How NOT To Evaluate Your Dialogue System: An Empirical Study of Unsupervised Evaluation Metrics for Dialogue Response Generation

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Abstract

We investigate evaluation metrics for end-to-end dialogue systems where supervised labels, such as task completion, are not available. Recent works in end-to-end dialogue systems have adopted metrics from machine translation and text summarization to compare a model’s generated response to a single target response. We show that these metrics correlate very weakly or not at all with human judgments of the response quality in both technical and non-technical domains. We provide quantitative and qualitative results highlighting specific weaknesses in existing metrics, and provide recommendations for future development of better automatic evaluation metrics for dialogue systems.

1 Introduction

Significant progress has been made in learning end-to-end systems directly from large amounts of text data for a variety of natural language tasks, such as question answering (Weston et al., 2015), machine translation (Cho et al., 2014), and dialogue response generation systems (Sordoni et al., 2015), in particular through the use of neural network models. In the case of dialogue systems, an important challenge is to provide a reliable evaluation of the learned systems. Typically, evaluation is done using human-generated supervised signals, such as a task completion test or a user satisfaction score (Walker et al., 1997; Möller et al., 2006). We call models that are trained to optimize for such supervised objectives supervised dialogue models, while those that are not unsupervised dialogue models.

While supervised models have historically been the method of choice, supervised labels are difficult to collect on a large scale due to the cost of human labour. Further, for free-form types of dialogues (e.g., chatbots), the notion of task completion is ill-defined since it may differ from one human user to another.

Unsupervised dialogue models are receiving increased attention. These models are typically trained (end-to-end) to predict the next utterance of a conversation, given several context utterances (Serban et al., 2015). This task is referred to as response generation. However automatically evaluating the quality of unsupervised models remains an open question. Automatic evaluation metrics would help accelerate the deployment of unsupervised dialogue systems.

Faced with similar challenges, other natural language tasks have successfully developed automatic evaluation metrics. For example, BLEU (Papineni et al., 2002) and METEOR (Banerjee and Lavie, 2005) are now standard for evaluating machine translation models, and ROUGE (Lin, 2004) is often used for automatic summarization. Since the machine translation task appears similar to the dialogue response generation task, dialogue researchers have adopted the same metrics for evaluating the performance of their models. However, the applicability of these methods has not been validated for dialogue-related tasks. A particular challenge in dialogues is the significant diversity in the space of valid responses to a given conversational context. This is illustrated in Table 1, where two reasonable proposed responses are given to the context; however, these responses do not share any words in common and do not have the same semantic meaning.

We investigate several evaluation metrics for dialogue response generation systems, including both statistical word based similarity met-
Context of Conversation
Speaker A: Hey John, what do you want to do tonight?
Speaker B: Why don’t we go see a movie?

Potential Responses
Response 1: Nah, I hate that stuff, let’s do something active.
Response 2: Oh sure! Heard the film about Turing is out!

Table 1: Example showing the intrinsic diversity of valid responses in a dialogue.

metrics such as BLEU, METEOR, and ROUGE, and word-embedding based similarity metrics derived from word embedding models such as Word2Vec (Mikolov et al., 2013). The BLEU metric, in particular, has been used recently to evaluate dialogue models (Li et al., 2015a; Galley et al., 2015a; Sordoni et al., 2015; Ritter et al., 2011a; Li et al., 2016).

We study the applicability of these metrics by using them to evaluate a variety of end-to-end dialogue models, including both retrieval models such as the Dual Encoder (Lowe et al., 2015) and generative models that incorporate some form of recurrent decoder (Serban et al., 2015). We use these models to produce a proposed response given the context of the conversation and compare them to the ground-truth response (the actual next response) using the above metrics.

When evaluating these models with the embedding-based metrics, we find that even though some models significantly outperform others across several metrics and domains, the metrics only very weakly correlate with human judgement, as determined by human evaluation of the responses. This is despite the fact that metrics such as BLEU have been seen significant recent use in evaluating unsupervised dialogue systems (Ritter et al., 2011a; Sordoni et al., 2015; Li et al., 2015b; Li et al., 2016). We highlight the shortcomings of these metrics using: a) a statistical analysis of our survey’s results; b) a qualitative analysis of examples taken from our data; and c) an exploration of the sensitivity of the metrics.

2 Related Work

Evaluation methods for supervised dialogue systems include the PARADISE framework (Walker et al., 1997), which simultaneously optimizes for task completion and alternative costs, such as number of utterances and agent response delay. Similarly, MeMo (Möller et al., 2006) evaluates dialogue systems through interactions with simulated users. An extensive overview of such metrics can be found in (Jokinen and McTear, 2009).

We focus on metrics that are model-independent, i.e. where the model generating the response does not also evaluate its quality; thus, we do not consider word perplexity, although it has been used to evaluate unsupervised dialogue models (Serban et al., 2015). This is because it is not computed on a per-response basis, and cannot be computed for retrieval models. Further, we only consider metrics that can be used to evaluate proposed responses against ground-truth responses, so we do not consider retrieval-based metrics such as recall, which has been used to evaluate dialogue models (Schatzmann et al., 2005; Lowe et al., 2015).

Several recent works on unsupervised dialogue systems adopt the BLEU score for evaluation. Ritter et al. (2011b) formulate the unsupervised learning problem as one of translating a context into a candidate response. They use a statistical machine translation (SMT) model to generate responses to various contexts using Twitter data, and show that it outperforms information retrieval baselines according to both BLEU and human evaluations. Sordoni et al. (2015) extend this idea using a recurrent language model to generate responses in a context-sensitive manner. They also evaluate using BLEU, however they produce multiple ground truth responses by retrieving 15 responses from elsewhere in the corpus, using a simple bag-of-words model. Li et al. (2015b) evaluate their proposed diversity-promoting objective function for neural network models using BLEU score with only a single ground truth response. A modified version of BLEU, deltaBLEU (Galley et al., 2015b), which takes into account several human-evaluated ground truth responses, is shown to have a weak to moderate correlation to human judgement using Twitter dialogues. However, such human annotation is often infeasible to obtain in practice. Galley et al. (2015b) also show that, even with several ground truth responses available, the standard BLEU metric correlates at best weakly with human judgements.

3 Evaluation Metrics

Given the context of a conversation and a proposed response, our goal is to automatically evaluate how appropriate and relevant the proposed response is to the conversation. We focus on metrics that compare it to the ground truth response of the
We first consider metrics that evaluate the amount of word-overlap between the proposed response and the ground-truth response. We examine the BLEU and METEOR scores that have been used for machine translation, and the ROUGE score that has been used for automatic summarization.

While these metrics have been shown to correlate with human judgement in their target domains (Papineni et al., 2002a; Lin, 2004), they have not been evaluated for dialogue systems.

We denote the set of ground truth responses as \( R \) and the set of proposed responses as \( \hat{R} \). The size of both sets is \( N \) (that is we assume that there is a single candidate ground truth response) and individual sentences are indexed using \( i \) (\( r_i \in R \)). The \( j \)'th token in sentence \( r_i \) is denoted \( w_{ij} \).

**BLEU.** BLEU (Papineni et al., 2002a) analyzes the co-occurrences of n-grams in the ground truth and the proposed responses. It first computes an n-gram precision for the whole dataset (we assume that there is a single candidate ground truth response per context):

\[
P_n(R, \hat{R}) = \frac{\sum_i \sum_k \min(h(k, r_i), h(k, \hat{r}_i))}{\sum_i \sum_k h(k, r_i)}
\]

where \( k \) indexes all possible n-grams of length \( n \) and \( h(k, r_i) \) is the number of n-grams \( k \) in \( r_i \). To avoid the drawbacks of using a precision score, namely that it favours shorter (candidate) sentences, the authors introduce a brevity penalty. BLEU-N where \( N \) is the maximum length of n-grams considered is defined as:

\[
\text{BLEU-N} := b(R, \hat{R}) \exp \left( \sum_{n=1}^{N} \beta_n \log P_n(R, \hat{R}) \right)
\]

\( \beta_n \) is a weighting that is usually uniform, and \( b(\cdot) \) is the brevity penalty. Note that BLEU is usually calculated at the corpus-level, and has been shown to correlate with human judgement in the translation domain when there are multiple ground truth candidates available.

**METEOR.** The METEOR metric (Banerjee and Lavie, 2005) was introduced to address several weaknesses in BLEU. It creates an explicit alignment between the candidate and target responses. The alignment is based on exact token matching, followed by WordNet synonyms, stemmed tokens, and then paraphrases. Given a set of alignments, the METEOR score is the harmonic mean of precision and recall between the proposed and ground truth sentence.

**ROUGE.** ROUGE (Lin, 2004) is a set of evaluation metrics used for automatic summarization. We consider ROUGE-L, which is a F-measure based on the Longest Common Subsequence (LCS) between a candidate and target sentence. The LCS is a set of words which occur in two sentences in the same order; however, unlike n-grams the words do not have to be contiguous, i.e. there can be other words in between the words of the LCS.

**3.2 Embedding-based Metrics**

An alternative to using word-overlap based metrics is to consider the meaning of each word as defined by a *word embedding*, which assigns a vector to each word. Methods such as Word2Vec (Mikolov et al., 2013) calculate these embeddings using distributional semantics; that is, they approximate the meaning of a word by considering how often it co-occurs with other words in the corpus. These embedding-based metrics usually approximate sentence-level embeddings using some heuristic to combine the vectors of the individual words in the sentence. The sentence-level embeddings between the candidate and target response are compared using a measure such as cosine distance. This does not depend on exact word-overlap between generated and actual responses, but still allows a quantitative comparison between responses generated by a dialogue system and the actual response of the conversation.

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1We only provide summaries of the metrics; we will add the mathematical details of all metrics using the extra page available at publication time.

2To the best of our knowledge, only BLEU has been evaluated in the dialogue system setting quantitatively by Galley et al. (2015a) on the Twitter domain. However, they carried out their experiments in a very different setting with multiple ground truth responses, which are rarely available in practice, and without providing any qualitative analysis of their results.
**Greedy Matching.** Greedy matching is the one embedding-based metric that does not compute sentence-level embeddings. Instead, given two sequences \( r \) and \( \hat{r} \), each token \( w \in r \) is greedily matched with a token \( \hat{w} \in \hat{r} \) based on the cosine similarity of their word embeddings \( (e_w) \), and the total score is then averaged across all words:

\[
G(r, \hat{r}) = \frac{\sum_{w \in r} \max_{\hat{w} \in \hat{r}} \cos(e_w, e_{\hat{w}})}{|r|}
\]

\[
GM(r, \hat{r}) = \frac{G(r, \hat{r}) + G(\hat{r}, r)}{2}
\]

This formula is asymmetric, thus we must average the greedy matching scores \( G \) in each direction. This was originally introduced for intelligent tutoring systems \( \text{(Rus and Linean, 2012)} \). The greedy approach favours responses with key words that are semantically similar to those in the ground truth response.

**Embedding Average.** The embedding average metric calculates sentence-level embeddings using additive composition, a method for computing the meanings of phrases by averaging the vector representations of their constituent words \( \text{(Folz et al., 1998; Landauer and Dumais, 1997; Mitchell and Lapata, 2008)} \). This method has been widely used in other domains, for example in textual similarity tasks \( \text{(Wieting et al., 2015)} \). The embedding average, \( \bar{e}_r \), is defined as the mean of the word embeddings of each token in a sentence \( r \):

\[
\bar{e}_r = \frac{\sum_{w \in r} e_w}{|\sum_{w \in r} e_w|}
\]

To compare a ground truth response \( r \) and retrieved response \( \hat{r} \), we compute the cosine similarity between their respective sentence level embeddings: \( EA := \cos(\bar{e}_r, \bar{e}_{\hat{r}}) \).

**Vector Extrema.** Another way to calculate sentence-level embeddings is using vector extremum \( \text{(Forgues et al., 2014)} \). For each dimension of the word vectors, take the most extreme value amongst all word vectors in the sentence, and use that value in the sentence-level embedding:

\[
e_{rd} = \begin{cases} 
\max_{w \in r} e_{wd} & \text{if } e_{wd} > \min_{w \in r} e_{wd} \\
\min_{w \in r} e_{wd} & \text{otherwise}
\end{cases}
\]

where \( d \) indexes the dimensions of a vector; \( e_{wd} \) is the \( d \)'th dimensions of \( e_w \) (\( w \)'s embedding).

Similarity between response vectors is again computed using cosine distance. Intuitively, this can be thought of as prioritizing informative words over common ones; words that appear in similar contexts will be close together in the vector space. Thus, common words are pulled towards the origin because they occur in various contexts, while words carrying important semantic information will lie further away. By taking the extremum along each dimension, we are therefore more likely to ignore common words.

### 4 End-to-End Dialogue Models

We now describe a variety of models that can be used to produce a response given the context of a conversation. These fall into two categories: retrieval models, and generative models. While we do not consider all available models, those selected cover a diverse range of end-to-end models that appear in recent literature, and provide a good sample of models for illustrating evaluation with existing metrics.

#### 4.1 Retrieval Models

Ranking or retrieval models for dialogue systems are typically evaluated based on whether they can retrieve the correct response from a corpus of pre-defined responses, which includes the ground truth response to the conversation \( \text{(Schatzmann et al., 2005)} \). Such systems can be evaluated using recall or precision metrics. However, when deployed in a real setting these models will not have access to the correct response given an unseen conversation. Thus, in the results presented below we remove the correct response from the corpus and ask the model to retrieve the most appropriate response from the remaining utterances.

We then evaluate each model by comparing the retrieved response to the ground truth response of the conversation. This closely imitates real-life deployment of these models, as it tests the ability of the model to generalize to unseen contexts.

**TF-IDF.** We consider a simple Term Frequency - Inverse Document Frequency (TF-IDF) retrieval model \( \text{(Lowe et al., 2015)} \). TF-IDF is a statistic that intends to capture how important a given word is to some document, which is calculated as:

\[
tfidf(w, c, C) = f(w, c) \times \log \frac{N}{|\{c \in C : w \in c\}|},
\]

where \( C \) is the set of all contexts in the corpus, \( f(w, c) \) indicates the number of times word \( w \) appeared in context \( c \), \( N \) is the total number of dialogues, and the denominator represents the number of dialogues in which the word \( w \) appears.
In order to apply TF-IDF as a retrieval model for dialogue, we first compute the TF-IDF vectors for each context and response in the corpus. We then produce two models: C-TFIDF computes the cosine similarity between an input context and all other contexts in the corpus, and returns the response from the context with the highest score, while R-TFIDF computes the cosine similarity between the input context and each response directly.

**Dual Encoder.** Next we consider the recurrent neural network (RNN) based architecture called the Dual Encoder (DE) model (Lowe et al., 2015). The DE model consists of two RNNs which respectively compute the vector representation of an input context and response, \( c, r \in \mathbb{R}^n \). The model then calculates the probability that the given response is the ground truth response given the context, by taking a weighted dot product: \( p(r | c, M) = \sigma(c^T M r + b) \) where \( M \) is a matrix of learned parameters and \( b \) is a bias. The model is trained using negative sampling to minimize the cross-entropy error of all (context, response) pairs. To our knowledge, our application of neural network models to large-scale retrieval in dialogue systems is novel.

| Model   | Embedding | Greedy | Vector | Embedding | Greedy | Vector |
|---------|-----------|--------|--------|-----------|--------|--------|
|         | Averaging | Matching | Extrema | Averaging | Matching | Extrema |
| R-TFIDF | 0.536 ± 0.003 | 0.370 ± 0.002 | 0.342 ± 0.002 | 0.483 ± 0.002 | 0.356 ± 0.001 | 0.340 ± 0.001 |
| C-TFIDF | 0.571 ± 0.003 | 0.373 ± 0.002 | 0.353 ± 0.002 | 0.531 ± 0.002 | 0.362 ± 0.001 | 0.353 ± 0.001 |
| DE      | 0.650 ± 0.003 | 0.413 ± 0.002 | 0.376 ± 0.001 | 0.597 ± 0.002 | 0.384 ± 0.001 | 0.365 ± 0.001 |
| LSTM    | 0.130 ± 0.003 | 0.097 ± 0.003 | 0.089 ± 0.002 | 0.593 ± 0.002 | 0.439 ± 0.002 | 0.420 ± 0.002 |
| HRED    | 0.580 ± 0.003 | 0.418 ± 0.003 | 0.384 ± 0.002 | 0.599 ± 0.002 | 0.439 ± 0.002 | 0.422 ± 0.002 |

Table 2: Models evaluated using the vector-based evaluation metrics, with 95% confidence intervals.

| Model   | Mean score | Mean of differences in #words between a ground truth response and proposed response |
|---------|-------------|----------------------------------------------------------------------------------|
| BLEU-1  | 0.1724      | < 0.01                                                                          |
| BLEU-2  | 0.0744      | < 0.01                                                                          |
| Average | 0.6587      | 0.6246 < 0.01                                                                   |
| METEOR  | 0.2386      | 0.2073 < 0.01                                                                   |
| Human   | 2.66        | 2.57 < 0.01                                                                     |

Table 5: Effect of differences in response length for the Twitter dataset, \( \Delta w \) is absolute difference in #words between a ground truth response and proposed response.

**4.2 Generative Models**

In addition to retrieval models, we also consider generative models. In this context, we refer to a model as generative if it is able to generate entirely new sentences that are unseen in the training set.

**LSTM language model.** The baseline model is an LSTM language model (Hochreiter and Schmidhuber, 1997) trained to predict the next word in the (context, response) pair. During test time, the model is given a context, encodes it with the LSTM and generates a response using a greedy beam search procedure (Graves, 2013). During test time, the model is given a context, encodes it with the LSTM and generates a response using a greedy beam search procedure (Graves, 2013).

**HRED.** Finally we consider the Hierarchical Recurrent Encoder-Decoder (HRED) (Serban et al., 2015). In the traditional Encoder-Decoder framework, all utterances in the context are concatenated together before encoding. Thus, information from previous utterances is far outweighed by the most recent utterance. The HRED model uses a hierarchy of encoders; each utterance in the context passes through an ‘utterance-level’ encoder, and the output of these encoders is passed through another ‘context-level’ encoder. This enables the handling of longer-term dependencies compared to a conventional Encoder-Decoder.

**4.3 Conclusions from an Incomplete Analysis**

When evaluation metrics are not explicitly correlated to human judgement, it is possible to draw misleading conclusions by examining how the metrics rate different models.

To illustrate this point, we compare the performance of selected models according to the embedding metrics on two different domains: the Ubuntu Dialogue Corpus (Lowe et al., 2015), which con-
Table 3: Correlation between each metric and human judgements for each response. Correlations shown in the human row result from randomly dividing human judges into two groups.

| Metric       | Spearman p-value | Pearson p-value | Spearman p-value | Pearson p-value |
|--------------|------------------|-----------------|------------------|-----------------|
| Greedy       | 0.2119 0.034     | 0.1994 0.047    | 0.05276 0.6      | 0.02049 0.84    |
| Average      | 0.2259 0.024     | 0.1971 0.049    | -0.1387 0.17     | -0.1631 0.10    |
| Extrema      | 0.2103 0.036     | 0.1842 0.067    | 0.09243 0.36     | -0.02903 0.98   |
| METEOR       | 0.1887 0.06      | 0.1927 0.055    | 0.06314 0.53     | 0.1419 0.16     |
| BLEU-1       | 0.1665 0.098     | 0.1288 0.2      | -0.02552 0.8     | 0.01929 0.85    |
| BLEU-2       | 0.3576 < 0.01    | 0.3874 < 0.01   | 0.03819 0.71     | 0.0586 0.56     |
| BLEU-3       | 0.3423 < 0.01    | 0.1443 0.15     | 0.0878 0.38      | 0.1116 0.27     |
| BLEU-4       | 0.3417 < 0.01    | 0.1392 0.17     | 0.1218 0.23      | 0.1132 0.26     |
| ROUGE        | 0.1235 0.22      | 0.09714 0.34    | 0.05405 0.5933   | 0.06401 0.53    |
| Human        | 0.9476 < 0.01    | 1.0 0.0         | 0.9550 < 0.01    | 1.0 0.0         |

5 Human Correlation Analysis

5.1 Data collection

We conducted a human survey to determine the correlation between human judgement on the quality of responses, and the score assigned by each metric. We aimed to follow the procedure for the evaluation of BLEU (Papineni et al., 2002a). 25 volunteers from the Computer Science department at the author’s institution were given a context and one proposed response, and were asked to judge the response quality on a scale of 1 to 5. In this case, a 1 indicates that the response is either not appropriate or sensible given the context, and a 5 indicates that the response is very reasonable.

Each volunteer was given 100 questions for each of the Ubuntu and Twitter datasets. These questions correspond to 20 unique contexts, with 5 different responses: one utterance randomly drawn from elsewhere in the test set, the response selected from each of the TF-IDF, DE, and HRED models, and a response written by a human annotator. These were chosen as they cover the range of qualities approximately uniformly, as seen in Figure 1. The questions were randomly permuted within each dataset during the experiments. Out of the 25 respondents, 23 had Cohen’s kappa scores $\kappa > 0.2$ w.r.t. the other respondents, which is a standard measure for inter-rater agreement (Cohen, 1968). The 2 respondents with low kappa scores were excluded from the analysis below.

5.2 Survey Results

We present correlation results between the human judgements and each metric in Table 3. We compute the Pearson correlation, which estimates linear...
Figure 1: Scatter plots showing the correlation between metrics and human judgement on the Twitter corpus (a) and Ubuntu Dialogue Corpus (b). The plots represent BLEU-2 (left), embedding average (center), and correlation between two halves of human respondents (right).

ear correlation, and Spearman correlation, which estimates any monotonic correlation.

The first observation is that in both domains the BLEU-4 score, which has previously been used to evaluate unsupervised dialogue systems, shows very weak if any correlation with human judgement. In fact we found that in our analysis, the BLEU-3 and BLEU-4 scores were near-zero for a majority of response pairs; for BLEU-4, only four examples had a score $> 10^{-9}$. Some of the embedding metrics and BLEU-2 show some positive correlation in the non-technical Twitter domain. However there is no metric that significantly correlates with humans on the Ubuntu Dialogue Corpus, quite possibly because the correct Ubuntu responses contain specific technical words, which are less likely to be generated or retrieved by a learned model.

Figure 1 illustrates the relationship between metrics and human judgements. We include only the best performing metric using word-overlaps, i.e. the BLEU-2 score (left), and the best performing metric using word embeddings, i.e. the vector average (center). These plots show how weak the correlation is: in both cases, they appear to be random noise. It seems as though the BLEU score obtains a positive correlation because of the large number of responses that are given a score of 0 (bottom left corner of the first plot). This is in stark contrast to the inter-rater agreement, which is plotted between two randomly sampled halves of the raters (right-most plots).

We also calculated the BLEU scores after removing stopwords and punctuation from the responses. As shown in Table 4 this weakens the correlation with human judgement for BLEU-2 compared to the values in Table 3 and suggests that BLEU is sensitive to factors that do not change the semantics of the response.

Finally, we examined the effect of response length on the metrics, by considering changes in scores for the cases where the response length differ in terms of words, between the ground truth response and the proposed response. Table 4 shows that BLEU and METEOR are particularly sensitive to this aspect, compared to the Embedding Average metric and human judgement.

5.3 Qualitative Analysis

In order to determine specifically why the metrics fail, we examine some qualitative samples where there is a disagreement between the metrics and human rating. We present in Figure 2 two examples where all of the embedding-based metrics and
Figure 2: Examples where the metrics rated the response poorly and humans rated it highly (left), and the converse (right). Both responses are given near-zero score by BLEU-N for N > 1.

BLEU-1 score the proposed response significantly differently than the humans.

The left of Figure 2 shows an example where the embedding-based metrics score the proposed response lowly, while humans rate it highly. It is clear from the context that the proposed response is reasonable – indeed both responses intend to express gratitude. However, the proposed response has a different wording than the ground truth response, and therefore the metrics are unable to separate the salient words from the rest. This suggests that the embedding-based metrics would benefit from a weighting of word saliency.

The right of the figure shows the reverse scenario: the embedding-based metrics score the proposed response highly, while humans do not. This is most likely due to the frequently occurring ‘i’ token, and the fact that ‘happy’ and ‘welcome’ may be close together in the embedding space. However, from a human perspective there is a significant semantic difference between the responses as they pertain to the context. Metrics that take into account the context may be required in order to differentiate these responses. Note that in both responses in Figure 2 there are no overlapping n-grams greater than unigrams between the ground truth and proposed responses; thus, all of BLEU-2,3,4 would assign a score near 0 to the response.

6 Discussion

We have shown that many metrics commonly used in the literature for evaluating unsupervised dialogue systems do not correlate strongly with human judgement. Here we elaborate on important issues arising from our analysis.

Constrained tasks. Our analysis focuses on relatively unconstrained domains. Other work, which separates the dialogue system into a dialogue planner and a natural language generation component, for applications in constrained domains, may find stronger correlations with the BLEU metric. Wen et al. (2015) provide an example of this, when they propose a model to map from dialogue acts to natural language sentences and use BLEU to evaluate the quality of the generated sentences. Since the mapping from dialogue acts to natural language sentences is more constrained and more similar to the machine translation task, it seems likely that BLEU will correlate better with human judgements. However, an empirical investigation is still necessary to justify this.

Incorporating multiple responses. Our correlation results assume that only one ground truth response is available given each context. Indeed, this is the common setting in most of the recent literature on training end-to-end conversation models. There has been some work on using a larger set of automatically retrieved plausible responses when evaluating with BLEU (Sordoni et al., 2015). However, there is no standard method for doing this in the literature. Future work should examine how retrieving additional responses affects the correlation with word-overlap metrics.

Searching for suitable metrics. While we provide evidence against existing metrics, we do not yet provide good alternatives for unsupervised evaluation. We do believe that embedding-based metrics hold the most promise, if they can be extended to take into account more complex models for modeling sentence-level compositionality. For example, the skip-thought vectors of Kiros et al. (2015) could be considered. Metrics that take into account the context of the conversation, or other utterances in the corpus could also be considered. Finally, a model could be learned using the data
collected from the human survey in order to provide human-like scores to proposed responses.

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Appendix: Full scatter plots

We present the scatterplots for all of the metrics consider and their correlation with human judgement, in Figures 3-7 below. As previously emphasized, there is very little correlation for any of the metrics, and the BLEU-3 and BLEU-4 scores are often close to zero.
Figure 3: Scatter plots showing the correlation between two randomly chosen groups of human volunteers on the Twitter corpus (left) and Ubuntu Dialogue Corpus (right).

Figure 4: Scatter plots showing the correlation between metrics and human judgement on the Twitter corpus (left) and Ubuntu Dialogue Corpus (right). The plots represent ROUGE (a) and METEOR (b).
Figure 5: Scatter plots showing the correlation between metrics and human judgement on the Twitter corpus (left) and Ubuntu Dialogue Corpus (right). The plots represent vector extrema (a), greedy matching (b), and vector averaging (c).
Figure 6: Scatter plots showing the correlation between metrics and human judgement on the Twitter corpus (left) and Ubuntu Dialogue Corpus (right). The plots represent BLEU-1 (a), BLEU-2 (b), BLEU-3 (c), and BLEU-4 (d).