Approximating Interactive Human Evaluation with Self-Play for Open-Domain Dialog Systems

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Abstract

Building an open-domain conversational agent is a challenging problem. Current evaluation methods, mostly post-hoc judgments of static conversation, do not capture conversation quality in a realistic interactive context. In this paper, we investigate interactive human evaluation and provide evidence for its necessity; we then introduce a novel, model-agnostic, and dataset-agnostic method to approximate it. In particular, we propose a self-play scenario where the dialog system talks to itself and we calculate a combination of proxies such as sentiment and semantic coherence on the conversation trajectory. We show that this metric is capable of capturing the human-rated quality of a dialog model better than any automated metric known to-date, achieving a significant Pearson correlation (r > .7, p < .05). To investigate the strengths of this novel metric and interactive evaluation in comparison to state-of-the-art metrics and human evaluation of static conversations, we perform extended experiments with a set of models, including several that make novel improvements to recent hierarchical dialog generation architectures through sentiment and semantic knowledge distillation on the utterance level. Finally, we open-source the interactive evaluation platform we built and the dataset we collected to allow researchers to efficiently deploy and evaluate dialog models.

1 Introduction

The goal of an open-domain conversational agent is to carry out natural social interactions with humans. Current state-of-the-art generative neural networks fail in producing key aspects of good natural conversation, including staying on topic, not being repetitive, and generating emotionally appropriate responses. One of the biggest challenges in training better dialog systems relates to the difficulty of evaluating them. Automatic metrics such as BLEU score relate poorly to human judgment of dialog quality [1], and while embedding-distance based metrics provide an alternative [2], we will show that they also do not correlate well with human evaluation. Without a reliable metric to optimize, training high quality dialog models remains difficult.

Since humans are the ultimate authority on what constitutes a good conversation, many authors rely on human ratings to evaluate their methods [3–5]. The predominant procedure for obtaining human ratings uses *static evaluation*: a context of several sentences, often originating from the dataset that dialog model was trained on, is used as input to generate a response (either a single utterance or

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Table 1: Static evaluation fails to capture a lack of diversity in a dialog model's responses, as well as its inability to track the conversation and respond in emotionally appropriate ways. We argue interactive evaluation is needed to evaluate dialog models, and show that our Emotion+Infersent (EI) models trained on a larger and more diverse corpus, produce better interactive dialog. We present strong evidence that our novel dialog self-play framework combined with psychologically motivated novel automated metrics can accurately estimate quality of a model with respect to its ability to carry out multi-turn open-domain conversations.

Static	Interactive	Interactive	Self-play
HRED - Cornell	HRED - Cornell	EI HRED - Reddit	EI HRED - Reddit
[Context]: you're weird. [HRED]: i'm sorry.	[User]: i'm feeling sad today. [HRED]: no. [User]: yes i am! [HRED]: i'm sorry, i'm sorry. i don't want to know. [User]: you're weird. [HRED]: i'm sorry.	[User] talk to me [EI HRED]: it's my job. [User]: i love you [EI HRED]: thank you for the kind words. [User]: do you love me? [EI HRED]: it's a bit personal, so I sent you a dm. [User]: i'm blushing	[EI HRED] i can't wait to see what i can do. [EI HRED] that's a good idea. [EI HRED] how do you deal with people? [EI HRED] i've been on reddit for a long time. [EI HRED] i am in the same boat.

multiple consecutive utterances). This particular generated response for this particular context is then provided for a human to evaluate. However, such observational evaluation of a static text sample is limited in capturing common failure modes of open-domain dialog systems, such as a lack of diversity in the responses, inability to track long-term aspects of the conversation, and inability to maintain a consistent persona [6]. Despite this, static evaluation is commonly used for evaluating these exact qualities [7, 8].

Conversation is inherently a process. In this paper, we argue that multi-turn interactive human evaluation is essential for evaluating this process, and for making progress in improving open-domain dialog models. A multi-turn interactive evaluation is open-ended, and allows the users to derive and control the trajectory of the conversation by saying whatever they want. As opposed to post-hoc observations of a generated response to a static context, this is an ultimate test of generalization. Table 1 illustrates an example where a bot generates a coherent static response, but interactive evaluation shows that the distribution of its responses has collapsed onto repeatedly saying the same phrase, a common problem in open domain dialog [9].

The relative sparsity of interactive human evaluation of dialog systems may relate to the difficulty and expense of collecting human data. Therefore, we develop a way to approximate human judgment of interactive dialog quality using a novel form of dialog self-play. We begin by moving beyond superficial word-level mapping by proposing a series of metrics to evaluate the quality of conversation motivated by findings in psychology. Specifically, inspired by the effectiveness of sense of humor in creating solidarity [10], style matching for forming relationship stability and social cohesiveness [11, 12], and the importance of active listening through forming follow up questions [13], we propose metrics to capture sentiment, semantics, and user engagement. We then fit a function that predicts human assessments of conversation quality given these metrics. This function is used to predict bot quality through self-play: for a fixed number of turns, the bot generates utterances which are fed back into itself as input in the next turn. The same metrics described above are computed on the self-play generated conversation, and the same function fit to human data is used to predict the bot quality. We show a very high Pearson correlation (r > .7, p < .05) between the predicted quality scores and the ground-truth human judgments of bot quality, suggesting self-play is a good proxy for interactive conversation assessment.

To demonstrate the relevance of the interactive evaluation and the proposed self-play evaluation, we perform extended experiments with different hierarchical architectures. In particular, we compare three recent hierarchical baselines: HRED [5], VHRED [3], VHCR [4]. Motivated by sentiment and semantics being key aspects of producing high quality conversations, we regularize the top level of the hierarchy to ensure it encodes such information, using model distillation [14]. Our results show the effectiveness of the proposed regularization in interactive evaluation in both the human-bot and the self-play scenarios.

This paper makes three main contributions: 1) demonstrates the necessity of multi-turn interactive evaluation to capture the quality of the dialog systems; 2) presents a novel self-play framework to estimate a new psychology-motivated hybrid quality score. These estimations are highly correlated with quality scores obtained from interactive human evaluation, more strongly than the state-of-the-art automated metrics; 3) proposes a new method of regularizing hierarchical seq2seq models with

knowledge distillation. All the code, data, and interactive evaluation platform resulting from our work are publicly available.

2 Related work

Interactive evaluation in dialog has been mostly limited to presenting the results of competitions (e.g. the Alexa prize [15, 16], or the Conversational Intelligence Challenge [6]). Those findings reveal that most bots do not perform well in interactive evaluation, due to repetitiveness, inability to balance dialog acts across the conversation, and inability to maintain a consistent persona [6]. Even work aimed at maintaining a persona does not test in an interactive setting [7, 8]. To the best of our knowledge, no prior work has compared multi-turn, interactive human evaluations of open-domain dialog models to traditional forms of evaluation.

Dialog systems remain difficult to train due to the lack of metrics that can effectively capture good dialog quality. Several authors have proposed training automatic predictors of human judgment or to combine human judgment with automatic metrics [17–19]. However, a state-of-the-art model trained to predict human judgments achieved a Pearson correlation of .44 with the ground truth [18].

Perhaps the lack of research into interactive evaluation relates to the difficulty and cost of collecting human ratings. We show that human judgments of the quality of an interactive evaluation can be automatically and reliably approximated using dialog model self-play. There is limited work investigating self-play for dialog systems: Shah et al. [20] use a task schema and user simulator to generate samples for input to a goal-directed dialog system, while Li et al. [9] use a copy of a dialog model to compute a reward function that can be optimized with reinforcement learning. However, we are not aware of prior work using self-play for approximating interactive human evaluation.

Interactive conversation necessitates tracking long-term aspects of the dialog like the topic and tone. Hierarchical recurrent neural networks (RNNs) have been proposed as a way to improve long-term tracking of the conversation, through maintaining both a word- and utterance-level RNN [3–5, 21, 22]. Yet dialog is more than language modeling, it requires topic and social coherence. Prior performance improvements to dialog models using topic information include appending topic as an additional input [23], or extracting topic information using Latent Dirichlet Allocation [24, 25]. Towards social and emotional coherence, previous works have investigated various features and loss functions based on emotion [26–30]. Given research highlighting the ineffectiveness of LDA for short texts [31], such as those involved in casual conversation, and the unavailability of topic and tone supervision at-scale, approaches overcoming these limitations are preferred. To the best of our knowledge, transferring sentiment and semantic information from a pre-trained model directly into a dialog model using knowledge distillation [14] has not been studied. Thus, we select a set of recent hierarchical dialog models and their improved versions through knowledge distillation for a thorough multi-turn interactive evaluation and comparison to traditional evaluation.

3 Knowledge distillation for sentiment and semantic regularization

To systematically compare multi-turn interactive evaluation of open-domain dialog with traditional forms of evaluation, we include a diverse set of models. Particularly, we build on three existing hierarchical seq2seq architectures designed for dialog. Here, we provide a brief summary; for detailed information, see [5, 3, 4]. The first baseline model, Hierarchical Recurrent Encoder Decoder (HRED) [5] extends a traditional seq2seq model by adding a third recurrent neural network (RNN), which is only updated after each dialog turn, or utterance. The idea behind this $Context\ RNN$ is that it could potentially track longer term aspects of the conversation, such as the topic; however, there is no guarantee that it will learn to do so. The decoder of the HRED model conditions on both the embedding produced by the encoder for the current utterance, h_n^e , and the embedding of the Context RNN for the previous utterance, h_{n-1}^e .

The second baseline model, Variational HRED (VHRED) [3], extends HRED with a variational constraint on the utterance embedding space z. Let $x_n = [w_{1n}, w_{2n} \dots w_{mn}]$ be the n-th utterance composed of tokens $w_{1..m}$. VHRED predicts x_n as follows:

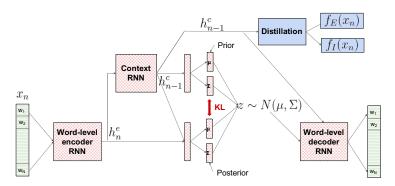


Figure 1: Illustration of the EI regularization (blue-solid) applied to VHRED baseline (red-checkered) to enforce encoding sentiment and semantics of an utterance in the Context RNN. The EI regularization can be similarly applied to HRED and VHCR.

$$h_n^e = f^e(x_{n-1}) \tag{1}$$

$$h_{n-1}^c = f^c(x_{n-1}, h_{n-1}^e) (2)$$

$$\mu, \Sigma = f(h_{n-1}^c) \tag{3}$$

$$p_{\theta}(z_n|x_{\leq n}) = N(z|\mu, \Sigma) \tag{4}$$

$$p(x_n|x_{< n}) = f^d(h_{n-1}^c, z_n)$$
(5)

Equations (1)-(5) describe the computation of VHRED at inference time where f^e , f^c , and f^d are Gated Recurrent Unit (GRU) networks for the encoder, context, and decoder RNNs, respectively; at training time, it allows the computation of z, μ , and Σ to condition on the encoding of the target utterance, h_n^e , giving the posterior distribution $p_{\Psi}(z_n|x_{\leq n})$. A Kullback-Leibler (KL) divergence constraint is placed between the posterior and prior, $D_{KL}(p_{\Psi}||p_{\theta})$.

The third model, Variational Hierarchical Conversation RNN (VHCR) [4] further extends VHRED by drawing a prior encoding $z^{conv} \sim N(0, I)$ for each conversation, allowing all parts of the model (f^c, μ, Σ) to condition on z^{conv} , which is unchanging throughout the conversation.

3.1 Emotion and Infersent regularization (EI)

While the hierarchical design of these models is motivated by a desire to allow tracking high-level, slow-changing aspects of the conversation like topic or tone, it is unclear that the network will be able to model these aspects without additional structure or information. We thus propose a regularization to the top level of the hierarchy, the Context RNN, to force it to encode both the sentiment and semantics of the utterance. To do this, we leverage a state-of-the-art sentiment detection model trained on a large Twitter corpus [32], as well as the recently proposed *Infersent* sentence-embedding model trained to predict the meaning (i.e. entailment, contradiction) of sentences [33], and distill them into the *Context RNN*.

First, we use these models to predict the emotional content, $f_E(x_n)$, and infersent embedding, $f_I(x_n)$ of each input utterance. We then add an additional network to the hierarchical models which predicts these values based on the context RNN embedding of the utterance: $f^{distill}(h_n^c) = \langle f_E(x_n), f_I(x_n) \rangle$. The goal is to transfer knowledge of emotion and semantics in text into the context RNN via knowledge distillation [14].

Figure 1 illustrates, in blue color, the EI regularization applied to the VHRED model. The regularization can be similarly applied to HRED and VHCR. In our experiments we refer to the regularized models as HRED-EI, VHRED-EI, and VHCR-EI, respectively, or, more generally, EI models as opposed to baseline models. The code for all our models is available at https://github.com/natashamjaques/neural_chat and was originally based on [4]. For details regarding hyper-parameter tuning refer to §A.12.

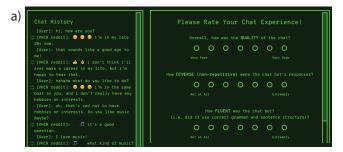




Figure 2: Screenshots of our Interactive Evaluation Platform (available at https://neural.chat): (a) chat window (left) and first part of the evaluation form (right); (b) second part of the evaluation form (to show all evaluation questions asked).

4 Interactive evaluation methodologies

4.1 Traditional evaluation

Automatic metrics Embedding-based metrics compare generated sentences to ground truth sentences using a vector representation of words [2]. In this work, we use three embedding metrics: embedding average, vector extrema, and greedy matching. These three metrics are used in previous open-domain dialog models [1, 3, 4]. We also use perplexity as a standard measure of the likelihood of the generated sentences with respect to the target outputs. Another common metric for variational models is the KL-Divergence between the posterior and the prior distribution, as a way of assessing the information encoded into the latent variables [21] (Figure 1 illustrates KL for the VHRED model). More information regarding embedding metrics can be found in §A.7.

Conventional static human evaluation We employ a similar method to previous work for our static human evaluation of generated responses [3, 4], sampling contexts from each corpus and asking humans to compare the generated responses. To reduce ambiguity, we exclude contexts shorter than 10 tokens and contexts containing <unknown> tokens. We recruited participants from Amazon Mechanical Turk (AMT) to compare generated sentences. Annotators could also select a third "tied" option. For each example (context and pair of generated sentences), we asked annotators to compare generated sentences based on quality, fluency, diversity, contingency, and empathy. Each batch of 100 pairwise comparisons were labeled by 6 - 8 annotators.

4.2 Interactive human evaluation

To address the limitations of static human evaluation, we built a platform for conducting interactive evaluation of dialog models with humans, which we make available in open-source to the community (see Figure 2). Annotators rated quality, fluency, diversity, relatedness, and empathy of a bot after interacting with it for at least 3 turns. Participants can also upvote or downvote each bot response. For more information about this platform, see §A.10. Our goal is to make this work transparent and reproducible, while adding diversity to the platforms future practitioners can choose to use (e.g. ParlAI [34], Plato Research Dialog System [35], ChatEval [36]).

4.3 Novel metrics and self-play

Inspired by real-world human interactions, we introduce novel metrics to capture the morphology of a conversation, i.e., how the users' responses progress over time and how the bot's responses interact with them. We propose a hybrid combination of these metrics, M_H , that is optimized to predict conversation quality on human data. We then apply M_H to self-play, i.e., the trajectory of bot-generated responses, and investigate how it relates to human ratings of conversation quality.

Sentiment metrics To approximate emotional tone of an utterance, we use a state-of-the-art sentiment detector trained on a large Twitter corpus [32]. This pre-trained model outputs an emotion embedding – a probability distribution over 64 most-frequently used emojis. To estimate the *Sentiment Coherence* between user's query and generated samples, we calculate the cosine similarity between their emotion embeddings. We define a set of weights over the 64 emojis and calculate the weighted sum over an

emotion embedding vector to derive a *Sentiment* score which is higher for positive sentiment and lower for negative sentiment (See §A.11). We define *Sentiment Transition* as the change between user's *Sentiment* before and after a bot response. Additionally, *Sentiment Min-Max* is defined by the slope of change between min and max *Sentiment* in user utterances over the course of a conversation. Since humor can be used to create solidarity [10], we count the number of "ha"s in the user response as a proxy for *Laughter*. The combination of these metrics provides a snapshot of the trajectory of sentiment in a conversation and quantifies if the bot is able to elicit positive emotions in the user.

Semantic metrics Language style matching is a strong predictor of relationship stability [11] and social cohesiveness [12]; thus, we introduce metrics to capture lexical similarity. We use *Infersent*, a state-of-the-art sentence-embedding model to encode the user and bot responses into a 4096-dimensional embedding space [33]. Infersent was trained to distinguish if two sentences are supporting, contradicting, or have a neutral relationship. We estimate *Semantic Similarity* by calculating the cosine similarity between the infersent embedding of the user's query and the generated bot sample. Additionally, we use the classic Word2Vec embeddings trained on Google News Corpus along with average, extrema, and greedy aggregation methods similar to Section 4.1 to derive *Average Word Coherence*, *Extrema Word Coherence*, and *Greedy Word Coherence* between user and bot responses.

Engagement metrics Asking questions is an important active listening skill which is linked to conversation management, attentiveness, and responsiveness [13, 37]. Therefore, we define *Question Score* to quantify if the bot is using question words and/or a question mark. We also introduce # Words as a proxy for user engagement that counts the number of words in their response.

Hybrid metric (M_H) We combine the aforementioned metrics (M_i) using linear regression, and optimize their coefficients (λ_i) to best predict human judgment of interactive conversation quality: $M_H = \sum \lambda_i * M_i + M_0$. We use a leave-bot-out scenario where we isolate all the human conversations with one of the dialog models, χ_j , as the hold-out test set. We train the $\lambda_{i,j}$ on the remaining quality ratings. We found that the learned λ_i s were stable across the training folds, only exhibiting small variations. Other researchers are encouraged to use our learned coefficients directly or adjust them according to their own interactive human evaluation dataset. See §A.2 for more details about the learned λ_i s.

Self-play as an approximation for interactive evaluation Since interactive human evaluation is costly, we propose a self-play scenario where the dialog system talks to itself, i.e. the bot generated responses are fed back into it as the next turn input. For each model χ_j , we generate 100 random conversations, fixed at 10 turns. The self-play trajectories created using model χ_j are treated as the hold-out set. Therefore, the trained $\lambda_{i,j}$ values based on all conversations except for the ones with χ_j are used to calculate M_H on each generated bot-bot conversation trajectory for χ_j . The estimated M_H values are averaged across conversation samples for χ_j . This value is used for comparison against the ground-truth interactive quality ratings aggregated on the bot-level.

5 Experiments

5.1 Datasets

A common source of data for open-domain dialog systems is movie scripts, among which the CORNELL dataset [38] is the largest and most commonly used. Therefore, we use it to benchmark against previous state-of-the-art results [4]. Its median conversation length is 3 utterances and the conversations are strictly between pairs of speakers. Recognizing that movie lines have limited conversation diversity, we also built a new corpus, REDDIT. Between the many different subreddits available, the conversations vastly differ on topic, language style, and participation patterns. We select the Casual Conversations forum (r/CasualConversations), a community of 607K conversationalists discussing a variety of topics. We collect a dataset of 109K conversations of at least 3 turns with the median conversation containing 7 utterances from conversational exchanges on the platform in 2018^2 . More more details about this dataset refer to §A.6.

²This REDDIT dataset is available at https://affect.media.mit.edu/neural_chat/datasets.

Table 2: Mean human ratings for Baseline and EI (Emotion+Infersent) models for HRED, VHRED, and VHCR architectures with 90% confidence intervals. See §5.2 for 3-factor ANOVA results.

		Cor	nell	Red	ddit
Model	Metric	Baseline	EI	Baseline	EI
	quality	2.182 ± 0.305	2.347 ± 0.313	2.527 ± 0.310	2.714 ± 0.299
	fluency	3.909 ± 0.387	4.000 ± 0.381	4.436 ± 0.349	4.786 ± 0.316
HRED	diversity	2.836 ± 0.374	2.735 ± 0.380	3.418 ± 0.386	3.554 ± 0.372
	contingency	2.200 ± 0.291	2.469 ± 0.336	2.382 ± 0.288	2.536 ± 0.322
	empathy	2.673 ± 0.352	2.490 ± 0.350	3.018 ± 0.329	3.107 ± 0.337
	quality	2.022 ± 0.309	2.333 ± 0.252	2.694 ± 0.392	2.864 ± 0.341
	fluency	3.109 ± 0.351	3.949 ± 0.396	4.250 ± 0.496	4.477 ± 0.402
VHRED	diversity	3.565 ± 0.442	4.385 ± 0.371	5.00 ± 0.468	4.705 ± 0.353
	contingency	2.261 ± 0.287	2.487 ± 0.346	2.472 ± 0.362	2.773 ± 0.370
	empathy	2.739 ± 0.374	2.564 ± 0.367	3.000 ± 0.393	3.341 ± 0.385
	quality	2.132 ± 0.247	2.548 ± 0.380	2.615 ± 0.350	2.692 ± 0.298
	fluency	2.679 ± 0.306	3.976 ± 0.380	3.923 ± 0.433	4.308 ± 0.395
VHCR	diversity	3.755 ± 0.340	4.238 ± 0.421	4.436 ± 0.455	4.231 ± 0.382
	contingency	2.189 ± 0.270	2.571 ± 0.356	2.077 ± 0.298	2.692 ± 0.354
	empathy	2.340 ± 0.316	2.714 ± 0.368	2.974 ± 0.434	3.288 ± 0.379

5.2 Interactive human evaluation

Table 1 (in §1) illustrates how EI regularization produces a higher quality conversation when compared to baseline. Rather than cherry-picking results, we make all of the bots evaluated in the study available at https://neural.chat/BRFZACDCOA/ for readers to assess interactively.

Table 2 summarizes human ratings of baseline and EI models obtained via interactive evaluation. In total, 565 ratings were captured. Each dialog model has been evaluated by a number of annotators, ranging from 36 to 56. For additional information about human annotators refer to §A.9. We ran a 3-factor ANOVA on the sum of user scores, where the independent variables are model architecture (HRED, VHRED, VHCR), EI regularization (Baseline, EI), and dataset (CORNELL, REDDIT). We found a significant main effect of EI regularization and dataset, but no significant difference between the three types of hierarchical models. We found that adding emotion and infersent (EI) regularization to baseline models improved the interactive chat experience significantly, F(554,1) = 9.016, p = .003. Further, the models trained on the REDDIT dataset performed significantly better, F(554,1) = 30.796, p < .001. This finding validates the hypothesis that distilling information about topic and tone into the top level of the hierarchy is useful for good conversation, and suggests that the REDDIT dataset could provide more realistic training for opendomain dialog and be valuable to the community. Additional ablation results are provided in §A.1.

5.3 Traditional metrics

Automatic metrics Several prior works have focused on ensuring that the variational KL term remains high in order to improve model quality (e.g. [4, 21]). However, we observe there is no consistency between human quality rating and KL (Table 3). See §A.8 for details about other human metrics, e.g. fluency, diversity, contingency, and empathy. Thus, it is not evident that KL captures human judgements of dialog quality. Even perplexity (a transformation of the cross-entropy loss used to train our models) falls short of capturing human quality judgments, underscoring the difficulty in effectively training good language models. We find embedding metrics show more promise in preserving the order of human quality ratings, but have only weak correlation with human ratings. We present evidence for our novel hybrid metric being a much stronger alternative.

Human static evaluation As shown in Table 4, while static human evaluation suggests EI regularization is effective due to a higher number of win judgments³, the results are noisy and difficult to interpret due to large confidence intervals and a high percentage of ties. The median inter-annotator agreement measured pairwise through Cohen's κ [39] for our human evaluation was only 0.176 and 0.120 for CORNELL and REDDIT respectively. This level of annotator agreement is lower than the

³We follow [4] to highlight the higher value between wins/losses and reporting 90% confidence intervals.

Table 3: Results of automatic traditional metrics for 1-turn responses of models per context of baseline and EI (Emotion + Infersent) models. PPL: perplexity, KL: KL divergence, Avg: Average, Ext: Extrema, Grd: Greedy

			Cornell				Reddit				•
Model	Version	PPL	KL	Avg	Ext	Grd	PPL	KL	Avg	Ext	Grd
HRED	baseline	52.311	-	.471	.329	.331	41.730	-	.649	.394	.474
HKED	EI	47.636	-	.560	.383	.400	41.245	-	.651	.398	.482
VHRED	baseline	49.414	.264	.539	.352	.395	36.240	.188	.635	.383	.464
VIKED	EI	50.526	.517	.545	.355	.394	35.510	.167	.636	.392	.465
VHCR	baseline	61.000	.562	.532	.345	.382	36.736	.267	.619	.371	.448
VIICK	EI	49.243	.475	.588	.369	.444	37.198	.231	.639	.394	.469

Table 4: Results from human static evaluation for EI (Emotion+Infersent) vs. BL (baseline) models as measured by pairwise comparisons of **Quality** with 90% confidence intervals.

		Cornell			Reddit	
Model	Wins %	Losses %	Ties %	Wins %	Losses %	Ties %
HRED-EI	40.8 ± 4.9	24.5 ± 4.9	34.8 ± 9.2	31.3 ± 5.2	29.5 ± 6.6	39.3 ± 10.7
VHRED-EI	36.9 ± 4.7	36.6 ± 5.6	26.6 ± 6.9	39.0 ± 7.0	34.0 ± 5.3	27.0 ± 8.9
VHCR-EI	33.0 ± 6.1	29.0 ± 5.4	38.0 ± 10.1	33.7 ± 7.9	27.3 ± 3.3	39.0 ± 8.6

median Cohen's κ of previous work [1] and explains the larger confidence intervals. Even after removing ambiguous examples (i.e. where equal number of annotators select each response as being better), large annotation variation persists. This may be due to subjectivity and ambiguity arising from different interpretations of <unknown> tokens or the short length of contexts in the CORNELL corpus (e.g. median length of conversation of 3 utterances). These findings further highlight the importance of an interactive evaluation as opposed to limited static responses.

5.4 Novel metrics applied to human data and self-play

We examine how the novel psychologically-inspired metrics relate to the trajectories of the 100 best and 100 worst quality conversations. This is only feasible with interactive evaluation. As shown in Figure 3, we observe that appropriate sentiment, coherent semantics, and engaging users are indispensable to attaining high quality ratings in interactive interaction. Comparing EI and baseline conditions, we see a replication of these trends (Figure 4). For example, EI elicits longer responses from users (greater engagement), with more laughter and higher semantic coherence.

Figure 5 summarizes the relationships between interactive human ratings and the automated metrics⁴. We observe that our sentiment metric applied to human data on its own has higher correlation with interactive human ratings than the commonly used metrics such as perplexity and embedding distance metrics. Most importantly, our novel hybrid metric, M_H , applied to self-play ⁵ aggregated on the model-level is strongly correlated with all human ratings (r > .7), while previous metrics achieved r < .5. This is a significant finding, suggesting that even without running interactive human evaluation, we can automatically approximate it through self-play. This metric is agnostic to the training set and model type and can be calculated on the trajectory of self-play utterances for any chatbot, regardless of its architecture. One interpretation is that the self-play framework keeps the conversation within the training set distribution, and the model is less likely to produce <unknown> tokens. Therefore, M_H and its sub-components have meaningful values and can be useful for quality approximation.

On a realistic conversation trajectory, M_H is a hybrid of conflicting objectives and thus is less susceptible to exploitation [40]. However, the purpose of the self-play metric (\hat{M}_H) in its current form is a post-hoc evaluation of a dialog model. There are precautions if one intends to directly optimize for \hat{M}_H or its sub-components, for example in a reinforcement learning scenario. The current formulation of self-play uses trajectories entirely generated by the same model. If one intends to optimize \hat{M}_H , we suggest calculating it on conversation trajectories between the bot and an external

⁴ For additional correlation results across the human metrics, between M_i s and human metrics on a bot-level, and Spearman and Kendall rank coefficients, see §A.3, §A.4, and §A.5 respectively.

⁵ Analyzing utterance overlap shows that these self-play conversations are distinct from the training corpus and exhibit high diversity for variational models. Details can be found in §A.13.

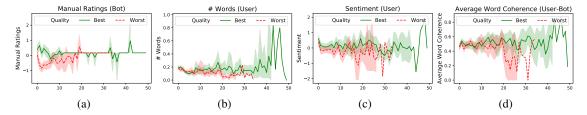


Figure 3: One hundred highest vs. lowest quality conversation trajectories; lines: mean, shaded area: 90% confidence intervals, x-axis: conversation turns. (a) Timing of upvote/downvote ratings: A bad first impression impedes overall rating. (b) Participants talk longer and use more words in conversations rated higher. (c) High-quality conversations elicit more positive user sentiment; many participants leave after expressing negative sentiment. (d) High-quality conversations are more semantically similar as measured by average word coherence between user query and bot responses. Users tend to leave the conversation when the bot responses are semantically dissimilar.

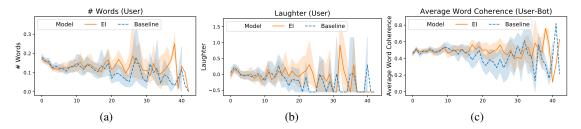


Figure 4: EI vs. baseline conversation trajectories; lines: mean, shaded area: 90% confidence intervals, x-axis: conversation turns. (a) EI elicits longer responses from users, suggesting that they are more engaged compared to the baseline models. (b) EI evokes more laughter from users compared to baseline. (c) EI has higher semantic coherence as measured by average word coherence. The same pattern applies to greedy and extrema word coherence.



Figure 5: Pearson correlations between five human metrics and automated metrics. Sentiment -U has higher correlation with interactive human ratings than prior metrics. Hybrid Metric $\mathbf{M_H}$ -B/B, our novel self-play based metric, has higher correlation across all human metrics more than any other metric proposed to-date. Notes: -U: Calculated on user response, -B: Calculated on bot response, -U/B: Calculated between user and bot response, -B/B: Calculated between consecutive bot utterances.

baseline model or a fixed copy [41], or adopting adversarial learning by maintaining a discriminator to distinguish between real/fake conversations [42]. This implicitly enforces generating realistic language. Additionally, we have shown how to successfully learn using sub-components of \hat{M}_H as reward functions [43].

6 Conclusions

A major obstacle in open-domain dialog generation is the predominant optimization of an objective function that does not closely match human judgment of conversation quality in a naturalistic chat. In this paper, we have argued that it is necessary to go beyond static evaluation by investigating the strengths of interactive evaluation and highlighting blind-spots of traditional static evaluation methods.

To alleviate this problem, we have combined interactive human data with psychologically-motivated measures and introduced a novel hybrid metric. Using this metric in a self-play framework provides results that are strongly correlated with human judgment of chatbot empathy (r > .8) and quality (r > .7). Additionally, we have demonstrated a significant improvement to several hierarchical seq2seq generative models using regularization of the utterance level of the hierarchy with knowledge distillation. Finally, we have open-sourced the platform together with a new REDDIT dataset.

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References

- [1] Chia-Wei Liu, Ryan Lowe, Iulian Serban, Mike Noseworthy, Laurent Charlin, and Joelle Pineau. How not to evaluate your dialogue system: An empirical study of unsupervised evaluation metrics for dialogue response generation. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pages 2122–2132, 2016.
- [2] Jeff Mitchell and Mirella Lapata. Vector-based models of semantic composition. *proceedings* of ACL-08: HLT, pages 236–244, 2008.
- [3] Iulian Vlad Serban, Alessandro Sordoni, Ryan Lowe, Laurent Charlin, Joelle Pineau, Aaron Courville, and Yoshua Bengio. A hierarchical latent variable encoder-decoder model for generating dialogues. In *Thirty-First AAAI Conference on Artificial Intelligence*, 2017.
- [4] Yookoon Park, Jaemin Cho, and Gunhee Kim. A hierarchical latent structure for variational conversation modeling. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pages 1792–1801, 2018.
- [5] Iulian V Serban, Alessandro Sordoni, Yoshua Bengio, Aaron Courville, and Joelle Pineau. Building end-to-end dialogue systems using generative hierarchical neural network models. In *Thirtieth AAAI Conference on Artificial Intelligence*, 2016.
- [6] Emily Dinan, Varvara Logacheva, Valentin Malykh, Alexander Miller, Kurt Shuster, Jack Urbanek, Douwe Kiela, Arthur Szlam, Iulian Serban, Ryan Lowe, et al. The second conversational intelligence challenge (convai2). *arXiv preprint arXiv:1902.00098*, 2019.
- [7] Pierre-Emmanuel Mazare, Samuel Humeau, Martin Raison, and Antoine Bordes. Training millions of personalized dialogue agents. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 2775–2779, 2018.
- [8] Jiwei Li, Michel Galley, Chris Brockett, Georgios Spithourakis, Jianfeng Gao, and Bill Dolan. A persona-based neural conversation model. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, volume 1, pages 994–1003, 2016.
- [9] Jiwei Li, Will Monroe, Alan Ritter, Dan Jurafsky, Michel Galley, and Jianfeng Gao. Deep reinforcement learning for dialogue generation. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pages 1192–1202, 2016.
- [10] Jennifer Hay. Functions of humor in the conversations of men and women. *Journal of pragmatics*, 32(6):709–742, 2000.
- [11] Molly E Ireland, Richard B Slatcher, Paul W Eastwick, Lauren E Scissors, Eli J Finkel, and James W Pennebaker. Language style matching predicts relationship initiation and stability. *Psychological science*, 22(1):39–44, 2011.

- [12] Amy L Gonzales, Jeffrey T Hancock, and James W Pennebaker. Language style matching as a predictor of social dynamics in small groups. *Communication Research*, 37(1):3–19, 2010.
- [13] Karen Huang, Michael Yeomans, Alison Wood Brooks, Julia Minson, and Francesca Gino. It doesn't hurt to ask: Question-asking increases liking. *Journal of personality and social psychology*, 113(3):430, 2017.
- [14] Geoffrey Hinton, Oriol Vinyals, and Jeff Dean. Distilling the knowledge in a neural network. *arXiv preprint arXiv:1503.02531*, 2015.
- [15] Iulian V Serban, Chinnadhurai Sankar, Mathieu Germain, Saizheng Zhang, Zhouhan Lin, Sandeep Subramanian, Taesup Kim, Michael Pieper, Sarath Chandar, Nan Rosemary Ke, et al. A deep reinforcement learning chatbot. *arXiv preprint arXiv:1709.02349*, 2017.
- [16] Anu Venkatesh, Chandra Khatri, Ashwin Ram, Fenfei Guo, Raefer Gabriel, Ashish Nagar, Rohit Prasad, Ming Cheng, Behnam Hedayatnia, Angeliki Metallinou, et al. On evaluating and comparing conversational agents. *arXiv* preprint arXiv:1801.03625, 4:60–68, 2018.
- [17] Chikara Hashimoto and Manabu Sassano. Detecting absurd conversations from intelligent assistant logs by exploiting user feedback utterances. In *Proceedings of the 2018 World Wide Web Conference on World Wide Web*, pages 147–156. International World Wide Web Conferences Steering Committee, 2018.
- [18] Ryan Lowe, Michael Noseworthy, Iulian Vlad Serban, Nicolas Angelard-Gontier, Yoshua Bengio, and Joelle Pineau. Towards an automatic turing test: Learning to evaluate dialogue responses. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1116–1126, 2017.
- [19] Tatsunori B Hashimoto, Hugh Zhang, and Percy Liang. Unifying human and statistical evaluation for natural language generation. *arXiv* preprint arXiv:1904.02792, 2019.
- [20] Pararth Shah, Dilek Hakkani-Tur, Bing Liu, and Gokhan Tur. Bootstrapping a neural conversational agent with dialogue self-play, crowdsourcing and on-line reinforcement learning. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 3 (Industry Papers)*, pages 41–51, 2018.
- [21] Xiaoyu Shen, Hui Su, Shuzi Niu, and Vera Demberg. Improving variational encoder-decoders in dialogue generation. In *Thirty-Second AAAI Conference on Artificial Intelligence*, 2018.
- [22] Tiancheng Zhao, Ran Zhao, and Maxine Eskenazi. Learning discourse-level diversity for neural dialog models using conditional variational autoencoders. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 654–664, 2017.
- [23] Shalini Ghosh, Oriol Vinyals, Brian Strope, Scott Roy, Tom Dean, and Larry Heck. Contextual lstm (clstm) models for large scale nlp tasks. *arXiv preprint arXiv:1602.06291*, 2016.
- [24] Jiwei Li and Dan Jurafsky. Neural net models of open-domain discourse coherence. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pages 198–209, 2017.
- [25] Chen Xing, Wei Wu, Yu Wu, Jie Liu, Yalou Huang, Ming Zhou, and Wei-Ying Ma. Topic aware neural response generation. In *Thirty-First AAAI Conference on Artificial Intelligence*, 2017.
- [26] Hao Zhou, Minlie Huang, Tianyang Zhang, Xiaoyan Zhu, and Bing Liu. Emotional chatting machine: Emotional conversation generation with internal and external memory. In *Thirty-Second AAAI Conference on Artificial Intelligence*, 2018.
- [27] Xianda Zhou and William Yang Wang. Mojitalk: Generating emotional responses at scale. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics* (Volume 1: Long Papers), pages 1128–1137, 2018.

- [28] Chenyang Huang, Osmar Zaiane, Amine Trabelsi, and Nouha Dziri. Automatic dialogue generation with expressed emotions. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 2 (Short Papers)*, pages 49–54, 2018.
- [29] Hannah Rashkin, Eric Michael Smith, Margaret Li, and Y-Lan Boureau. I know the feeling: Learning to converse with empathy. *arXiv preprint arXiv:1811.00207*, 2018.
- [30] Hannah Rashkin, Eric Michael Smith, Margaret Li, and Y-Lan Boureau. Towards empathetic open-domain conversation models: A new benchmark and dataset. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 5370–5381, 2019.
- [31] Xiaohui Yan, Jiafeng Guo, Yanyan Lan, and Xueqi Cheng. A biterm topic model for short texts. In *Proceedings of the 22nd international conference on World Wide Web*, pages 1445–1456. ACM, 2013.
- [32] Bjarke Felbo, Alan Mislove, Anders Søgaard, Iyad Rahwan, and Sune Lehmann. Using millions of emoji occurrences to learn any-domain representations for detecting sentiment, emotion and sarcasm. In 2017 Conference on Empirical Methods in Natural Language ProcessingConference on Empirical Methods in Natural Language Processing. Association for Computational Linguistics, 2017.
- [33] Alexis Conneau, Douwe Kiela, Holger Schwenk, Loïc Barrault, and Antoine Bordes. Supervised learning of universal sentence representations from natural language inference data. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pages 670–680, 2017.
- [34] Alexander H Miller, Will Feng, Adam Fisch, Jiasen Lu, Dhruv Batra, Antoine Bordes, Devi Parikh, and Jason Weston. Parlai: A dialog research software platform. arXiv preprint arXiv:1705.06476, 2017.
- [35] Alexandros Papangelis, Yi-Chia Wang, Piero Molino, and Gokhan Tur. Collaborative multiagent dialogue model training via reinforcement learning. arXiv preprint arXiv:1907.05507, 2019.
- [36] Joao Sedoc, Daphne Ippolito, Arun Kirubarajan, Jai Thirani, Lyle Ungar, and Chris Callison-Burch. Chateval: A tool for chatbot evaluation. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics (Demonstrations)*, pages 60–65, 2019.
- [37] Graham D Bodie, Kellie St. Cyr, Michelle Pence, Michael Rold, and James Honeycutt. Listening competence in initial interactions i: Distinguishing between what listening is and what listeners do. *International Journal of Listening*, 26(1):1–28, 2012.
- [38] Cristian Danescu-Niculescu-Mizil and Lillian Lee. Chameleons in imagined conversations: A new approach to understanding coordination of linguistic style in dialogs. In *Proceedings of the 2nd Workshop on Cognitive Modeling and Computational Linguistics*, pages 76–87. Association for Computational Linguistics, 2011.
- [39] Joseph L Fleiss, Jacob Cohen, and Brian S Everitt. Large sample standard errors of kappa and weighted kappa. *Psychological Bulletin*, 72(5):323, 1969.
- [40] Kalyanmoy Deb. Multi-objective optimization. In *Search methodologies*, pages 403–449. Springer, 2014.
- [41] Abdelrhman Saleh, Natasha Jaques, Asma Ghandeharioun, Judy Hanwen Shen, and Rosalind Picard. Hierarchical reinforcement learning for open-domain dialog. *arXiv* preprint arXiv:1909.07547, 2019.
- [42] Jiwei Li, Will Monroe, Tianlin Shi, Sébastien Jean, Alan Ritter, and Dan Jurafsky. Adversarial learning for neural dialogue generation. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pages 2157–2169, 2017.
- [43] Natasha Jaques, Asma Ghandeharioun, Judy Hanwen Shen, Craig Ferguson, Agata Lapedriza, Noah Jones, Shixiang Gu, and Rosalind Picard. Way off-policy batch deep reinforcement learning of implicit human preferences in dialog. *arXiv preprint arXiv:1907.00456*, 2019.

A Supplementary Materials

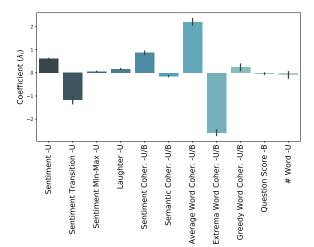
A.1 Ablation models results

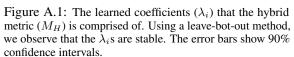
We conducted additional evaluations of ablations of our EI models to determine whether emotion or infersent regularization provided the most benefit. The results in Table A.1 reveal that this depends on the dataset and the model in question. We also checked whether simply appending the emotion and infersent embedding of an utterance to the top level of the hierarchy could provide the same benefit as knowledge distillation, even though this would require retaining copies of the DeepMoji and Infersent models, and would be more computationally expensive at inference time. Table A.1 reveals that the *input-only* models do not out-perform the knowledge-distillation EI models on automatic metrics.

Table A.1: Automatic metrics computed on ablations of the EI models, trained with distillation from only the emotion recognition model (EI_{emo}), the infersent model (EI_{inf}), or receiving emotion and infersent only as input, without knowledge distillation (input-only). Whether emotion or semantics provides the most benefit depends on the dataset and the model.

			C	Cornell				I	Reddit		
Model	Version	PPL	KL	Avg	Ext	Grd	PPL	KL	Avg	Ext	Grd
	baseline	52.311	-	.471	.329	.331	41.730	-	.649	.394	.474
	input only	47.911	-	.549	.381	.392	41.227	-	.644	.395	.469
HRED	EI_{emo}	48.619	-	.562	.359	.416	47.395	-	.541	.310	.371
	EI_{inf}	47.988	-	.562	.381	.405	41.083	-	.646	.394	.472
	EI	47.636	-	.560	.383	.400	41.245	-	.651	.398	.482
	baseline	49.414	.264	.539	.352	.395	36.240	.188	.635	.383	.464
	input only	49.819	.442	.543	.353	.393	40.248	.312	.630	.377	.456
VHRED	EI_{emo}	51.346	.636	.552	.358	.401	36.212	.199	.631	.380	.458
	EI_{inf}	52.143	.702	.539	.346	.392	36.518	.222	.637	.381	.463
	EI	50.526	.517	.545	.355	.394	35.510	.167	.636	.392	.465
	baseline	61.000	.562	.532	.345	.382	36.736	.267	.619	.371	.448
	input only	50.966	.558	.531	.344	.382	37.342	.287	.608	.365	.431
VHCR	EI_{emo}	52.407	.590	.585	.374	.442	37.449	.254	.619	.366	.444
	EI_{inf}	53.085	.575	.544	.356	.390	37.109	.199	.629	.378	.457
	EI	49.243	.475	.588	.369	.444	37.198	.231	.639	.394	.469

A.2 Hybrid metric coefficients





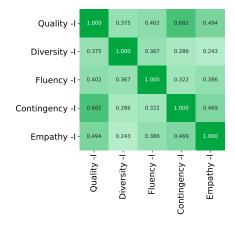


Figure A.2: Correlation matrix showing the relationships between different aspects of interactive human evaluation. We observe a strong correlation across these aspects.

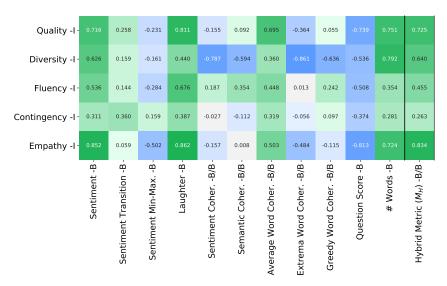


Figure A.3: Correlation matrix showing the relationships between different automated metrics on self-play trajectories and interactive human ratings aggregated on the bot-level. We observe that inducing positive sentiment as measured by Sentiment and Laughter, and being able to generate longer sentences in self-play are associated with higher quality model ratings. It is worth mentioning that maintaining extreme similarity in sentiment or semantics or just asking questions in self-play conversation trajectories could backfire by reducing the diversity of generated responses, though applicable to interactive human data. Most importantly, our novel hybrid metric applied to self-play (M_H -B/B) is highly correlated with all human ratings of the dialog model. **Postfixes:** -I: Interactive human evaluation, -B: Calculated on bot response, -B/B: Metric applied to self-play on two consecutive bot generated utterances when the bot converses with itself.

We optimized the coefficients of sub-components of the hybrid metric using a leave-bot-out scenario. As shown in Figure A.1, we observe that λ_i s are stable across these training iterations. However, because we have optimized a linear regression equation and some of the features have overlapping information, such as different aggregation methods for calculating word coherence, we do not suggest using λ_i s for direct interpretation; further investigation is required.

A.3 Human interactive ratings correlation table

Figure A.2 provides detailed information about different metrics from interactive human ratings. We observe that quality is highly correlated with other aspects of the conversation. Specifically, it is most strongly correlated with contingency, which further highlights the importance of semantic metrics of bot-generated responses in a good quality conversation. It also has high correlation with empathy that could better be captured by sentiment metrics.

A.4 Self-play correlation table

Figure A.3 provides detailed information about the introduced metrics applied to self-play. We observe that several sentiment, semantic, and engagement metrics also transfer to self-play trajectories and the introduced hybrid metric, M_H , is highly correlated with human quality ratings aggregated on a bot-level. However, exploiting sentiment or semantic similarity in a self-play scenario should be avoided as it hurts ratings of the model, especially diversity of responses.

A.5 Additional correlation statistics

Figure A.4 and A.5 provide Spearman's ρ and Kendall's τ correlation coefficients between human metrics and automated metrics. These tests do not assume a linear correlation as opposed to the Pearson correlation. Similarly to the Pearson correlation results provided in Figure 5, these values provide additional evidence, further confirming the superiority of sentiment metric as well as the newly proposed self-play approximation of the hybrid metric M_H .

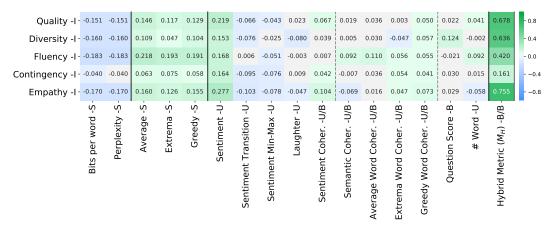


Figure A.4: Spearman correlations between five human metrics and automated metrics. Sentiment -U has higher correlation with interactive human ratings than prior metrics. Hybrid Metric $\mathbf{M_H}$ -B/B, our novel self-play based metric, has higher correlation across all human metrics more than any other metric proposed to-date. Notes: -U: Calculated on user response, -B: Calculated on bot response, -U/B: Calculated between user and bot response, -B/B: Calculated between consecutive bot utterances.

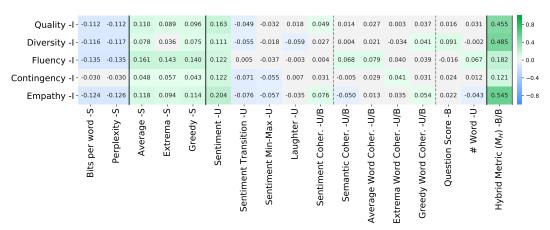


Figure A.5: Kendall correlations between five human metrics and automated metrics. **Sentiment -U** has higher correlation with interactive human ratings than prior metrics. **Hybrid Metric M_H -B/B**, our novel self-play based metric, has higher correlation across all human metrics more than any other metric proposed to-date. **Notes:** -U: Calculated on user response, -B: Calculated on bot response, -U/B: Calculated between user and bot response, -B/B: Calculated between consecutive bot utterances.

A.6 Reddit casual conversation corpus details

Using the 1.7 Billion post comments dataset hosted on Google BigQuery, we extracted post ids for all posts on r/CasualConversation from July 2018 to December 2018. For each post, we built a conversation tree of comments and subsequent replies to extract three-turn dialog. We removed links, excluded [removed] and [deleted] tag comments, and only used text before "edit" comments to preserve the original content in the conversation. We make this dataset available for public use at https://affect.media.mit.edu/neural_chat/datasets.

A.7 Embedding-based metrics

Embedding Average Taking the mean word embedding of the generated sentence e_g and the target sentence e_t , the embedding average metric is the cosine distance between the two.

$$\bar{e}_t = \frac{\sum_{w \in t} e_w}{\left| \sum_{w' \in t} e_{w'} \right|} \tag{6}$$

$$AVG(\hat{e}_t, \hat{e}_g) = cos(\bar{e}_t, \bar{e}_g)$$
(7)

Context: Person 1: when are you leaving? Person 2: tomorrow. Person 1: i'm going to miss you. Person 2: that's what you said the other night. Response A: well, i mean it more now. Response B: i don't know.								
	Response A is better	Response B is better	About the same					
Which response would you rate higher in quality ?	0	0	0					
Which response is more fluent? i.e. better grammar and sentence structure	0	0	0					
Which response is more related to the conversation context?	0	0	0					
Which response is more empathetic? i.e. more supportive of the people speaking in the conversation context	0	0	0					

Figure A.6: Static single-turn evaluation interface crowdworkers see.

Vector Extrema The extrema vector for a sentence can be calculated by taking the most extreme value for each dimension $(e_w^{(d)})$ among the word vectors in the sentence. The extrema embedding metric is again the cosine distance between the extrema sentence vectors.

$$\hat{e}_{t}^{(d)} = \begin{cases} \max_{w \in t} e_{w}^{(d)} & \text{if } e^{(d)} > |\min_{w' \in t} e_{w'}^{(d)}| \\ \min_{w \in t} e_{w}^{(d)} & \text{otherwise} \end{cases}$$
(8)

$$Ext(\hat{e}_t, \hat{e}_a) = cos(\hat{e}_t, \hat{e}_a) \tag{9}$$

Greedy Matching The greedy matching distance is computed by matching word vectors in a source sentence (s) with the closest words vectors in the target sentence (s).

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

$$GRD(s, t) = \frac{G(s, t) + G(t, s)}{2}$$
(10)

$$GRD(s,t) = \frac{G(s,t) + G(t,s)}{2}$$
(11)

Static evaluation setup details

We replicated the static evaluation found in previous work [3, 4]. We sampled conversation contexts from the test set of each corpus and generated samples by each model based on these contexts. After filtering by context length (>10 tokens) and removing contexts which contain <unknown>tokens, we sampled 100 examples. We divided each set of 100 examples into two batches of 50 for annotators to rate. Annotators recruited through Amazon Mechanical Turk were first trained with an example question. Annotators must be in the United States and had to correctly answer all training questions before beginning the task. Figure A.6 shows the interface displayed to crowdworkers in the static evaluation task. We asked annotators to select which sentence was better for quality, fluency, relatedness, and empathy. Note that in static single-turn evaluation, annotators only rate a single bot-generated response; thus they cannot judge the diversity of response generation in the dialog model and only rate the remaining four qualities. Table A.2 summarizes the results for all 4 metrics and is an uncondensed version of table 4. One notable exception to the pattern of EI models winning is fluency; baseline models trained on the CORNELL corpus generated more fluency wins.

Noting the high disagreement between annotators in this task, we further examined the ambiguous examples in the human evaluation test set. We define an ambiguous example as a question where

Table A.2: Results from human static evaluation for EI vs. Baseline models for HRED, VHRED, and VHCR models across quality, fluency, relatedness and empathy pairwise comparisons with 90% confidence intervals

			Cornell	7.1		Reddit	
Model	Metric	Wins %	Losses %	Ties %	Wins %	Losses %	Ties %
	quality	40.8 ± 4.9	24.5 ± 4.9	34.8 ± 9.2	31.3 ± 5.2	29.5 ± 6.6	39.3 ± 10.7
HRED	fluency	10.3 ± 4.4	17.3 ± 4.1	72.5 ± 8.1	22.8 \pm 5.3	20.0 ± 7.1	57.3 ± 11.2
TIKED	relatedness	36.3 ± 6.5	28.7 ± 4.8	35.0 ± 7.9	34.3 ± 2.8	30.3 ± 7.8	35.5 ± 9.7
	empathy	37.8 ± 7.2	24.5 ± 5.6	37.8 ± 8.9	32.5 ± 3.4	31.2 ± 5.9	36.3 ± 8.0
	quality	36.9 ± 4.7	36.6 ± 5.6	26.6 ± 6.9	39.0 ± 7.0	34.0 ± 5.3	27.0 ± 8.9
VHRED	fluency	23.4 ± 9.6	27.7 ± 8.3	48.9 ± 16.3	29.0 \pm 13.6	23.3 ± 9.3	47.7 ± 21.6
VIIKED	relatedness	37.4 ± 5.4	33.1 ± 7.2	29.7 ± 9.6	38.3 ± 5.6	33.0 ± 5.1	28.7 ± 9.0
	empathy	36.6 ± 9.4	34.0 ± 8.4	29.4 ± 15.8	34.7 ± 8.7	33.7 ± 6.7	31.7 ± 10.9
	quality	33.0 ± 6.1	29.0 ± 5.4	38.0 ± 10.1	33.7 ± 7.9	27.3 ± 3.3	39.0 ± 8.6
VHCR	fluency	13.5 ± 4.1	25.5 \pm 4.3	66.0 ± 7.7	24.7 ± 7.2	18.3 ± 5.2	57.0 ± 10.2
VIICK	relatedness	40.8 ± 4.8	26.8 ± 6.8	32.5 ± 10.5	28.3 ± 6.6	31.3 ± 3.6	40.3 ± 8.4
	empathy	32.8 ± 6.6	28.0 ± 7.8	39.3 ± 13.7	30.3 ± 3.9	24.0 ± 4.6	45.7 ± 7.6

Table A.3: Count of ambiguous examples in human static evaluation.

		Cornell		Reddit			
	HRED	VHRED	VHCR	HRED	VHRED	VHCR	
Quality	12	13	15	26	15	9	
Fluency	4	10	10	12	20	6	
Relatedness	11	12	10	15	13	7	
Empathy	16	9	12	14	17	7	

an equal number of annotators select the first sentence as better as the second sentence. If the two examples were similar, annotators would select the "tied" option. An equal number of selections for each answer as the winner indicates a disagreement in perception. Table A.3 summarizes the number of ambiguous examples per model and metric out of 100 in total for each box. After removing these ambiguous example from calculating wins, losses and ties, the results are similar to table A.2. The number of ambiguous samples further highlights the noisy and unreliable nature of static single-turn evaluation.

A.9 Interactive evaluation details

For our interactive evaluation, we built a platform to mimic a natural chat setting. Figure A.7 is an example conversation within the platform that interactive evaluation participants see. Annotators can optionally click the up and down arrows beside each chatbot response to give feedback on the specific utterance. Once 3 or more turns of the conversation has taken place, participants may click

```
[User]: hey

[EI VHRED reddit]: hi . how are you ?

[User]: i'm alright, how bout you?

[EI VHRED reddit]: □ □ □ i m going to be a pharmacist one day at a time.

[User]: oh yeah? that's a good goal.

[EI VHRED reddit]: □ □ i don't know what you're going through, though.

[User]: i've just been working way too hard on this paper deadline.

[EI VHRED reddit]: □ □ hey man, i'm sorry you're having a rough day!

[User]: it's okay, it'll get better soon.

[EI VHRED reddit]: □ it's been a long time since i've been working on it.

[User]: yeah, exactly.

SEND
```

Figure A.7: Interactive evaluation chat interface

Table A.4: Summary table of ratings collected per model.

		Cornell		Reddit			
	HRED	VHRED	VHCR	HRED	VHRED	VHCR	
Baseline	55	46	53	55	36	39	
EI	49	39	42	56	44	52	

"Close Chat and Rate". This will take them to the rating page where the conversation to be rated is presented along side the 7 point Likert scale questions used to asses the conversation (Figure 2).

Participants both from Amazon Mechanical Turk and from the authors' institution were recruited for interactive evaluation. Although the minimum required number of turns is 3, the average number of responses per conversation of participants varied between 3.00-10.58 turns with the average at 5.43 turns. Table A.4 summarizes the number of ratings collected for each model.

The average rating each annotator gave differed significantly between annotators. As a result, we also computed scores for interactive evaluation after normalizing each annotator's scores. We restricted ratings down to only annotators who completed 10 or more ratings which left 301 ratings. Similar to Table 2, the mean ratings for EI (Emotion+Infersent) models were higher than the mean ratings for the baseline models.

A.10 Website server setup and configuration

The server was hosted on a Google Cloud Platform virtual instance with 64GB of RAM and a NVIDIA Tesla P100 graphics card. The backend was a Django program being served by NGINX and uWSGI. For simplicity, we opted to have the Django process import the chatbots into the same Python process as Django, rather than have the two connect to each other via other means such as sockets. This configuration decreased development time and increased reliability, but it would need to be revisited if the server needed to scale several orders of magnitude past what was required for this study. The current configuration was still able to support hundreds of simultaneous users and host more than 30 bots concurrently.

The chatbots were kept in a separate project from the Django project and maintained separately from the server code. Each chatbot extended an abstract class that defined key methods for the Django program to use, and was registered to a globally accessible dictionary via a decorator. The Django project was provided the path to the Chatbots project in its PYTHONPATH, so it could import the dictionary in which all the chatbot objects had been registered and use that to dynamically determine which chatbots were available and to access them in its views.

It is important to note that the chatbots used PyCUDA, and PyCUDA does not work in a multiprocessing environment. Because of this, uWSGI needed to be configured to only have one python process and to disable any attempt at multiprocessing. Furthermore, the chatbots required substantial startup times, so all chatbots are kept in memory at all times in the Django process. In order to keep all the chatbots in memory concurrently, we needed a very high amount of RAM on our server and opted for a 64GB virtual instance, and a GPU with 16GB RAM. This combination of CUDA to run the chatbots on the GPU with a high amount of RAM to keep all bots in memory at the same time resulted in incredibly fast server response times, with effectively no increase in response time when using the bots in requests compared to requests that did not.

For further information and instructions on server configuration, please read the server documentation available at https://github.com/asmadotgh/neural_chat_web.

A.11 Emotion embedding details

We calculate emotion embeddings of an utterance using a using a state-of-the-art sentiment-detection model [32]. This pre-trained model outputs a probability distribution over 64 most-frequently used emojis as presented in [32]). We define a set of weights over the emojis and calculate the weighted sum over an emotion embedding vector to derive a *Sentiment* score which is higher for positive sentiment and lower for negative sentiment (See Figure A.8).

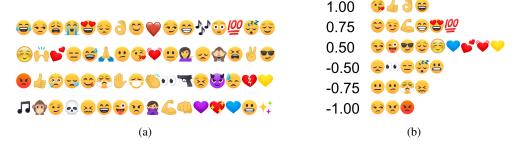


Figure A.8: (a) 64-most frequent emojis as predicted by [32] used for calculating emotion embeddings. (b) Assigned weights used for reducing the 64-dimensional emotion embedding into a *Sentiment* score.

A.12 Hyper-parameter tuning details

For the baseline models that were trained on the CORNELL dataset, we used the parameters reported in [5, 3, 4] that achieved state-of-the-art results for HRED, VHRED, and VHCR models trained on the same dataset, respectively. For EI models, we compared a combination of values for encoder hidden size (400, 600, 800, 1250), decoder hidden size (400, 600, 800, 1250), context size (1000, 1250), embedding size (300, 400, 500), word drop (0, .25), sentence drop (0, .25), beam size (1, 5). Learning rate (.0001), dropout (.2) were fixed. Batch size 80 was used. If due to memory limitation the job was not successfully completed, batch size 64 was used. Additionally, we tuned the EI parameters, i.e., emotion weight (25, 150), infersent weight (25K, 30K, 50K, 100K), emotion sizes (64, 128, 256), infersent sizes (128, 1000, 2000, 4000). Due to limited computational resources, we were not able to run a grid search on the aforementioned values. Instead we used combinations of the parameters that heuristically were more viable.

For the models that were trained on the REDDIT dataset, a set of properly tuned baseline parameters were non-existent. Thus, to ensure fair comparison, we used a similar approach for baseline and EI hyper-parameter tuning: We explored a combination of values for encoder hidden size (400, 600, 800, 1250), decoder hidden size (400, 600, 800, 1250), context size (1000, 1250), embedding size (300, 400, 500, 600), word drop (0, .25), sentence drop (0, .1, .25), and beam size (1, 5). Learning rate (.0001), dropout (.2) were fixed. Batch size 64 was used. If due to memory limitation the job was not successfully completed, batch size 32 was used. Due to limited computational resources, we were not able to run a grid search on all the aforementioned values. Instead we used combinations of the parameters that heuristically were more viable. To ensure fair comparison, any selected combination was tested for both baseline and EI models. Then, for EI models, we tuned the parameters that were solely relevant to the EI design, such as the weight of emotion and infersent term in the loss function and the size of the added discriminator networks: Emotion weight (25), infersent weight (25K, 50K, 100K), emotion sizes (64, 128, 256), infersent sizes (100, 128, 1000, 2000, 4000). See Table A.5 for a summary of the final selected parameters.

A.13 Self-Play Overlap Analysis

As a post-hoc sanity check on the conversations generated from self-play, we check whether there is i) overlap among generated conversations, and ii) overlap between these conversations and the training set. High overlap among generated conversations would indicate that there is a lack of diversity in the conversations generated by self-play while high overlap with the training set suggests self-play may be memorizing training dialog.

To measure overlap between the 100 conversations generated in each model, we consider all 3 and 5 consecutive conversational turns over the 10 turns in each conversation. We compare each pair of conversations in the 100 generated conversations in total to compute a percentage of conversations which contain overlap in this pairwise comparison. Table A.6 summarizes these results and illustrates that overlap is not significant for most models. The exception is the non-variational models trained on the Cornell corpus (e.g. HRED Cornell). Qualitative evaluation reveals that these are degenerate cases where "what?" or "I don't know" or "I'm sorry" are repeated multiple turns.

To measure repetition with respect to the training set, we take all 2-turn and 3-turn windows in the self-play generated conversations and compare with the entire training set to check whether there is

Table A.5: Hyper-parameters used for different models.

Dataset	Version	Model	Batch size	Dropout	Decoder hidden size	Encoder hidden size	Context size	Embedding size	Word drop	Sentence drop	Beam size	Emotion weight	Emotion discriminator layer size	Infersent weight	Infersent discriminator layer size
	Baseline	HRED VHRED	80 80	.2	400 1000	400 1000	1000 1000	300 400	.0	.0	5 5	-	-	-	-
	Daseille	VHCR	80	.0	1000	1000	1000	500	.25 .25	.25	5	-	-	_	_
Cornell -		HRED	64	.2	1000	1000	1000	500	.0	.0	1	25	128	100K	4000
	EI	VHRED	80	.2	1250	1250	1000	600	.0	.0	1	25	128	30K	128
		VHCR	32	.2	1000	1000	1250	600	.0	.0	1	25	128	25K	4000
		HRED	64	.2	1000	1000	1000	500	.0	.0	1	-	-	-	-
	Baseline	VHRED	32	.2	1250	1250	1000	600	.0	.0	1	-	-	-	-
Reddit -		VHCR	32	.2	1000	1000	1250	600	.0	.25	1	-	-	-	-
Reduit -		HRED	64	.2	1000	1000	1000	500	.0	.0	1	25	128	25K	2000
	EI	VHRED	32	.2	1250	1250	1250	600	.0	.0	1	25	128	100K	4000
		VHCR	32	.2	1000	1000	1250	600	.0	.0	1	25	128	100K	4000

Table A.6: Percentage of pairs of conversations in each 100 sample for each model where there are 3 or 5 consecutive conversation turns that are exactly the same.

		Cor	nell	Reddit			
Model	Version	3-turn overlap	5-turn overlap	3-turn overlap	5-turn overlap		
HRED	baseline	19.49%	1.76%	2.02%	0.24%		
TIKED	EI	6.48%	0.30%	2.12%	0.16%		
VHRED	baseline	0%	0%	0%	0%		
VIIKED	EI	0.16%	0%	0.16%	0%		
VHCR	baseline	0%	0%	0%	0%		
VIICK	EI	0%	0%	0%	0%		

Table A.7: Percentage of of conversations (100 sample for each model) where there are 2 or 3 consecutive conversation turns that match the training set.

		Cor	nell	Reddit			
Model	Version	2-turn overlap	3-turn overlap	2-turn overlap	3-turn overlap		
HRED	baseline	58%	0%	0%	0%		
TIKED	EI	65%	0%	0%	0%		
VHRED	baseline	8%	0%	5%	0%		
VIIKED	EI	5%	0%	12%	0%		
VHCR	baseline	4%	0%	4%	0%		
VIICK	EI	3%	0%	3%	0%		

overlap. Table A.7 shows the percentage of conversations (100 total for each model) where there is a 2-turn or 3-turn dialog appearing exactly in the training set. Since each conversation is 10 turns long, all of the conversations are distinct from the training set and no conversation contains more than 2-turns of overlap with the training set. The 2-turn overlap again appears due to cases where "what?" and "hi" are repeated for 2 turns.