Bidimensional Leaderboards: Generate and Evaluate Language Hand in Hand

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Abstract

Natural language processing researchers have identified limitations of evaluation methodology for generation tasks, with new questions raised about the validity of automatic metrics and of crowdworker judgments. Meanwhile, efforts to improve generation models tend to focus on simple n-gram overlap metrics (e.g., BLEU, ROUGE). We argue that new advances on models and metrics should each more directly benefit and inform the other. We therefore propose a generalization of leaderboards, bidimensional leaderboards (BILLBOARDS), that simultaneously tracks progress in language generation tasks and metrics for their evaluation. Unlike conventional unidimensional leaderboards that sort submitted systems by predetermined metrics, a BILLBOARD accepts both generators and evaluation metrics as competing entries. A BILLBOARD automatically creates an ensemble metric that selects and linearly combines a few metrics based on a global analysis across generators. Further, metrics are ranked based on their correlations with human judgments. We release four BILLBOARDS for machine translation, summarization, and image captioning.

We demonstrate that a linear ensemble of a few diverse metrics sometimes substantially outperforms existing metrics in isolation. We release four BILLBOARDS for machine translation, summarization, and image captioning. We demonstrate that a linear ensemble of a few diverse metrics sometimes substantially outperforms existing metrics in isolation. Our mixed-effects model analysis shows that most automatic metrics, especially the reference-based ones, overrate machine over human generation, demonstrating the importance of updating metrics as generation models become stronger (and perhaps more similar to humans) in the future.

1 Introduction

Recent modeling advances have led to improved natural language generation in applications such as machine translation and summarization (Ng et al., 2019; Raffel et al., 2020; Brown et al., 2020, inter alia). This progress is typically measured with automatic scores, such as BLEU (Papineni et al., 2002) and ROUGE (Lin, 2004), evaluated by modeling researchers themselves. These metrics allow for fast, inexpensive development cycles. They were adopted based on reported correlations with human judgments at the time the metrics were introduced, but it has since been established that the correspondence can collapse when models of different types are compared (Callison-Burch et al., 2006) and ROUGE (Lin, 2004), evaluated by modeling researchers themselves. These metrics allow for fast, inexpensive development cycles. They were adopted based on reported correlations with human judgments at the time the metrics were introduced, but it has since been established that the correspondence can collapse when models of different types are compared (Callison-Burch et al., 2006) or models become increasingly powerful (Ma et al., 2019; Edunov et al., 2020).

Meanwhile, many evaluation metrics that improve correlations with human judgments have been proposed (Clark et al., 2019; Zhang et al., 2020b; Sellam et al., 2020; Hess et al., 2021, inter alia), but this progress is largely ignored by the
community of researchers focused on advancing models. Indeed, we found that 68% of the machine translation papers from NAACL 2020 and ACL 2020 evaluated their models solely by BLEU, and only 5% measured the performance with recent metrics that use contextual representations, such as COMET (Rei et al., 2020) and BERTScore (Zhang et al., 2020b). Similarly, automatic evaluation in 66% of the summarization papers was done only in terms of ROUGE. We believe this separation between generation modeling and automatic evaluation represents a missed opportunity for each subcommunity to more rapidly benefit from the advances of the other.

We therefore propose an abstraction of conventional leaderboards, bidimensional leaderboards (BILLBOARDS), that simultaneously facilitates progress in natural language generation and its evaluation (Fig. 1). A BILLBOARD accepts two types of submissions related to a given task and dataset: generators and metrics. Unlike conventional leaderboards, model ranking is not tied to a predetermined set of metrics; the generators are ranked based on the metric that currently correlates best with human judgments. Metric submissions are ranked by their correlations to human judgments and each is stored as an executable program, which will then be used to evaluate future generation submissions. Our BILLBOARD includes a sparse regression that selects and linearly combines three existing metrics, revealing complementary strengths. All leaderboard scores are readily reproducible, allowing research on generation models and automatic metrics to benefit from each other.

We release four BILLBOARDS spanning three generation tasks: the WMT20 EN-DE and WMT20 ZH-EN machine translation tasks (Barrault et al., 2020), the CNNDM summarization task (Hermann et al., 2015), and the MSCOCO image captioning task (Lin et al., 2014). Using the collective analyses of BILLBOARDS, our main findings are as follows.

- A simple linear combination of a few (diverse) metrics can sometimes improve correlations. This finding quantifies complementary effects of different metrics and encourages metric developers to seek out aspects of generated text quality not yet measured by existing metrics.
- Using linear mixed-effects models, we find that most automatic metrics, especially conventional, reference-based ones such as BLEU and ROUGE, overrate machines over humans in all tasks. This result provides further support for the claim that the metrics should be continually evaluated and updated as our generation models become stronger (and perhaps, closer to humans) in the future.
- When only one reference is available per instance, COMET-QE (a strong referenceless metric with crosslingual contextual representations; Rei et al., 2020) achieves higher correlations with human judgments than all reference-based metrics. This raises a concern about the current standard evaluation practice in machine translation and summarization that uses reference-based metrics with a single reference per instance.
- Our findings confirm many others who report that recent metrics achieve substantially higher correlations with human judgments than popular metrics like BLEU and ROUGE in BILLBOARDS. We believe these metrics continue to be used mainly because modeling researchers value consistency and accessibility of evaluation practice over long periods of time. BILLBOARDS provide a way to maintain long-term comparability of system output while also drawing better conclusions about system quality, using advances in evaluation. All generators keep being evaluated with new metrics on BILLBOARDS.

2 Bidimensional Leaderboards

We propose BILLBOARDS to simultaneously drive progress in natural language generation and its evaluation, which are often disconnected in current research. We first describe the general framework (§2.1) and the automatic analyses they provide (§2.2-2.3). We then discuss our design choices (§2.4) and the rubric-based, human judgment data necessary to initialize BILLBOARDS (§2.5).

2.1 Billboard Framework

The leaderboard paradigm has driven research on state-of-the-art model performance on many tasks in various fields, including computer vision and natural language processing (e.g., ImageNet, Russakovsky et al., 2015; MSCOCO, Lin et al., 2014; SQuAD, Rajpurkar et al., 2016). As applications and tasks become more diverse, however, the conventional leaderboard paradigm presents a seri-
ous challenge: the assumption becomes too strong that predetermined, automatic metrics can reliably score the system performance over time. In particular, scores from automatic metrics often diverge from human judgments in language generation tasks especially when models become increasingly powerful (Ma et al., 2019) or they are applied to different domains (Liu and Liu, 2008).

Much recent work proposed new evaluation metrics that improve correlations with human judgments in certain generation tasks (Clark et al., 2019; Zhang et al., 2020b; Sellam et al., 2020; Hessel et al., 2021, inter alia), but most developers of generation models are not benefiting from them (See Appendix A for our analysis of papers from NAACL/ACL 2020). From the perspective of generation model developers, it is not clear which of these many metrics in the literature is most reliable in which generation task or dataset, resulting in community-wide overuse of long-standing metrics like BLEU and ROUGE. Developers of evaluation metrics, on the other hand, are missing the opportunity to apply their metrics to new generation models and compare their metrics with the existing ones. We propose BILLBOARDS that bridge this gap between generation modeling and evaluation development.

Generators, Metrics, and Scores A BILLBOARD for a language generation task consists of sets of generators and evaluation metrics: $G = \{G_i\}_{i=1}^I, M = \{M_j\}_{j=1}^J$. Each generator $G_i$ takes as input $X_k$ (e.g., source text in machine translation) and generates text: $Y_{i,k} = G_i(X_k)$. A metric $M_j$ assigns a score to each generated text given the generation input and the corresponding set of references $R_k$: $s_{i,j,k} = M_j(Y_{i,k}, R_k, X_k)$. The last two arguments to the function are optional; some metrics do not require references (i.e., referenceless or quality estimation metrics) or the generation input (e.g., BLEU and ROUGE). We then compute the aggregate score $s_{i,j}$ by averaging $s_{i,j,k}$ over all $K$ test samples.

Rankings In contrast to standard leaderboards, BILLBOARDS have a dynamic set of evaluation metrics, and generators are not ranked by a predefined metric. We first rank the metrics by measuring their correlations to human judgments as commonly done in the generation evaluation literature (Zhang et al., 2020b; Sellam et al., 2020). Let $h_{i,k}$ be a human score for $Y_{i,k}$ (i.e., output from generator $G_i$ on input $X_k$). We compute the instance-level Pearson correlation for every metric $M_j$ between $h_{i,k}$ and $s_{i,j,k}$ ($M_j$ score for $Y_{i,k}$). All metrics are ranked by their correlations. We then use the top metric $M_j^*$ to rank the generators in the descending order of $s_{i,j^*}$. We defer our discussions on alternative design choices (§2.4) and human evaluations (§2.5). We note, however, that the overall framework of BILLBOARDS still holds regardless of these decisions.

2.2 Ensemble of Metrics

So far, we have assumed that metrics are used individually in isolation, but BILLBOARDS provide a unique opportunity to examine metrics collectively. Different metrics can capture different aspects of generation quality; even if a metric is not sufficiently informative in isolation, it might reflect an important aspect of text quality that the existing metrics overlook. Here we consider a straightforward and interpretable ensemble of metrics using a regression model with $\ell_1$ regularization (Tibshirani, 1994). Let the ensemble’s score be

$$\hat{h}_{i,k} = \sum_{j=1}^J w_j \cdot s_{i,j,k},$$

where $w_j$ is a scalar coefficient associated with the $j$th metric. We optimize the vector of coefficients $w$ with the pairs of output text and a human score $\{Y_{i,k}, h_{i,k}\}_{k=1}^K$ from the test data:

$$w = \arg\min_w \sum_{k=1}^K \left( h_{i,k} - \hat{h}_{i,k} \right)^2 + \lambda \|w\|_1$$

The $\ell_1$ regularization produces sparse coefficients and improves interpretability by removing highly correlated metrics. Moreover, it avoids the need for practitioners to run many metrics to obtain an ensemble score when used outside our BILLBOARDS. Our goal for the ensemble is to provide a useful signal to the research community, rather than to achieve the best possible correlation with human judgments at a given time; we tune $\lambda$ to get three non-zero coefficients. Every metric is standardized by its mean and standard deviation on the test data.

Similar to the individual metrics, we rank this ensemble metric by its correlation to the human judgment scores. To make fair comparisons, we simulate situations that the ensemble metric is applied to a newly submitted generator that has no human evaluations. Specifically, we perform cross validation that holds out the human judgments for each generator $G_i$ and runs regression on the rest;
we then apply these $J$ regression models to the corresponding held-out data and calculate the overall correlation. We will see that the ensemble metric outperforms all individual metrics in some cases, suggesting that different metrics can capture different aspects.

**Reproducibility** The ensemble metric is updated every time a new metric is submitted (Fig. 1). For better reproducibility, we keep track of every past ensemble metric with a signature that indicates its coefficients, $\lambda$, and input metrics in the backend. Similar to the SACREBLEU package (Post, 2018), model developers can report the signature for easy replication of their scores from the ensemble metric.\footnote{E.g., ensemble.wmt20-zh-en+refs.AB+version.1.} Further, all generation outputs are saved on the leaderboards, so model developers can download outputs from all past models and compare in any way.

### 2.3 Mixed-Effects Model Analysis

Recent work (Kasai et al., 2021c) observed that automatic metrics tend to overrate machine-generated text over human one on the MSCOCO image captioning task (Chen et al., 2015). This problem is particularly severe in conventional metrics that are based on n-gram overlap such as BLEU and CIDEr (Vedantam et al., 2015). This raises a significant concern about the continuous use of these conventional metrics in generation tasks as models become increasingly powerful (and more similar to humans); those metrics unintentionally discourage researchers from developing human-like, strong generation models. To quantify this undesirable property, we propose a linear mixed-effects model that compares the two groups of machine-and human-generated text. The underlying model assumes that $s_{i,j,k}$, the score from metric $M_j$ for generator $G_i$, and test example $k$ can be expressed as (the intercept term is suppressed for brevity):

$$s_{i,j,k} = \beta_{0j}^{M} \cdot \mathbb{1} (G_i \text{ is machine}) + \beta_{1j}^{M} h_{i,k} + \gamma_k + \epsilon_{i,j,k},$$

where $\gamma_k$ is the random effect for example $k$, and $\epsilon_{i,j,k}$ is Gaussian noise. Intuitively, $\beta_{0j}^{M}$ measures how much metric $M_j$ overrates machine generation over human one, compared against the human judgment $h_{i,k}$. $\beta_{0j}^{M} = 0$ means being neutral, and indeed we will find that $\beta_{0j}^{M}$ is significantly positive in most cases ($\S4$). We standardize all metric scores over the test samples to compare the size of $\beta_{0j}^{M}$. We apply the lme4 package (Bates et al., 2015).

### 2.4 Design Choices and Discussion

In our current setup, we make several design choices for metrics and their rankings:

- **M.1** Metrics are expected to positively correlate with the generation output quality.
- **M.2** Metrics are ranked by their instance-level Pearson correlations with human judgment scores.
- **M.3** When available, reference-based metrics use multiple references per instance.

M.1 implies that we need to take the negative of metric scores that are intended to negatively correlate (e.g., TER, Snover et al., 2006). This normalization is also done in WMT metric competitions (Callison-Burch et al., 2007, 2008, inter alia).

While instance-level correlations are commonly used to evaluate and compare automatic metrics for various language generation tasks (Sellam et al., 2020; Fabbi et al., 2021; Hessel et al., 2021, inter alia), there are several alternatives to M.2. For example, Pearson, Spearman’s rank, or Kendall rank correlations can be used on a system (i.e., generator) level (Callison-Burch et al., 2007; Macháček and Bojar, 2014; Mathur et al., 2020b). However, such system-level correlations would substantially reduce data points to compare automatic scores, resulting in many ties in the ranking. Spearman’s and Kendall rank correlations become brittle when multiple generators are similar in overall output quality; penalizing a metric for swapping two similar generators is misleading (Macháček and Bojar, 2014). Moreover, if a metric can perform well on an instance level, it can be used to augment human judgments by, for example, flagging likely wrong ratings (Mathur et al., 2020b). Thus, we encourage researchers to develop metrics that correlate well with human judgments on an instance level. Prior work also points out other problems in ranking metrics like outlier effects where outlier systems have a disproportionately large effect on the overall correlation (Mathur et al., 2020b,a). We therefore assume M.2 in the current version of BILLBOARDS, but this can be modified in a future version.

M.3 is supported by our experimental results in §4 that multiple references substantially improve reference-based metrics, and a single reference is often insufficient to outperform strong reference-less metrics. Some metrics have specifications for multiple references (e.g., BLEU, CIDEr). In the other cases, we evaluate outputs against every reference and take the maximum score, following prior
work on image captioning evaluation (Zhang et al., 2020b; Hessel et al., 2021).\(^4\)

### 2.5 Human Evaluation

Human evaluations are required to initialize BILLSBOARDS; they are used to rank metrics, train the metric ensembling model, and assess how much each metric overrates machines. Recent work, however, points out problems when evaluations are done by crowdsworkers even when extensive quality controls are performed (Gillick and Liu, 2010; Toral et al., 2018; Freitag et al., 2021; Clark et al., 2021; Fabbri et al., 2021). Freitag et al. (2021) show that rubric-based machine translation evaluations by professional translators led to substantially different generator rankings from the crowdsourced evaluations in WMT 2020 (Barrault et al., 2020), where WMT participants or Amazon Mechanical Turkers directly assess each translation’s adequacy by a single score (direct assessment). These crowdworker evaluations depend highly on individual annotators’ discretion and understanding of the annotation scheme (Freitag et al., 2021; Clark et al., 2021), making it difficult to decompose, interpret, and validate (Kasai et al., 2021c). Moreover, these direct assessment scores make it difficult to interpret evaluation results for downstream applications where some aspects are particularly important (e.g., accessibility for people with visual impairments on the image captioning task, Gleason et al., 2020; gender bias in machine translation, Stanovsky et al., 2019).

Motivated by this line of work, we perform meta-evaluations to compare crowdsourced and rubric-based expert evaluations. Fig. 2 plots overall scores for test examples in the WMT20 ZH-EN (Barrault et al., 2020; Freitag et al., 2021) and CNNDM summarization (Fabbri et al., 2021) tasks. Each instance is evaluated by averaging the same number of crowdworkers and expert scores for fair comparisons. We see that substantially many instances fall into disagreement: crowdsworkers give much higher scores than experts (lower right square), or the reverse (upper left square). We sample and shuffle 20/25 examples from either type and ask a meta-evaluator to make a binary decision (good or bad quality).\(^5\) We see that meta-evaluations...
agree more with the expert evaluations (e.g., 22 and 0 in the upper left and lower right squares for CNNDM, respectively). In the examples on the left, crowdworkers fail to properly assess a valid translation with different structure than the reference (posted a video to celebrate vs. congratulated via video) or a summary that combines information from different parts of the article. The examples on the right illustrate that crowdworkers can be fooled by inaccurate yet fluent generations (does not know the reason vs. does not know if Sanchez decided). Given this result, we decide to initialize our BILLBOARDS with rubric-based expert evaluations for all generation tasks. Nonetheless, crowdsourced evaluations can scale up more easily, and we encourage future work to explore ways to improve them.

3 Experiments

Having established the framework and design choices, we set up BILLBOARDS for three natural language generation tasks: machine translation, summarization, and image captioning. To maximize the performance of reference-based metrics, we use as many references as possible for each task. See §4 for an analysis on the effect of varying numbers of references.

3.1 Tasks

**Machine Translation** We experiment with two language pairs from the WMT 2020 news translation task (Barrault et al., 2020): Chinese→English (WMT20 ZH-EN) and English→German (WMT20 EN-DE). We use outputs from all submitted translation systems. These two language pairs have expert, rubric-based scores (MQM) from Freitag et al. (2021) for a subset of 10 submitted systems, including the top-performing systems and human translations. Each output sentence is evaluated by three professional translators. Following Freitag et al. (2021), the three scores are averaged to get an instance-level score.

We use all human translations available as a reference set for reference-based metrics. Concretely, every test instance in WMT20 ZH-EN has two translations provided by different human translation services: Human-A and Human-B (Barrault et al., 2020). In addition to Human-A and Human-B, WMT20 EN-DE provides a translation that is created by linguists who are asked to paraphrase Human-A and Human-B as much as possible (Human-P, Freitag et al., 2020). These paraphrased translations are shown to increase correlations with human judgments by mitigating the translationese effect and diversifying the reference when the generation quality is measured by reference-based metrics (Freitag et al., 2020).

Along with all submitted generators in WMT20 ZH-EN and WMT20 EN-DE, we train three transformer baselines with the fairseq library (Ott et al., 2019) and place them in our BILLBOARDS: transformer-base, transformer-large, and transformer-large-ensemble with similar hyperparameters (e.g., 6-layer encoder and decoder) to the ones trained on WMT16 EN-DE data in Vaswani et al. (2017). These baselines allow researchers to compare their translation models without resource-intensive techniques such as back-translation (Sennrich et al., 2016a), model ensembling, and deep encoders (Kasai et al., 2021a). These techniques are all used in top-performing systems of WMT20 (Wu et al., 2020a; Kiyono et al., 2020) but might be infeasible in many research settings. See Appendix B for a list of all hyperparameters for the baselines.

**Summarization** We use the CNN/DailyMail corpus (CNNDM, Hermann et al., 2015; Nallapati et al., 2016). We use the standard train/dev./test split and 24 models from Fabbri et al. (2021). 100 test articles are annotated with 10 summaries written by humans (Kryscinski et al., 2019). For those 100 articles, rubric-based, expert evaluations for 18 generators, including human-written highlights, are provided by Fabbri et al. (2021). Each output summary is evaluated by three experts along four dimensions: coherence (collective quality of all summary sentences), consistency (factual alignment with the article, penalizing for hallucinations), fluency (quality of the individual sentences), and relevance (selection of important content). An instance-level score is computed by averaging scores over the three experts.

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We make our preprocessed data and the baseline models available at https://github.com/jungokasai/billboard.

Some of the model outputs are lowercased and/or tokenized. In these cases, we apply the NLTK detokenizer (Bird et al., 2009) and/or Stanford CoreNLP truecaser (Manning et al., 2014). We encourage, however, future model developers to provide clean, untokenized output to improve the reproducibility and transparency of evaluation results (Post, 2018; Kasai et al., 2021c).
Ensemble of Metrics

| Dataset       | G | M | Top Gen. | Single Metrics | Ensemble of Metrics |
|---------------|---|---|----------|----------------|--------------------|
|               |   |   |          | Top Metric | Linear Combination | Corr. |
| WMT20 ZH-EN   | 19| 15| Huoshan  | COMET 0.55   | COMET-QE+1.48      | 0.61 |
| WMT20 EN-DE   | 17| 11| Tohoku   | COMET 0.49   | COMET+0.36        | 0.51 |
| CNNDM         | 26| 15| Lead-3   | COMET 0.41   | COMET-QE+0.02     | 0.51 |
| MSCOCO        | 4 | 15| VinVL-large | RefCLIP-S 0.45 | RefCLIP-S+1.51    | 0.45 |

Table 1: Summary of BILLBOARDS as of Dec. 4th, 2021. Huoshan: Wu et al. (2020a); Tohoku: Kiyono et al. (2020); VinVL-large: Zhang et al. (2021); COMET: COMET-QE: Rei et al. (2020); BLEURT: Sellam et al. (2020); Prism-ref: Thompson and Post (2020); BERTScore: Zhang et al. (2020b); RefCLIP-S: Hessel et al. (2021); RefOnlyC: Kasai et al. (2021c). COMET-QE is a referenceless metric. BLEURT is specifically trained to evaluate into-English translations. RefCLIP-S uses image features unlike most metrics for image captioning.

4 Results and Analysis

Here we discuss the current results and make several key observations about the state of language generation evaluation. Table 1 summarizes the four BILLBOARDS. It is particularly noteworthy that COMET, a metric designed for machine translation, achieves the best correlation on the CNNDM summarization task as well. COMET evaluates the similarity between the crosslingual representations from XLM-RoBERTa (Conneau et al., 2020) for input text and its translation candidate. But these crosslingual representations can, of course, be used monolingually for English summarization. This illustrates an additional benefit of BILLBOARDS that centralize different generation tasks and find surprising task transferability of learning-based metrics. See Appendices B and C for lists of all participating generators and metrics.

Human-A vs. Human B on WMT20 ZH-EN is arbitrary, we found that swapping the roles would still lead to similar results (See Appendix E).

4.2 Mixed-Effects Models

Our mixed-effects model analyzes how much every automatic metric overrates machines over humans (§2.3). This means that we need to free up one human generation per instance to measure its scores in the reference-based metrics. For machine translation, we score Human-B using the reference set of Human-A (WMT20 ZH-EN) or Human-A and Human-P (WMT20 EN-DE). For CNNDM, we use concatenated highlights as human-generated summaries and use the 10 human-written summaries from Kryscinski et al. (2019) as the reference. We follow Kasai et al. (2021c) for MSCOCO and score their randomly-selected Human caption using the other four as the reference. As the distinction between the reference and human generation (e.g.,

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Prior work used a concatenation of author-written highlights as a reference, but here we do not add it to the reference set. This is because these highlights are sometimes noisy (e.g., containing urls) or lack coherence because they are concatenations of separate bullet points (Fabbri et al., 2021).

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We found a major reason for the anomaly in CNNDM: an outlier generator (the GPT-2 zero-shot model; Ziegler et al., 2019) has a disproportionately large effect on the regression models. The ensemble metric outperformed the top individual metric of COMET when the zero-shot model was removed.
metrics at a time (Table 2). We see that only dropping COMET-QE would result in a decrease in the correlation score. This implies that the referenceless metric provides important information that the others do not.

| Removed Metric | COMET | COMET-QE | BLEURT | BLEU |
|----------------|-------|----------|--------|------|
| Correlation    | 0.61  | 0.61     | 0.57   | 0.61 |

Table 2: Ensemble ablation studies on WMT20 ZH-EN. Only removing COMET-QE leads to a correlation drop. See Appendix D for the other datasets.

### Mixed-Effects Models

Seen in Table 3 are the results from our analysis that measures how much metrics overrate machines over humans (§2.3). We see that the fixed-effect coefficient $\beta_0$ is significantly positive in most cases. Referenceless metrics tend to have smaller coefficients. This can be due to the more diverse nature of human text than machine-generated text; reference-based metrics give a low score to human text that differs from the references even if it is of high quality. The conventional n-gram overlap-based metrics (BLEU, ROUGE, and CIDEr) have particularly large coefficients. These results suggest that the evaluation practice should be regularly updated as our generation model becomes stronger (and perhaps, more similar to human generation) in the future. Note that unlike the other tasks, “human-generated text” for CNNDM summarization is an automatic concatenation of author highlights, which contains substantial noise (Fabbri et al., 2021). This might explain the neutral and negative coefficients.

### Effects of the Number of References

Fig. 3 plots correlations over varying numbers of references. COMET was the top-performing reference-based metric regardless of the number of references, but we observe that it underperforms the referenceless metric when only one reference is given. Model performance in machine translation and summarization is commonly measured by applying reference-based metrics against one reference per instance in the research community. Our finding thus raises a further concern about the current evaluation practice. Finally, we observed that popular choices of BLEU and ROUGE metrics have much lower correlation scores than the recent metrics over various numbers of references, in line with the recent studies (Mathur et al., 2020a, inter alia).

### 5 Related and Future Work

#### Related Benchmarks

WMT organizes the metric competition track in parallel with the translation task every year (Mathur et al., 2020b; Barrault et al., 2020, inter alia). Participants submit automatic scores for the translation outputs from the parallel translation task. Unfortunately, most of these new metrics are not used by subsequent machine translation work, perhaps because they are tested solely against the concurrent translation submissions and it is up to model developers to execute or even implement new metrics. The GEM workshop (Gehrmann et al., 2021) conducts extensive analysis of models and evaluation methods over a wide set of generation tasks. BILLBOARDS ease the burden through standard leaderboard experience where generator developers only need to
upload generation outputs for the test split. BILLBOARDS also offer automatic ensembling of metrics and quantify the diversity that a new metric adds. The human-in-the-loop GENIE leaderboard (Khashabi et al., 2021) centralizes crowdsourced evaluations for generation tasks. The current BILLBOARD setup is based on rubric-based, expert evaluation data from previous work, but future work can explore ways to improve crowdsourced evaluations and use them to update BILLBOARDS.

From Bidimensional to Multidimensional BILLBOARDS lend themselves to a natural extension: multidimensional leaderboards. In particular, generation models have more aspects than generation quality, such as training and inference efficiency, sample efficiency, and robustness. These aspects are often ignored in the current leaderboard paradigm but are important to better serving practitioners’ needs (Schwartz et al., 2019; Ethayarajh and Jurafsky, 2020). There are ongoing modeling and benchmarking efforts especially for efficient machine translation (Heafield et al., 2020; Peng et al., 2021; Kasai et al., 2021b, inter alia). We leave this extension to future work and specifically target the gap between generation modeling and evaluation in this work.

6 Conclusion

We introduced BILLBOARDS, a simple yet powerful generalization of leaderboards that bridges the gap between generation modeling and evaluation research. We established four BILLBOARDS on machine translation, summarization, and image captioning tasks. We demonstrated that their built-in analysis of metric ensembling and mixed-effects modeling revealed key insights into the current state of natural language generation and its evaluation methods. BILLBOARDS allow for a standard leaderboard experience both on the modeling and evaluation sides. We invite submissions from researchers through our website.

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Appendices

A Case Studies of Evaluation Practice

Fig. 4 depicts breakdowns of evaluation metrics used in the papers on machine translation and summarization from NAACL and ACL 2021. We examined all papers whose title contains “machine translation” and “summarization.” We see the clear gap between generation modeling and evaluation research; most researchers do not take advantage of recent metrics that correlate better with human judgments.

B Participating Generators

Here we list the generators submitted in the initial BILLBOARDS.

B.1 WMT20 ZH-EN

| Hyperparameter                  | Value     |
|---------------------------------|-----------|
| label smoothing                 | 0.1       |
| # max tokens                   | 4096      |
| dropout rate                    | 0.1       |
| encoder embedding dim           | 1024      |
| encoder ffn dim                 | 4096      |
| # encoder att heads             | 16        |
| decoder embedding dim           | 1024      |
| decoder ffn dim                 | 4096      |
| # decoder att heads             | 16        |
| max source positions            | 1024      |
| max target positions            | 1024      |
| Adam lr                         | $5 \times 10^{-4}$ |
| Adam $\beta_1$                  | 0.9       |
| Adam $\beta_2$                  | 0.98      |
| lr-scheduler                    | inverse square |
| warm-up lr                      | $1 \times 10^{-7}$ |
| # warmup updates                | 4000      |
| # max updates                   | 600K      |
| # GPUs                          | 8         |
| length penalty                  | 0.6       |

Table 4: Transformer-base fairseq hyperparameters and setting.

We use all 16 submissions for the WMT20 ZH-EN task (Barrault et al., 2020) as well as our own three transformer baselines that were implemented in fairseq (Ott et al., 2019). Our baselines allow researchers to compare their translation models without resource-intensive techniques such as backtranslation (Sennrich et al., 2016a), model ensembling, and deep encoders (Kasai et al., 2021a). Tables 4 and 5 list the hyperparameters. We generally follow the setting from Vaswani et al. (2017).

B.2 WMT20 EN-DE

Similar to WMT20 ZH-EN, we use all 14 submissions for the WMT20 EN-DE task along with our three transformer baselines. The same hyperparameters are chosen as in WMT20 ZH-EN (Tables 4 and 5). We preprocess both English and German text by Moses tokenizer and joint BPE with 32K operations. All embeddings are shared. We apply Moses detokenizer to get the final outputs. Table 7 lists all generators and their automatic evaluation scores from the top-performing metric (ensemble in this case).

We use newstest-2019 as the dev. set and the official training data. We apply moses tokenization (Koehn et al., 2007) and BPE with 32K operations (Sennrich et al., 2016b) to English text. We tokenize Chinese text with the Jieba package, following Hassan et al. (2018). Separately from English, BPE with 32K operations are then applied to Chinese. The decoder input and output embeddings are tied. Moses detokenization is applied to get the final outputs in the last step. We make the three models and preprocessed train/dev. data publicly available. Table 6 lists all generators and their automatic evaluation scores from the top-performing metric (ensemble in this case).
Figure 4: Breakdowns of evaluation metrics used in the papers on machine translation and summarization from NAACL and ACL 2021. We examined all papers whose title contains “machine translation” and “summarization” and disregarded papers primarily on evaluation metrics. “QA” metrics use a QA system to evaluate summaries (e.g., Eyal et al., 2019). “Specialized” indicates specialized evaluation in a particular dimension, rather than the overall generation quality, such as document-level evaluations on contrastive sets (Voita et al., 2019).

Table 6: WMT20 ZH-EN generators and reference papers. The score column indicates the score from the metric that currently correlates best with the human judgments (ensemble).

Table 7: WMT20 EN-DE generators and reference papers. The score column indicates the score from the metric that currently correlates best with the human judgments (ensemble).

B.3 CNNDM Summarization

We submit all 26 models from Fabbri et al. (2021). Table 7 shows all models and their automatic evaluation scores from the top-performing metric (COMET).

B.4 MSCOCO Image Captioning

We submit the four strong models from the literature (Kasai et al., 2021c). They share similar pipeline structure but vary in model architecture, (pre)training data, model size, and (pre)training objective. Table 9 shows the models with their papers and automatic scores from the top-performing metric (RefCLIP-S).
Table 8: CNNDM summarization generators and reference papers. They are from Fabbri et al. (2021), but we apply detokenization (Bird et al., 2009) and/or truecasing (Manning et al., 2014) to standardize the model outputs for better, reproducible evaluations. The score column indicates the score from the metric that currently correlates best with the human judgments (COMET).

| Generator                  | Description            | Score |
|----------------------------|------------------------|-------|
| Lead-3                     | First 3 sentences      | -0.011|
| TS                         | Raffel et al. (2020)   | -0.030|
| BART                       | Lewis et al. (2020)    | -0.032|
| Pegasus-dynamic-mix        | Zhang et al. (2020a)   | -0.044|
| RNES                       | Wu and Hu (2018)       | -0.049|
| Unified-ext-abs            | Hsu et al. (2018)      | -0.056|
| Pegasus-huge-news          | Zhang et al. (2020a)   | -0.056|
| REFRESH                    | Narayan et al. (2018)  | -0.067|
| ROUGESal                   | Pasunuru and Bansal (2018) | -0.073|
| Human-H                    | Highlights             | -0.075|
| NEUSUM                     | Zhou et al. (2018)     | -0.083|
| BanditSum                  | Dong et al. (2018)     | -0.083|
| LATENT                     | Zhang et al. (2018)    | -0.099|
| Closed-book-decoder       | Jiang and Bansal (2018) | -0.112|
| Multi-task-Ent-QG          | Guo et al. (2018)      | -0.117|
| Pointer-Generator          | See et al. (2017)      | -0.144|
| UniLM                      | Dong et al. (2019)     | -0.151|
| Bottom-Up                  | Gehrmann et al. (2018) | -0.160|
| JEC                        | Xu and Durrett (2019)  | -0.167|
| Fast-abs-r1                | Chen and Bansal (2018) | -0.189|
| NeuralTD                   | Bölüm et al. (2019)    | -0.215|
| Improve-obs                | Kryściński et al. (2018) | -0.329|
| BertSum-obs                | Liu and Lapata (2019)  | -0.341|
| STRASS                     | Boucarrat et al. (2019) | -0.405|
| GPT-2-zero-shot            | Ziegler et al. (2019)  | -0.441|
| SENECA                     | Sharma et al. (2019)   | -0.735|

Table 9: MSCOCO image captioning generators and reference papers. The score column indicates the score from the metric that currently correlates best with the human judgments (RefCLIP-S).

| Generator      | Description       | Score |
|----------------|-------------------|-------|
| VinVL-large    | Zhang et al. (2021) | 83.78 |
| VinVL-base     | Zhang et al. (2021) | 83.45 |
| Unified-VLP    | Zhou et al. (2020)  | 82.59 |
| Up-Down        | Anderson et al. (2018) | 80.63 |

Table 10 discusses details and configurations of the automatic metrics that we implement in our initial BILLBOARDs.

C Participating Metrics

D Additional Ensemble Metric Ablations

Seen in Table 11 are ablation studies for the ensemble metrics where one of the three selected metrics is removed at a time. Dropping one metric often has no impact on the correlation score, suggesting that these metrics are highly redundant and capture similar aspects of the output quality. BILLBOARDs encourage researchers to explore ways to diversify automatic evaluations by updating the ensemble metric every time a new metric is submitted.

20SCAREBLEU implementation of sentence-level BLEU-4: https://github.com/mjpost/sacreBLEU/blob/v1.2.12/sacrebleu.py#L999.
21HuggingFace implementation (Wolf et al., 2020).
22https://github.com/mjpost/sacrebleu.
23https://www.nltk.org/_modules/nltk/translate/meteor_score.html.
24https://github.com/m-popovic/chrF.
25https://github.com/salaniz/pycocoevalcap.
26https://github.com/rwth-i6/CharacTER.
27https://github.com/thomasScialom/summa-ga.
28https://huggingface.co/metrics/bleurt.
29https://github.com/Unbabel/COMET/.
30https://github.com/thompsonb/prism.
31https://github.com/salaniz/pycocoevalcap.
Table 11: Correlations from ensemble ablation studies. One of the three selected metrics is removed at a time, and a new Lasso regression model is trained on the remaining metrics. The bigger the correlation drop is, the bigger the contribution is from the removed metric. **COMET-QE** is a referenceless metric.

### E Additional Mixed-Effects Analysis

Table 12 presents fixed effect coefficients that measure how much each automatic metric *overrates* machines over humans (§2.3). With some exceptions in CNNDM summarization, almost all automatic metrics *underrate* human generations (significantly positive coefficients). Table 13 swaps the roles of human-generated text, but we still see similar patterns: almost all metrics overrate machines over humans, but the problem is mitigated in **COMET-QE**, a referenceless, quality estimation metric. This confirms that our findings hold independently of the design choice.

### F Crowdworker vs. Rubric-based Expert Evaluations

Seen in Table 14 are examples where crowdworker evaluators (Barrault et al., 2020) and professional translators (Freitag et al., 2021) disagree: crowdworkers give lower scores to the human-generated translations than the machine-generated ones. The first case requires document-level context to properly evaluate. Document-level context and diversity in high-quality human translations can mislead crowdworkers.
| Source      | WMT20 ZH-EN                                                                 | Human-A                                                                 | Human-B                                                                 |
|-------------|-----------------------------------------------------------------------------|-------------------------------------------------------------------------|-------------------------------------------------------------------------|
| Huoshan     | 希望兴安省继续为日俄企业提高便利条件。 It is hoped that **Xing’an Province** will continue to provide convenient conditions for Belarusian enterprises. | He hoped that **Hung Yen Province** would continue to provide convenient conditions for Belarusian enterprises. | He hoped that this could continue in the future.                         |
| Human-A     |                                                                             |                                                                         |                                                                         |
| Human-B     |                                                                             |                                                                         |                                                                         |

Table 14: Examples where crowdworker evaluators (Barrault et al., 2020) and professional translators (Freitag et al., 2021) disagree: crowdworkers give lower scores to the human-generated translations than the machine-generated ones. The first case requires document-level context to properly evaluate. 兴安省 is Hung Yen Province in Vietnam in this context, but there is entity ambiguity (Xing’an Province that existed in Republic of China.). The second one illustrates the diversity of human generations that mislead crowdworkers.