the references. Please read the checklist guidelines carefully for information on how to answer these questions. For each question, change the default [TODO] to [Yes], [No], or [N/A]. You are strongly encouraged to include a justification to your answer, either by referencing the appropriate section of your paper or providing a brief inline description. For example:

- Did you include the license to the code and datasets? [Yes] See Section X.
- Did you include the license to the code and datasets? [No] The code and the data are proprietary.
- Did you include the license to the code and datasets? [N/A]

Please do not modify the questions and only use the provided macros for your answers. Note that the Checklist section does not count towards the page limit. In your paper, please delete this instructions block and only keep the Checklist section heading above along with the questions/answers below.

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper’s contributions and scope? [Yes] Our main contribution is proposing cluster-based, which present higher correlations with human judgments (see §5.2). We probe clusters in §6.
   (b) Did you describe the limitations of your work? [Yes] We discuss limitations in §4.1 and §6.
   (c) Did you discuss any potential negative societal impacts of your work? [No] We foresee no negative societal impacts.
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes] Yes, we believe our paper conforms to them.

2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [Yes] In §4.1 we discuss the assumptions in the proof.
   (b) Did you include complete proofs of all theoretical results? [Yes] In App. A we provide the full decomposition of our comparison in §4.1.

3. If you ran experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [No] The url was removed for anonymisation. We will include them in CR.
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes] In each experiment section we provide their full experimental setup.
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [Yes] Our plots in Figs. 1 and 2 include error bars.
   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [No] We did not, as we did not record this. Our method, though, is not particularly computationally intensive.

4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
   (a) If your work uses existing assets, did you cite the creators? [Yes] We provide citations in the corresponding experimental setups.
   (b) Did you mention the license of the assets? [No]
   (c) Did you include any new assets either in the supplemental material or as a URL? [No] We did not collect new data. We will link our code for CR if the paper is accepted.
   (d) Did you discuss whether and how consent was obtained from people whose data you’re using/curating? [N/A] We are not collecting new data and only used publicly released datasets (with open licenses).
   (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [No] We are not collecting new data. We did not perform an analysis of the used datasets concerning these issues.
5. If you used crowdsourcing or conducted research with human subjects...
   (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A] We are not collecting new data.
   (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A] We are not collecting new data.
   (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [N/A] We are not collecting new data.
A String vs. Cluster-based Kullback–Leibler Decomposition

The decomposition in eq. (15) can be shown as follows:

\[
\text{KL}(p_w \| q_w) = \sum_{w \in W} p(w) \log \frac{p(w)}{q(w)}
\]

(16)

\[
\begin{align*}
\text{KL}(p_w \| q_w) & \overset{(1)}{=} \sum_{c=1}^{K} \sum_{w \in W} p(c, w) \log \frac{p(c) p(w \| c)}{q(c) q(w \| c)} \\
& = \sum_{c=1}^{K} \sum_{w \in W} p(c, w) \left( \log \frac{p(c)}{q(c)} + \log \frac{p(w \| c)}{q(w \| c)} \right) \\
& = \text{KL}(p(c) \| q(c)) + \underbrace{\text{KL}(p(w \| c) \| q(w \| c))}_{\geq 0} \\
& \geq \text{KL}(p_c \| q_c)
\end{align*}
\]

where again (1) follows from the fact that \( p(c, w) = p(w) \), which is true because the cluster assignment is deterministic, i.e.:

\[
p(c \mid w) = 1 \{ c = \phi(\text{PLM}(w)) \}
\]

B Related Work

Over the years, a number of evaluation metrics have been proposed for language generation tasks (such as translation and summarization); the most well-established and commonly-used include BLEU (Papineni et al., 2002), ROUGE (Lin, 2004) and METEOR (Banerjee and Lavie, 2005). However, these metrics—which rely on \( n \)-gram statistics—have been shown to correlate poorly with human judgement (Reiter, 2018). Recent metrics have improved upon these correlations with more advanced techniques, e.g., BEER (Stanojević and Sima’an, 2014), MoverScore (Zhao et al., 2019) and BLEURT (Sellam et al., 2020). These metrics, though, are intended for language generation tasks with a strict set of reference texts. While reasonably effective for directed generation tasks, they do not transfer well to the open-ended domain.

For tasks in which there is not a clear reference, e.g., story generation, basic statistics are typically employed to provide a preliminary evaluation of generated text. Such statistics include \( n \)-gram repetitions (Welleck et al., 2020), Zipfian coefficient (Holzman et al., 2020), or the perplexity of generated text (Fan et al., 2018). Final assessments of language generation systems are still often performed using human evaluations, as automatic metrics on their own have not proven sufficient for differentiation between top-end language generation systems.

Automatic evaluation metrics based on statistical divergences have been proposed by a number of different authors. In the context of language generators, for instance, Meister and Cotterell (2021) assessed the quality of language models while using a number of divergences between distributions over surface statistics in text corpora. Most similar to our work, Pillutla et al. (2021) present MAUVE, which is one of the divergence measures we investigate here (namely, \( \Delta_{\text{AUC}} \), presented in §2).\textsuperscript{14} Besides proposing this AUC divergence metric, Pillutla et al. (2021) also propose a new way to approximate it using clusters over word embeddings. However, while they propose measuring \( \Delta_{\text{AUC}}(p_c, q_c) \) as an approximation to \( \Delta_{\text{AUC}}(p_w, q_w) \), we show that, in practice, they do not compute the same quantity—highlighting the difference between these divergences. Further, we propose the use of distributions over clusters as a general approach to perform automatic evaluation of language generation—evaluating multiple cluster-based divergences—and providing an analysis of the root of the effectiveness of this paradigm.

Prior works have similarly used pretrained language models for the evaluation of text generators. For example, BLEURT uses BERT embeddings, training a regression model to predict scores of text using

\textsuperscript{14}The area under the curve computed in MAUVE is inspired on the information frontier divergences originally proposed by Djolonga et al. (2020). Specifically, Djolonga et al. proposed a framework that measures the trade-off between precision and recall using Rényi divergences.
human judgements. Our work differs from these on a number of axes: our method for evaluation is theoretically motivated, centered around divergence measures—well-established measurements of statistical distances. Further, our work focuses on open-ended generation. Finally, we present an in-depth analysis of the properties encoded by our quantisation of the embedding space of the PLMs used in our evaluation.

C Experimental Setup

Embedding Models. To obtain text embeddings for our input strings, we use several different PLM. Namely, we use the four sizes of GPT-2 (Radford et al., 2019), as well as BERT-base and BERT-large (both cased; Devlin et al., 2019). For the former, we use the embedding of the final token. For the latter, we use the embedding associated with the special CLS token. All texts are truncated to 512 tokens (for experiments in §6.2, this truncation is performed before any manipulations of the text), in order to ensure that all models can process the input text in their context.

For our probing analysis in §6, we employ the following datasets:

- **Sentiment.** To analyse sentiment, we use Yelp Polarity (Zhang et al., 2015), a dataset extracted from the Yelp Dataset Challenge 2015, which contains binary sentiment classifications for highly polar Yelp reviews. We use 10k examples randomly sampled from the training set and 5k examples randomly sampled from the test set.

- **Authorship.** To analyse authorship, we use News Category, a dataset consisting of 200k news headlines from the years 2012–2018 obtained from HuffPost. We scrape entire articles from the URLs provided by the dataset. We only use the subset of articles for which the article’s author has ≥ 400 articles within the dataset, giving us a training set of 32k and a test set of 6k with 46 unique authors.

- **Topic.** To analyse topic, we use the 20 NewsGroup dataset, which contains 18k newsgroups posts (partitioned into train and test sets using the original splits) on 20 topics, such as subcategories of science, politics and religion. The distribution over text topics is relatively uniform.
Figure 6: Correlations between string- and cluster-based divergences and human judgement scores using a diverse set of estimators (either different PLM(\cdot) when defining \(p_c\), or language models when approximating \(p_w\)). Legend: \(\Delta_{\exp}\) in dark green; \(\Delta_{\to}\) in orange; \(\Delta_{\leftarrow}\) in blue; \(\Delta_{\text{JS}}\) in pink; \(\Delta_{\text{AUC}}\) in lime green.
Figure 7: Accuracy when predicting different attributes of text from their cluster assignments. Same plot as Fig. 3 albeit using embeddings from BERT.

Figure 8: $\Delta_{AUC}$ scores between reference text and alternate text distributions as a function of number of clusters used to estimate $\hat{p}_c$ and $\hat{q}_c$. Importantly, in this figure, we compare the first 2500 sentences ($p^{(1)}$) in the human-generated WebText test set to these same strings, but under the proposed interventions. I.e., for all points corresponding to an (altered) distribution $p^{(1)}$, we estimate our cluster distributions on the same set of human-generated sentences, but where the strings in one group have been intervened on. The baseline distribution $p^{(2)}$ still represents the final 2500 sentences in WebText (as in the original plot); and baseline distribution $q$ is text sampled from GPT-2 XL.
Figure 9: $\Delta$ scores between reference text and alternate text distributions as a function of number of clusters used to estimate $\hat{p}_c$ and $\hat{q}_c$. Results shown for embeddings produced using multiple LMs.