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

# Chia-Wei $Liu^1$ , Ryan $Lowe^{1*}$ , Iulian V. Serban $^{2*}$ , Michael Noseworthy $^{1*}$ , Laurent Charlin $^1$ , Joelle Pineau $^1$

<sup>1</sup> School of Computer Science, McGill University

{chia-wei.liu,ryan.lowe,michael.noseworthy}@mail.mcgill.ca {lcharlin, jpineau}@cs.mcgill.ca ^2 DIRO, Université de Montréal

iulian.vlad.serban@umontreal.ca

## Abstract

We investigate evaluation metrics for endto-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 judgements 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., 2002a) and ME-TEOR (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 dialoguerelated 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-

<sup>\*</sup> Denotes equal contribution.

#### **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.

rics 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 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. Rit-(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 humanevaluated 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

conversation. In particular, we investigate two approaches: word based similarity metrics and word-embedding based similarity metrics.

## 3.1 Word Overlap-based Metrics

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-occurences 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:

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

 $\beta_n$  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<sup>3</sup>. 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 wordoverlap 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.

<sup>&</sup>lt;sup>1</sup>We only provide summaries of the metrics; we will add the mathematical details of all metrics using the extra page available at publication time.

<sup>&</sup>lt;sup>2</sup>To 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.

<sup>&</sup>lt;sup>3</sup>To maintain statistical independence between the task and each performance metric, it is important that the word embeddings used are trained on corpora which do not overlap with the task corpus. Otherwise the assumptions of independent and identically distributed (i.i.d.) training and test data examples are incorrect, which could lead to spurious and potentially misleading correlations between data examples.

**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 (Rus and Lintean, 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 (Foltz 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 (Wieting et al., 2015). The embedding average,  $\bar{e}$ , 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 extrema (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:

$$e_{rd} = \left\{ \begin{array}{ll} \max_{w \in r} e_{wd} & \text{if } e_{wd} > |\min_{w' \in r} e_{w'd}| \\ \min_{w \in r} e_{wd} & \text{otherwise} \end{array} \right.$$

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 extrema 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 predefined responses, which includes the ground truth response to the conversation (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 (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:  $\operatorname{tfidf}(w,c,C)=f(w,c)\times\log\frac{N}{|\{c\in C:w\in c\}|},$  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.

	Ubu	ntu Dialogue Co	rpus	Twitter Corpus			
	Embedding	Greedy	Vector	Embedding	Greedy	Vector	
	Averaging	Averaging Matching Extrem		Averaging	Matching	Extrema	
R-TFIDF	$0.536 \pm 0.003$	$0.370 \pm 0.002$	$0.342 \pm 0.002$	$0.483 \pm 0.002$	$0.356 \pm 0.001$	$0.340 \pm 0.001$	
C-TFIDF	$0.571 \pm 0.003$	$0.373 \pm 0.002$	$0.353 \pm 0.002$	$0.531 \pm 0.002$	$0.362 \pm 0.001$	$0.353 \pm 0.001$	
DE	$\textbf{0.650} \pm \textbf{0.003}$	$0.413 \pm 0.002$	$0.376 \pm 0.001$	$\textbf{0.597} \pm \textbf{0.002}$	$0.384 \pm 0.001$	$0.365 \pm 0.001$	
LSTM	$0.130 \pm 0.003$	$0.097 \pm 0.003$	$0.089 \pm 0.002$	$0.593 \pm 0.002$	$0.439 \pm 0.002$	$0.420 \pm 0.002$	
HRED	$0.580 \pm 0.003$	$0.418 \pm 0.003$	$0.384 \pm 0.002$	$\textbf{0.599} \pm \textbf{0.002}$	$0.439 \pm 0.002$	$\textbf{0.422} \pm \textbf{0.002}$	

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

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:  $p(r \text{ is correct}|c, r, M) = \sigma(c^T M r + b) \text{ where } M$ 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.

	Spearman	p-value	Pearson	p-value
BLEU-1	0.1580	0.12	0.2074	0.038
BLEU-2	0.2030	0.043	0.1300	0.20

Table 4: Correlation between BLEU metric and human judgements after removing stopwords and punctuation for the Twitter dataset.

## 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

	Mean score				
	$\Delta w \le 6$	$\Delta w >= 6$	p-value		
	(n=47)	(n=53)			
BLEU-1	0.1724	0.1009	< 0.01		
BLEU-2	0.0744	0.04176	< 0.01		
Average	0.6587	0.6246	0.25		
METEOR	0.2386	0.2073	< 0.01		
Human	2.66	2.57	0.73		

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

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-

	Twitter			Ubuntu				
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	-0.002903	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

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.

tains technical vocabulary and where conversations are often oriented towards solving a particular problem or obtaining specific information, and a non-technical Twitter corpus collected following the procedure of Ritter et al. (2010), where the dialogues cover a diverse set of topics often without any particular goal. We consider these two datasets since they cover contrasting dialogue domains, i.e. technical help vs casual chit-chat, and because they are amongst the largest publicly available corpora, making them good candidates for building data-driven dialogue systems.

Results on the proposed embedding metrics are shown in Table 2. For the retrieval models, we observe that the DE model significantly outperforms both TFIDF baselines on all metrics across both datasets. Further, the HRED model significantly outperforms the basic LSTM generative model in both domains, and appears to be of similar strength as the DE model.

Based on these results, one might be tempted to conclude that there is some information being captured by these metrics, that significantly differentiates models of different quality. However, as we show in the next section, the embedding-based metrics correlate only weakly with human judgement on the Twitter corpus, and not at all on the Ubuntu Dialogue Corpus. Although this may not come as a surprise to some researchers in the dialogue system community, the fact remains that BLEU has been frequently used to evaluate unsupervised dialogue systems (Li et al., 2015a; Li et al., 2016; Galley et al., 2015a; Ritter et al., 2011a).

## 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 <sup>4</sup>; 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 lin-

<sup>&</sup>lt;sup>4</sup>Studies asking humans to evaluate text often rate different aspects separately, such as 'adequacy', 'fluency' and 'informativeness' of the text (Hovy, 1999; Papineni et al., 2002b). Our evaluation focuses on adequacy. We did not consider fluency because 4 out of the 5 proposed responses to each context were generated by a human. We did not consider informativeness because in the domains considered, it is not necessarily important (in Twitter), or else it seems to correlate highly with adequacy (in Ubuntu).

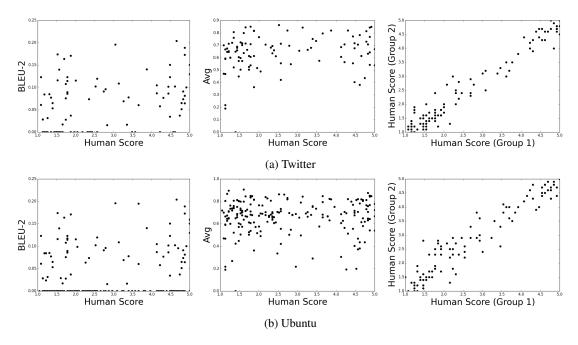


Figure 1: Scatter plots showing the correlation between metrics and human judgement on the Twitter corpus (a) and Ubuntu Dialogue Corpus (b). The plots represent BLEU-2 (left), embedding average (center), and correlation between two halves of human respondents (right).

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 ran-

dom 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

<sup>&</sup>lt;sup>5</sup>The reason BLEU-3 and BLEU-4 have any correlation is because of the smoothing constant, which gives a tiny weight to unigrams and bigrams despite the absence of higher-order n-grams. Thus, they behave as a scaled version of BLEU-2.

Context of Conversation	Context of Conversation		
A: dearest! question. how many thousands of people	A: never felt more sad than i am now		
can panaad occupy?	B: @user aww why?		
B: @user panaad has <number> k seat capacity while rizal</number>	A: @user @user its a long story! sure you wanna know		
has <number> k thats why they choose rizal i think.</number>	it? bahaha and thanks for caring btw <heart></heart>		
Ground Truth Response	Ground Truth Response		
A: now i know about the siting capacity . thanks for the	A: @user i don 't mind to hear it i 've got all day and		
info @user great evening.	youre welcome <number></number>		
Proposed Response	Proposed Response		
A: @user makes sense. thanks!	A: @user i know, i 'm just so happy for you!!!!!!!		

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 di-

alogue 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.

#### References

- [Banerjee and Lavie2005] S. Banerjee and A. Lavie. 2005. METEOR: An automatic metric for mt evaluation with improved correlation with human judgments. In *Proceedings of the ACL workshop on intrinsic and extrinsic evaluation measures for machine translation and/or summarization.*
- [Cho et al.2014] K. Cho, B. Van Merriënboer, C. Gulcehre, D. Bahdanau, F. Bougares, H. Schwenk, and Y. Bengio. 2014. Learning phrase representations using rnn encoder-decoder for statistical machine translation. *arXiv* preprint arXiv:1406.1078.
- [Cohen1968] Jacob Cohen. 1968. Weighted kappa: Nominal scale agreement provision for scaled disagreement or partial credit. *Psychological bulletin*, 70(4):213.
- [Foltz et al.1998] P. W. Foltz, W. Kintsch, and T. K. Landauer. 1998. The measurement of textual coherence with latent semantic analysis. *Discourse processes*, 25(2-3):285–307.
- [Forgues et al.2014] G. Forgues, J. Pineau, J.-M. Larcheveque, and R. Tremblay. 2014. Bootstrapping dialog systems with word embeddings.
- [Galley et al.2015a] Michel Galley, Chris Brockett, Alessandro Sordoni, Yangfeng Ji, Michael Auli, Chris Quirk, Margaret l, Jianfeng Gao, and Bill Dolan. 2015a. deltaBLEU: A discriminative metric for generation tasks with intrinsically diverse targets. In Proceedings of the Annual Meeting of the Association for Computational Linguistics and the International Joint Conference on Natural Language Processing (Short Papers).
- [Galley et al.2015b] Michel Galley, Chris Brockett, Alessandro Sordoni, Yangfeng Ji, Michael Auli, Chris Quirk, Margaret Mitchell, Jianfeng Gao, and Bill Dolan. 2015b. deltableu: A discriminative metric for generation tasks with intrinsically diverse targets. arXiv preprint arXiv:1506.06863.
- [Graves2013] A. Graves. 2013. Generating sequences with recurrent neural networks. *arXiv preprint arXiv:1308.0850*.
- [Hochreiter and Schmidhuber1997] S. Hochreiter and J. Schmidhuber. 1997. Long short-term memory. *Neural Computation*, 9(8):1735–1780.
- [Hovy1999] Eduard Hovy. 1999. Toward finely differentiated evaluation metrics for machine translation. In *Proceedings of the Eagles Workshop on Standards and Evaluation*.
- [Jokinen and McTear2009] K. Jokinen and M. McTear. 2009. *Spoken Dialogue Systems*. Morgan Claypool.

- [Kiros et al.2015] Ryan Kiros, Yukun Zhu, Ruslan R Salakhutdinov, Richard Zemel, Raquel Urtasun, Antonio Torralba, and Sanja Fidler. 2015. Skipthought vectors. In *Advances in Neural Information Processing Systems*, pages 3276–3284.
- [Landauer and Dumais1997] Thomas K Landauer and Susan T Dumais. 1997. A solution to plato's problem: The latent semantic analysis theory of acquisition, induction, and representation of knowledge. *Psychological review*, 104(2):211.
- [Li et al.2015a] Jiwei Li, Michel Galley, Chris Brockett, Jianfeng Gao, and Bill Dolan. 2015a. A diversity-promoting objective function for neural conversation models. *CoRR*, abs/1510.03055.
- [Li et al.2015b] Jiwei Li, Michel Galley, Chris Brockett, Jianfeng Gao, and Bill Dolan. 2015b. A diversity-promoting objective function for neural conversation models. arXiv preprint arXiv:1510.03055.
- [Li et al.2016] Jiwei Li, Michel Galley, Chris Brockett, Jianfeng Gao, and Bill Dolan. 2016. A personabased neural conversation model. *arXiv preprint arXiv:1603.06155*.
- [Lin2004] Chin-Yew Lin. 2004. Rouge: A package for automatic evaluation of summaries. In *Text summarization branches out: Proceedings of the ACL-04 workshop*, volume 8.
- [Lowe et al.2015] Ryan Lowe, Nissan Pow, Iulian V. Serban, and Joelle Pineau. 2015. The ubuntu dialogue corpus: A large dataset for research in unstructured multi-turn dialogue systems. In SIGDIAL.
- [Mikolov et al.2013] T. Mikolov, I. Sutskever, K. Chen, G. S. Corrado, and J. Dean. 2013. Distributed representations of words and phrases and their compositionality. In *Advances in neural information processing systems*, pages 3111–3119.
- [Mitchell and Lapata2008] J. Mitchell and M. Lapata. 2008. Vector-based models of semantic composition. In *ACL*, pages 236–244.
- [Möller et al.2006] S. Möller, R. Englert, K.P. Engelbrecht, V.V. Hafner, A. Jameson, A. Oulasvirta, A. Raake, and N. Reithinger. 2006. Memo: towards automatic usability evaluation of spoken dialogue services by user error simulations. In *INTER-SPEECH*.
- [Papineni et al.2002a] K. Papineni, S. Roukos, T Ward, and W Zhu. 2002a. BLEU: a method for automatic evaluation of machine translation. In *Proceedings of the 40th annual meeting on Association for Computational Linguistics (ACL)*.
- [Papineni et al.2002b] Kishore Papineni, Salim Roukos, Todd Ward, John Henderson, and Florence Reeder. 2002b. Corpus-based comprehensive and diagnostic MT evaluation: Initial Arabic, Chinese, French, and Spanish results. In *Proceedings of*

- the second international conference on Human Language Technology Research, pages 132–137.
- [Ritter et al.2010] A. Ritter, C. Cherry, and B. Dolan. 2010. Unsupervised modeling of twitter conversations. In *North American Chapter of the Association for Computational Linguistics (NAACL)*.
- [Ritter et al.2011a] Alan Ritter, Colin Cherry, and William B. Dolan. 2011a. Data-driven response generation in social media. In *Proceedings of the Conference on Empirical Methods in Natural Language Processing*, EMNLP '11, pages 583–593, Stroudsburg, PA, USA. Association for Computational Linguistics.
- [Ritter et al.2011b] Alan Ritter, Colin Cherry, and William B Dolan. 2011b. Data-driven response generation in social media. In *Proceedings of the conference on empirical methods in natural language processing*, pages 583–593. Association for Computational Linguistics.
- [Rus and Lintean2012] V. Rus and M. Lintean. 2012. A comparison of greedy and optimal assessment of natural language student input using word-to-word similarity metrics. In *Proceedings of the Seventh Workshop on Building Educational Applications Using NLP*, pages 157–162, Stroudsburg, PA, USA. Association for Computational Linguistics.
- [Schatzmann et al.2005] J. Schatzmann, K. Georgila, and S. Young. 2005. Quantitative evaluation of user simulation techniques for spoken dialogue systems. In 6th Special Interest Group on Discourse and Dialogue (SIGDIAL).
- [Serban et al.2015] I. V. Serban, A. Sordoni, Y. Bengio, A. Courville, and J. Pineau. 2015. Building End-To-End Dialogue Systems Using Generative Hierarchical Neural Networks. In AAAI Conference on Artificial Intelligence. In press.
- [Sordoni et al.2015] A. Sordoni, M. Galley, M. Auli, C. Brockett, Y. Ji, M. Mitchell, J. Nie, J. Gao, and B. Dolan. 2015. A neural network approach to context-sensitive generation of conversational responses. In Conference of the North American Chapter of the Association for Computational Linguistics (NAACL-HLT 2015).
- [Walker et al.1997] M.A. Walker, D.J. Litman, C.A. Kamm, and A. Abella. 1997. Paradise: A framework for evaluating spoken dialogue agents. In *Proceedings of the eighth conference on European chapter of the Association for Computational Linguistics*, pages 271–280. Association for Computational Linguistics.
- [Wen et al.2015] Tsung-Hsien Wen, Milica Gasic, Nikola Mrksic, Pei-Hao Su, David Vandyke, and Steve Young. 2015. Semantically conditioned lstm-based natural language generation for spoken dialogue systems. arXiv preprint arXiv:1508.01745.

- [Weston et al.2015] J. Weston, A. Bordes, S. Chopra, and T. Mikolov. 2015. Towards ai-complete question answering: A set of prerequisit toy tasks. *arXiv* preprint arXiv:1502.05698.
- [Wieting et al.2015] J. Wieting, M. Bansal, K. Gimpel, and K. Livescu. 2015. Towards universal paraphrastic sentence embeddings. *CoRR*, abs/1511.08198.

## **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.

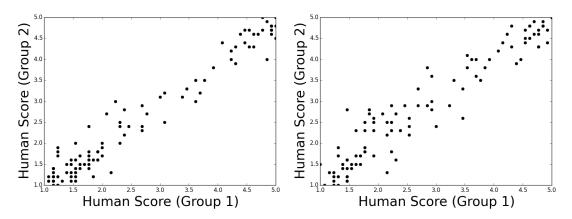


Figure 3: Scatter plots showing the correlation between two randomly chosen groups of human volunteers on the Twitter corpus (left) and Ubuntu Dialogue Corpus (right).

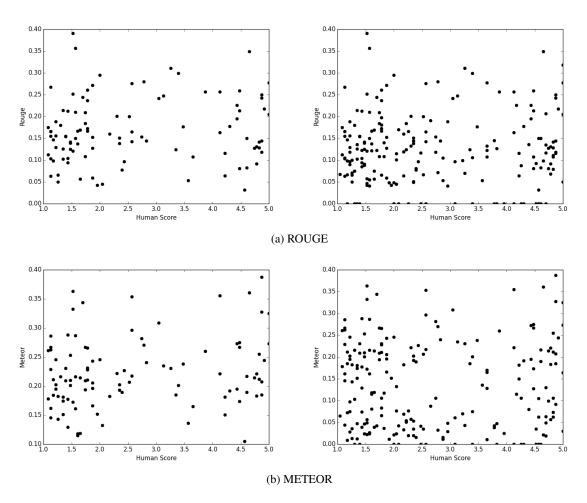


Figure 4: Scatter plots showing the correlation between metrics and human judgement on the Twitter corpus (left) and Ubuntu Dialogue Corpus (right). The plots represent ROUGE (a) and METEOR (b).

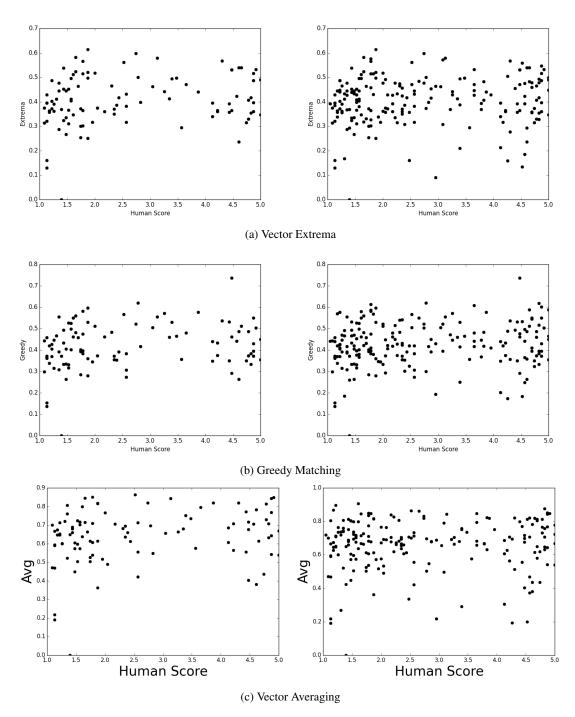


Figure 5: Scatter plots showing the correlation between metrics and human judgement on the Twitter corpus (left) and Ubuntu Dialogue Corpus (right). The plots represent vector extrema (a), greedy matching (b), and vector averaging (c).

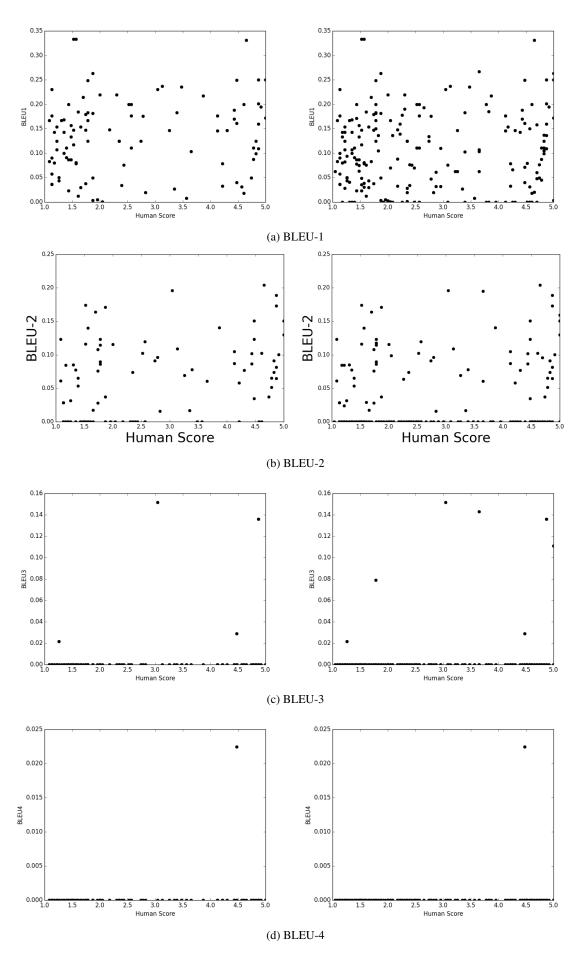


Figure 6: Scatter plots showing the correlation between metrics and human judgement on the Twitter corpus (left) and Ubuntu Dialogue Corpus (right). The plots represent BLEU-1 (a), BLEU-2 (b), BLEU-3 (c), and BLEU-4 (d).