CORAL: Contextual Response Retrievability Loss Function for Training Dialog Generation Models

Bishal Santra*
CNeRG Lab, IIT Kharagpur

Ravi Ghadia
IIT Kharagpur

Manish Gupta†
Microsoft R&D India

Pawan Goyal‡
IIT Kharagpur

Abstract

In the field of Natural Language Processing, there are many tasks that can be tackled effectively using the cross-entropy (CE) loss function. However, the task of dialog generation poses unique challenges for CE loss. This is because CE loss assumes that, for any given input, the only possible output is the one available as the ground truth in the training dataset. But, in dialog generation, there can be multiple valid responses (for a given context) that not only have different surface forms but can also be semantically different. Furthermore, CE loss computation for the dialog generation task does not take the input context into consideration and, hence, it grades the response irrespective of the context. To grade the generated response for qualities like relevance, engagingness, etc., the loss function should depend on both the context and the generated response. To address these limitations, this paper proposes CORAL, a novel loss function based on a reinforcement learning (RL) view of the dialog generation task with a reward function that estimates human preference for generated responses while considering both the context and the response. Furthermore, to overcome challenges such as high sample complexity of RL training and a large action space, we propose a mix-policy training algorithm. Notably, using CORAL we can train dialog generation models without assuming the ground-truth as the only correct response. Extensive comparisons on benchmark datasets demonstrate that CORAL based models outperform strong state-of-the-art baseline models of different sizes.

1 Introduction

Choosing the right loss function is crucial to get the expected behavior from deep learning based models trained for any task. While the token-level cross-entropy (CE) loss continues to excel in training natural language generation (NLG) models for various tasks, including dialog-response generation [27, 47], it is well accepted that CE is not the most appropriate choice of loss function for training dialog generation models. Finding the right loss function for training dialog generation is still an open problem and an active area of research [35, 48, 29, 21].

The CE loss is computed by comparing the predicted token probabilities to the ground truth target sequence from the dataset. Thus, computation of CE loss is unconditional or context-free, as it does not depend on the input prompt/context in the case of conditional NLG tasks like dialog generation. To be able to generate responses with qualities like relevance, coherence, etc., the loss function should ideally consider both the context and the generated response. While training any NLG model using the CE loss, the probability of the ground truth response is maximized. Here, we make an implicit assumption that the ground truth is the only response possible for the given context. This is a major

* bsantraigi at gmail.com
† gmanish at microsoft.com
‡ pawang at cse.iitkgp.ac.in

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Figure 1: Schematic of CE and CORAL losses (training time): CORAL optimizes a measure of compatibility, the $R_3$ reward (based on response retrieval models), between the context and a candidate response. Compared to CORAL, CE is more strict and relies only on ground truth response targets for training. CORAL utilizes responses sampled from the trained network and updates its decoding-probability based on its $R_3$ reward value. We utilize transformer-Seq2Seq models for our dialog generation experiments. The context input is represented as $[c_1, ..., c_L]$, and the target response is denoted as $r = [r_1, ..., r_T]$ which can either be the ground truth or a sample from the network.

Concern as this property does not hold for most dialogs where each context may have a large number of possible responses [8].

Previous attempts in training Seq2Seq dialog generation models using the CE loss have led to various complications. Mode collapse is one of the most common issues when training a Seq2Seq model with the CE loss, mainly at smaller scales [18, 21]. Here, the model just ends up assigning a high probability to one or more generic and bland responses e.g. “I don’t know”, “I have a problem”, “Yes”, etc., irrespective of the context. Previous research works have also explored various augmentations to the model architecture [33, 49] and/or the loss function [34, 35, 48, 21] to resolve the common problems with CE, as mentioned above.

To train dialog generation models that maximize some user-expected qualities, we propose to directly optimize an estimate of human perceived quality of a context-response pair. Sinha et al. [36], Yeh et al. [45] have shown that the output score of a dialog response retrieval model (trained on the same domain) correlates strongly with human perception of dialog response quality. Further, Santra et al. [32] showed that representations learned by a response retrieval model (using binary cross-entropy or a contrastive loss) capture important dialog understanding features even better than large-scale dialog generation models trained using CE.

Motivated by these findings, we introduce a novel loss function called Contextual Response Retrievability (CORAL) for training dialog generation models. This loss function optimizes a response-retrieval model’s score, referred to as the Response Retrievalability Reward ($R_3$), as shown in Fig. 1. Our proposed learning-framework uses reinforcement learning (RL) to optimize the $R_3$ reward between context and generated responses. To evaluate the effectiveness of CORAL, we train transformer-based Seq2Seq models [38] using the DailyDialog dataset [20, 40] for open-domain dialog generation and the DSTC7-Ubuntu dataset [46] for domain-specific dialog generation. We compare the performance against state-of-the-art CE-based Seq2Seq models and various other baselines using both automatic metrics and through human evaluation. In summary, our contributions are: (1) the proposal of the CORAL loss function that directly optimizes for an estimate of human preference of a ⟨context, response⟩ pair, which is the first of its kind to also rely on the context, (2) a recipe for training improved seq2seq dialog models using the CORAL loss in a reinforcement learning setup, utilizing both on-policy and off-policy response samples, and (3) experimental evidence of the effectiveness of CORAL against strong baseline models using CE or its variants.

2 Literature Review

Inspired by the initial success of Sequence-to-Sequence (Seq2Seq) models in the machine translation task, Ritter et al. [26] proposed a similar approach for training open-domain dialog (chitchat) generation models, using the CE loss. However, this vanilla approach suffered multiple shortcomings, such as token repetition in output generations, generic/bland responses that are ignorant of the context,

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4These problems are specific to dialog systems only and may or may not apply to other NLG tasks.
etc. To remedy these shortcomings of the vanilla Seq2Seq architecture for the dialog generation task, various solutions have been proposed over the years. Serban et al. [33], Santra et al. [31] proposed methods for learning hierarchical representations of the context. Serban et al. [34], Shen et al. [35], Zhao et al. [48], Bao et al. [3] developed latent variable models to capture the stochastic nature of the task. Recently, a significant amount of focus has been on pretraining large dialog generation models [47, 3, 27, 1] using the transformer architecture, following its recent unmatched success in almost every domain. Another set of important directions in dialog generation involve the development of response retrieval/next-utterance selection models [23, 5, 41, 44, 16, 32, 13] and retrieval augmented generation or RAG [43, 10, 4, 17, 50, 17, 11] models. RAG models use the power of response retrieval models to select plausible responses/related knowledge from a large pre-existing corpus, and generate a response based on that. A significant difference between RAG and our approach is that we use the response-retrieval model as an optimization objective during training and do not use any external data source or knowledge-bases.

Cross-entropy loss, while a popular choice for training dialog generation models, has its limitations in that it can only evaluate the generated response with respect to the ground truth response. To overcome this, various reinforcement learning (RL) based training algorithms have been proposed for training dialog generation models, which allow for optimizing other qualities of the model and output generation, e.g., coherence of the response. Li et al. [18] employed RL to optimize for long-term success, while Li et al. [19] incorporated adversarial learning and policy-gradient to create a discriminator-based reward function. Additionally, Sankar and Ravi [30], Zhao et al. [49], Saleh et al. [29] utilized RL to learn latent discrete-action spaces for the purpose of training interpretable dialog generation models.

In this paper, we propose a novel reward function based on response retrieval models for training RL-based dialog models. Sinha et al. [36] recently demonstrated that scores from retrieval models [5, 12, 15] correlate strongly with human judgments for model-generated responses. Hence, this paper explores the possibility of using this “retrievability score” as an optimization target and thoroughly analyzes it under different experimental settings to understand its effectiveness for dialog generation.

3 Proposed Approach

Our proposed approach focuses on training a dialog generation model in a reinforcement learning (RL) setting by optimizing a novel reward function based on human preference estimates. To design the reward function, which we call $R_3$, we use a response retrieval model as explained in Section 3.1. We then propose a novel loss function, CORAL, which is based on this RL view of the dialog generation task to maximize the $R_3$ reward function, in Section 3.2. We use the CORAL loss to train a transformer-based Seq2Seq model instead of the traditional cross-entropy loss, as illustrated in Fig. 1. Furthermore, to overcome challenges such as high sample complexity of RL training and a large action space, we propose a mix-policy training algorithm in Section 3.3. Our approach effectively trains the dialog generation model, enhancing its ability to generate high-quality, human-like responses in natural language conversations.

3.1 $R_3$ Reward Function

Although cross-entropy loss is the norm for training Seq2Seq models on various tasks, it does not correlate with any quality that we expect a dialog generation model to possess [22]. So, a natural research question is how we can design an alternative objective function that might be able to improve qualities like relevance, coherence, topicality, engaging etc. in a dialog system.

The task of response retrieval or next utterance selection [23] involves predicting whether, given a dialog context and a candidate response, the response is a valid continuation to the context. Sinha et al. [36] showed that output probabilities from a model trained with tasks akin to response retrieval correlate strongly with human preferences for dialog responses, which means that the output (a value between 0 and 1) indicates whether a human annotator would rate the response as a coherent and on-topic continuation to the context. Based on this idea, we train a response retrieval model (on a given dataset) and define the output probability from the finetuned retrieval model as the reward function to be optimized by a dialog generation model. We refer to this output probability score from a response retrieval model as the contextual Response Retrievability Reward ($R_3$).
Training the Reward Model  We experiment with two model architectures for designing the reward function: ESIM (Enhanced Sequential Inference Model) [5] and BERT (Bidirectional Encoder Representations from Transformers) [7]. ESIM is an LSTM and cross-attention based model for sentence-pair classification. For further details about the ESIM architecture, please refer to the works by Chen et al. [6], Chen and Wang [5]. The BERT-based response retrieval model is designed by adding a classification layer on top of the CLS output representation (final-layer) and then finetuning the whole model for the response retrieval task.

The response retrieval model is trained in a self-supervised setting using the binary cross-entropy (BCE) loss. The data for training the model is gathered as follows. We create positive and negative ⟨context, response⟩ pairs for this task from the target dialog dataset itself (same as the one to be used for dialog generation training). For creating the positive samples, we extract context-response (CR) pairs by unrolling dialogs from the dataset. Then for each positive CR-pairs, we generate n (=4) negative CR-pairs by pairing the context with random utterances from other dialogs in the dataset.

3.2 CORAL Loss Function

To be able to optimize the proposed $R_3$ reward function, which is not differentiable w.r.t. the policy network (implemented as a Seq2Seq model) parameters, we pose the response generation problem as a reinforcement learning (RL) task. Then, we apply REINFORCE [42] to obtain a differentiable objective function, as described next. Each instance of the context-to-response generation task is considered as an episode in the RL formulation. The state consists of the tokenized dialog context and the set of response tokens generated until the previous timestep. Each episode consists of several actions taken by the agent, in our case the decoder, spanning the generation of a complete response. Each action corresponds to generation of an output token. The episode ends when the agent generates an EOS (end-of-sequence) token or has produced a max number of allowed tokens ($T$). Then the response retrieval model generates the $R_3$ reward, for the ⟨context $c$, generated response $r$⟩ pair.

The updates to the weights $\theta$ of the Seq2Seq (S2S) model $P(r|c)$, that maximize the expected return, $\mathbb{E}_{r \sim P(r|c)} [R_3(r, c)]$ are determined by the Episodic REINFORCE algorithm [42] as follows.

$$\Delta \theta = \eta R_3(c, r) \sum_{t=1}^{T} \frac{\partial \log P(r_t|r_{<t}, c)}{\partial \theta}$$

(1)

where $\eta$ is the learning rate, and $r$ is a response sampled from the learned policy $P(r|c)$. Loss function to be minimized (for an autoregressive decoder) can then be written as follows:

$$L_{CORAL} = -R_3(c, r) \sum_{t=1}^{T} \log P(r_t|r_{<t}, c)$$

(2)

Fig. 1 illustrates how this Eq. 2 is used to compute the proposed CORAL loss function.

3.3 Training Algorithm

Mix-Policy Training Using CORAL Loss  RL training can be either on-policy or off-policy, depending on whether samples are generated from the parameterized policy network (the Seq2Seq model in our case) or obtained from a dataset of human generated examples. For pure on-policy training, we will have to rely on response sequences randomly sampled from the decoder. But, because of the combinatorial complexity of the response space, it is highly unlikely that we would obtain any valid utterances/response candidates during on-policy training. Off-policy learning, on the other hand, becomes reliant on the ground truth responses only and cannot leverage any benefits of exploration. A mix of on-policy and off-policy training (henceforth referred as mix-policy) can potentially leverage both on-policy samples for better exploration and the ground truth responses for stabilizing the RL training process. Thus, to direct the model towards generating grammatically and semantically valid utterances, we perform mix-policy sample generation. To control the amount of mixing, we introduce a hyperparameter called $p^+$ (detailed below). The contributions from these two different types of samples are mixed as per the following equation. We also weigh positive response

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5If (A, B, C, D, E, F, G) is the sequence of utterances in a dialog, then it can be unrolled to create multiple CR-pairs, such as, ⟨(A),B⟩, ⟨(A, B),C⟩, ⟨(A, B, C),D⟩, and so on.
We use a standard transformer-based Seq2Seq (S2S) architecture for training warmed up (first 1000 steps) and decayed linearly. We use a single NVIDIA V100-32GB GPU-based

Although CORAL is derived from quite a different viewpoint, under certain hyperparameter settings (1) Probability of positive samples ($p_+$) denotes the probability with which we use the ground truth (off-policy) response samples during mix-policy training. (2) Margin ($m$) denotes the minimum reward that we expect from model generations. We use a fixed margin value as the baseline reward for the RL training.

Hyperparameters of CORAL: (1) Probability of positive samples ($p_+$) denotes the probability with which we use the ground truth (off-policy) response samples during mix-policy training. (2) Margin ($m$) denotes the minimum reward that we expect from model generations. We use a fixed margin value as the baseline reward for the RL training.

Although CORAL is derived from quite a different viewpoint, under certain hyperparameter settings ($m = 0$, $p_+ = 1$, $R_3 \in (0, 1)$) CORAL approximates a sample-weighted version of the CE loss. Also, training of a dialog generation model using CE may over-weigh generic responses more than the informative ones. A more detailed account of the similarities/differences between CORAL and CE are in the appendix.

### 4 Experimental Setup

#### 4.1 Model Setup

We use a standard transformer-based Seq2Seq (S2S) architecture for training a dialog generation model using the CORAL loss as shown in right part of Fig. 1. We train our models using early-stopping, up to a maximum of 50 epochs, based on validation-$R_3$ (average $R_3$ score of generated responses on the validation set). We use Adam optimizer with a peak learning rate of $10^{-4}$ that is warmed up (first 1000 steps) and decayed linearly. We use a single NVIDIA V100-32GB GPU-based systems for training our individual CORAL models.

Retrieval Models ESIM has two LSTM-based encoder layers for encoding the context and a candidate response, interleaved by a cross-attention layer. The sigmoid output from the ESIM model
is used as the score for a context-response pair. Since BERT is a pretrained transformer-encoder model, we add a one-hidden layer MLP on top of the [CLS] token embedding. These models are finetuned on corresponding dialog datasets for the response retrieval task. We obtain the reward ($R_3$) by subtracting the margin ($m$) (between 0 and 1) from the output score (sigmoid output).

**CORAL** We implemented the dialog generation model using transformer-based Seq2Seq models with 6 self-attention layers, 8 self-attention heads and 1,024 as the size of hidden representations, for both the encoder and the decoder. We use the wordpiece tokenizer from BERT.

**CORAL-BB** This variant of the CORAL model is initialized with the pretrained-weights from the facebook/Blenderbot-400M-distill checkpoint which allows us to leverage the power of the large-scale pre-training while also fine-tuning it using the proposed RL-based training algorithm. CORAL-BB uses the same architecture and tokenization as the Blenderbot model (2 encoder and 12 decoder layers).

4.2 Datasets

We use DailyDialog (DD) [20] and DSTC7-Ubuntu [46] datasets for all our experiments. DD is an open-domain dialog dataset in English. DSTC7-Ubuntu is a domain-specific dataset based on conversations from a Linux IRC channel. We create context-response (CR) pairs by unrolling the dialogs while ensuring a minimum of two previous utterances in the context. DD contains 76052, 7069 and 5740 CR pairs for train, validation and test, resp., and DSTC7-Ubuntu contains 470860, 23478 and 3247 pairs, resp. However, Wen et al. [40] recently showed that there are some leaks between the splits of the DD dataset, and proposed a cleaned version (DD$_c$) containing new splits of 60243, 6644, 5986 CR pairs for train, validation and test, resp.

4.3 Baselines

**Non-pretrained Baselines:** (1) **Mirror** [21]: Seq2Seq model that extends CVAE [35], and is trained with a backward-reasoning loss function. It optimizes for generating final and pre-final utterances in a bidirectional fashion. This is state-of-the-art loss function for training small-scale dialog generation models outperforming [35, 48, 29]. (2) **AdaLabel** [39]: Uses adaptive label smoothing and soft-target distribution to prevent the model from being overconfident over a single choice. (3) **ALDGen** [19]: Includes a discriminator to differentiate between human-generated and machine-generated dialogs, and a generator to optimize the score given by the discriminator, using RL.

**Pretrained Baselines:** We consider zero-shot as well as fine-tuned variants of the following. (1) **Blenderbot** [27]: Transformer-based S2S model pretrained on a large dialog corpus based on Reddit and finetuned on Blended-Skill-Talk dataset [37]. (2) **DialoGPT** [47]: GPT-2 [25] based language model further finetuned on dialogs from Reddit. (3) **DialogRPT** [9]: A response ranking model trained on a dataset of upvote/downvote and number of replies on Reddit comments. For generation, it reranks sampled responses from DialoGPT and returns the one with highest rank.

4.4 Evaluation Metrics

We use a standard set of referenced evaluation metrics (BLEU, METEOR) and a few recently proposed reference-free metrics (MaUde, DEB) for automatic evaluation. BLEU [24] and METEOR [2] measure lexical-overlap between n-grams of the predicted and ground truth response. MaUde [36, 45] captures suitability between a context and a response without a ground truth reference. It is based on a response retrieval model and can be optimized through CORAL loss function. We report results for two MaUde variants based on ESIM [6, 5] and BERT [7] finetuned on the target datasets. DEB [28] is a BERT-based dialog evaluation metric that is trained on a large-scale dataset of Reddit conversations (DEB(r)) and finetuned on a dataset of multiple relevant and adversarial responses for each context (DEB(a)). Distinct-n [22] measures n-gram diversity in generated responses.

5 Results and Discussions

5.1 Automatic Evaluation

In Table 1, we present the automatic evaluation results for response generation using non-pretrained, zero-shot and finetuned baselines and our proposed models separately for both the DD$_c$ and DSTC7
For our proposed CORAL models, we found \( p^+ = 0.8 \) for DSTC7-Ubuntu and \( m = 0 \) and \( p^+ = 0.8 \) for DD, as the best hyperparameters. For CORAL-BB, we found the best values to be \( p^+ = 0.6 \), \( m = 0.2 \). Fig. 1 in Appendix shows sensitivity analysis for \( p^+ \) and \( m \).

The focus of this work has been to propose a framework that can train dialog generation models by optimizing estimates of human preference. Prior works [22, 45] have shown that reference-based metrics (e.g., BLEU, METEOR) have poor correlation with human ratings. Hence, we focus on evaluating models against reference-free relevance metrics such as MaUde and DEB.

In terms of MaUde and DEB, models of the CORAL family outperform all baselines by a significant margin. The diverse and high quality responses justify the choice and design of the CORAL loss function. Especially our Blenderbot initialized CORAL-BB models (in block D of Table 1) outperform all pretrained dialog generation models that use standard CE loss based finetuning. Because of the extensive pretraining done, we do not expect non-pretrained CORAL models to fully outperform pretrained baselines. Still, we observe that CORAL is able to beat all the zero-shot models for DSTC7-Ubuntu. Further, for DSTC7-Ubuntu, surprisingly, our non-pretrained CORAL models outperform even strong finetuned baselines which are \( \sim 4x \) in size. These results indicate that, by using an estimate of human preference as the training objective, it is possible to train models that are specifically good at achieving better relevance scores.

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8We also report results on the original DD dataset in the Appendix.
Amongst variants of the CORAL family, we observe that mix-policy training often achieves higher relevance scores than off-policy training, indicating the benefits of allowing exploration. The off-policy training approach, which essentially reweighs response samples in CE loss using the R3 reward, also performs better than the baseline models trained using standard CE loss. This shows that not all samples from the training dataset contribute equally or positively to CE-based training. Simply downsampling certain samples using the R3 reward helps us train dialog generation models that can generate responses more relevant to the context.

Diversity of the generated responses is indicated by the Dist-1 and Dist-2 metrics. We observe that non-pretrained CORAL models have better diversity compared to pretrained ones. We also observe that, for CORAL-BB models, output length and diversity are inversely related. This could be because as the model outputs longer generations, it tends to reuse similar ngrams.

Our results in Table 1 also demonstrate the disconnect between lexical-overlap metrics (BLEU, METEOR) and the relevance metrics (MaUde and DEB) as shown in several prior works [22, 36, 45]. For DSTC7-Ubuntu, Adalabel achieves highest BLEU and METEOR scores despite the poor relevance values. On the other hand, for DDc, the CORAL model with the highest MaUde also attains the highest BLEU score.

In terms of avg. length of the generated responses, the general trend is that the pretrained models outperform other baselines (i.e., trained from scratch) and the same holds true for CORAL models. Though it should be noted that lengthier generation does not necessarily mean better quality responses.

We trained two types of baseline as well as CORAL models. One set of models have been initialized (for finetuning or used as is for zero-shot) from pretrained dialog generation models. We observe that pretraining gives a significance boost to the relevance scores of the model among the CE-based baselines (block A versus B in Table 1). The second set of improvements in relevance score comes from finetuning these pretrained models on the task dataset. This can be observed by comparing the zero-shot pretrained models with the fine-tuned ones (block B versus C in Table 1). And the final improvements are obtained when these pretrained models are finetuned using the CORAL loss function, which can be observed by comparing Blenderbot-finetuned versus CORAL-BB.

5.2 Hyperparameter Sensitivity Analysis

To better understand the effects of various hyperparameters (see Section 3.3) on the final trained model, we perform extensive experiments by varying p+, m and sampling method. The complete set of results is displayed in Fig. 1 in the appendix. All the comparisons are done based on the best average reward obtained by the model on validation set. In general, the mix-policy setup outperforms off-policy training routines. For DD, lower margin values tend to have higher R3 scores. But, for DSTC7-Ubuntu and DDc, in case of mix-policy training, the R3 increases with margin. We observed that mix-policy training using nucleus sampling performed better than with RandomNegatives.

5.3 Human Evaluation Study

As automatic evaluation metrics cannot capture all the nuances of how humans assess a model generated response, we also run a crowdsourced human evaluation study for various models. We used the Appen.com platform to run these surveys. Three different annotators based out of USA, rated a context-response pair in terms of engagement, relevance, fluency and coherence on a 0-2 scale: No (0), Somewhat (1), Yes (2). Detailed annotation questionnaire is in the Appendix. This evaluation
Table 2: Sample generations from DialogRPT (FT), Blenderbot (FT) and CORAL-BB₇₉₇₃(mixp).

| Context | Human: Yes, here it is. | DialogRPT: Yes, I do. I’ll just take it to the Apple Store. Thanks. I’ll be back in a minute. Bye. | Blenderbot: I’m afraid I don’t have it with me. Can you give me your name, phone number, and phone number so I can make sure that I can get it back to me in the next day or two? If not, I won’t be able to return it to you. | CORAL-BB₇₉₇₃(mixp): Yes, I have my receipte with me. I’ll return it to you in a few minutes. |
|---------|--------------------------|---------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------|
| Context | I like to play computer games, read books, go shopping, and play pool. | DialogRPT: I like to play computer games, read books, go shopping, and play pool. | Blenderbot: I don’t have a favorite. I like all of them. What do you think of the new Star Wars movie? I think it’s going to be great! | CORAL-BB₇₉₇₃(mixp): I like playing video games, too. I also like going to the theater to see a movie. |
| Context | I like to play pool. | DialogRPT: I like to play pool. | Blenderbot: Thank you very much. I’ll be back in a few minutes. Would you like anything to drink? | CORAL-BB₇₉₇₃(mixp): I’m glad you like it. It’ll be my first time living in a new apartment. |
| Context | Are you ready for the camping trip? | DialogRPT: You’re going to have a great time! I’m sure you’ll have a great time! | Blenderbot: Camping trips are so much fun. You’re going to have a great time! | CORAL-BB₇₉₇₃(mixp): What are you going to do in the woods? |

5.4 Case Study: Generation Quality

We provide samples generated from CORAL-BB₇₉₇₃(mixp) and some baseline models (DialogRPT (FT), Blenderbot (FT)) in Table 2. We find that responses generated by CORAL present information more consistently (coherence) than the baselines (example 1). We also notice that DialogRPT is more repetitive and in some cases just repeats a previous utterance (example 4). The examples also show that Blenderbot and CORAL-BB are more engaging then DialogRPT as well as ground truth responses. In general, we find that CORAL-BB responses are more conversational; the responses show that the speaker is interested in the other person’s opinion and is willing to continue the conversation (examples 3 and 4).

Error analysis: To gain insights into the limitations of CORAL, we conducted an error analysis on responses generated by our best model across two datasets. Broad error buckets include difficulties in correctly attributing the next responses to user vs bot, tendency to generate relevant but divergent follow-ups, and occasional generation of consecutive utterances as a single response. More details are in Appendix.

6 Conclusion

In this paper, we proposed CORAL, a novel loss function to circumvent shortcomings of CE loss for dialog generation. Specifically, using mix-policy based training in CORAL, we can train dialog generation models without assuming the ground-truth as the only correct response, and the value of the loss function is based on both the context and the response. The CORAL loss is based on pretrained response retrieval models that, in prior literature, have been shown to correlate with human preferences. Experiments over two diverse benchmarks have shown that it comprehensively outperforms other strong baseline models (non-pretrained, zero-shot as well as finetuned). We plan to extend this framework for more efficient training using advanced RL methods and ideas from
Finally, we hope that our work will open up interesting areas for future research about how to train better reward functions that can capture other aspects of response qualities.

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A Similarities and Differences between CORAL and CE Loss Functions

In this section, we explore the similarities and differences between the proposed CORAL loss and the CE loss function. Although CORAL is derived from quite a different viewpoint, under certain hyperparameter settings CORAL approximates a weighted version of the CE loss.

1. If we only consider positive samples as candidate responses and set the score range (score ∈ [0, 1]) and margin m (m ≠ 0) such that \( R_3 \) is always greater than zero, CORAL is equivalent to a weighted version of CE.

2. Cross-entropy loss has always relied strictly on the positive responses in the dataset. CORAL utilizes both positive and negative response candidates.

3. Training of a dialog generation model using CE may over-weigh generic responses more than more informative ones as there is no mechanism for automatically assigning weights to different ⟨context, response⟩ pairs. CORAL has provision for assigning different weights for different ⟨context, candidate response⟩ pairs.

4. CORAL uses randomly sampled response candidates for training which allows us to utilize more samples of ⟨context, response⟩ pairs during training. This provides a richer training signal from the same dataset.

5. CE loss decomposes to a token level comparison between the predicted and the target token. Its main goal is to increase the probability of the tokens in ground truth response strictly in the given form and order. CORAL loss works quite differently as it treats responses as whole units. It will either increase or decrease probability of responses as a whole, based on their semantics and compatibility to the context.

B Hyperparameter Sensitivity Analysis

We conducted extensive experiments to examine the impact of different hyperparameters on the final trained model. Specifically, we varied \( p^+, m \), and the sampling method. The comprehensive results can be found in Figure 3. To make comparisons, we focused on the best average reward achieved by the model on the validation set.

In general, the mix-policy setup consistently outperformed off-policy training routines. When considering the DD scenario, we noticed that lower margin values tended to yield higher \( R_3 \) scores. However, for DSTC7-Ubuntu and DD_c, the mix-policy training approach demonstrated an increase in \( R_3 \) as the margin value increased. Notably, we observed that mix-policy training using nucleus sampling outperformed RandomNegatives.

C Error Analysis

Table 3: We did an error analysis of the generated response samples by our CORAL-BB-BERT (mixp) model on both datasets. This error analysis study was done on a set of 25 randomly selected context-response pairs from each dataset.

| Error Type                                | DD_c | DSTC7 |
|-------------------------------------------|------|-------|
| No Errors                                 | 19   | 16    |
| Type 1: Not Topical                       | 0    | 1     |
| Type 2: Agents mixed in response          | 1    | 0     |
| Type 3: Wrong agent responds              | 2    | 1     |
| Type 4: Generated 2 consecutive utterances| 1    | 1     |
| Type 5: Relevant but incorrect followup   | 2    | 5     |
| Type 6: Relevant but incoherent to context| 0    | 1     |

To gain insights into the limitations of the CORAL model and identify potential areas for improvement, we conducted an error analysis study on the responses generated by our best models (config: CORAL-BB-BERT-mixp). We found that, while the use of the R3 reward ensured consistent generation of contextually relevant responses, there are still a few subtle errors that our models make. These errors included difficulties in correctly attributing the next responses to user or the bot (4% DD_c, 0% DSTC7), the tendency to generate relevant but divergent follow-ups (8% DD_c, 20% DSTC7), and occasional generation of consecutive utterances as a single response (4%). Quite notably, we observe
Figure 3: Hyperparameter Sensitivity Analysis/Ablation Studies: These plots showcase the effect of $p^+$ and margin on the final validation-$R_3$ score obtained by the corresponding CORAL model. Each lineplot corresponds to a single $p^+$ value as indicated by the legend. Note: The $R_3$ values are not comparable across any two plots.
significant variations in error distributions between the datasets (DD₃ and DSTC7), likely stemming from the technical nature of the DSTC7-Ubuntu dataset. We believe that these limitations appear from the current design of the $R_3$ function which focuses on topical relevance and coherence to the context. These limitations sometimes percolate down to the CORAL model trained using the $R_3$ reward function. To address these errors, we propose potential solutions such as incorporating specific self-supervision signals into the loss function during training of the reward model and utilizing better pretrained base models. We believe that implementing these measures can greatly contribute to resolving the identified limitations and improving the overall performance of the model.

D Human Annotation Guidelines

For each of the three dialog qualities, the detailed instructions and examples are shown below. These instructions were available to the workers as a dropdown item in the UI, for each question. A screenshot of the actual UI is shown in Fig. 4. Following instructions were given to the annotators to help them understand the individual aspects (Engaging, Relevant, Fluent and Coherent).

D.1 Engaging

A response is considered engaging if it can engage the user. This might be an inquisitive question or an interesting response that can be followed-up on.

- No: the response is boring and does little to engage the user.
  - Hi there.
  - Oh wow! That’s cool!
- Somewhat: the response is not particularly engaging but still leaves room for follow-up.
  - My favourite colour is blue.
  - Nope. I’m not very good with cooking.
- Yes: the response is actively engaging the user and trying to move forward the conversation.
  - I have a feeling that if you can dodge a wrench you can dodge a ball.
  - What kind of shows do you like?

D.2 Relevant

A response is considered relevant if it is on topic and a valid/reasonable continuation of the conversation. An irrelevant response is one that is completely off topic, or abruptly tries to change the topic of conversation.

- No: the response is irrelevant. It is completely off topic or abruptly tries to change the topic of conversation.
  - User: I think I’m starting to feel sick actually System: My favorite movie is Parasite
  - User: Can you play dodge ball? System: What kind of shows do you like?
- Somewhat: the response is a valid continuation of the conversation, but is somewhat generic or tangential to the main topic. For example, it begins with a generic acknowledgement of the topic then changes topics.
  - User: Have you tried seafood pancake? System: It’s okay. I like beef bulgogi, but I’m not a huge fan of kimchi.
  - User: It’s going great, I just finished reading ‘1001 inventions that changed the world’ System: That sounds interesting. My favorite movie is Parasite.
- Yes: the response is relevant, on topic and a valid continuation of the conversation.
  - User: lol... wanna join us for dodge ball? System: Sounds like fun! I’m in!
  - User: I think I like most foods. I really like steak System: Steak is good. I especially love it when it’s well done.
D.3 Fluent

A response is considered fluently written if it follows all the rules of English grammar and is coherent.

- No: the response is not fluently written.
  - System: Therefore you are. Still how long? I don’t know if I can.
  - System: OK let’s do it. Pardon me? Why it shouldn’t be?

- Somewhat: the response is somewhat fluent, but makes a minor mistake or is confusing.
  - System: I am 18 of your Earth years.
  - System: Glad to hear it. What’s new? Oh. Maybe you should get some rest?

- Yes: the response is written fluently.
  - System: I have a feeling that if you can dodge a wrench you can dodge a ball.
  - System: The Last Airbender, and Arrested Development are my favorites.
D.4 Coherent

A response is considered coherent if it is logically connected and easy to understand in the context of the conversation. It presents a clear and organized train of thought.

- **No**: the response is not logical or does not make sense in the context of the conversation.
  - I like pizza. The sky is green.

- **Somewhat**: the response is somewhat logical and somewhat easy to understand, but it could be improved.
  - I’m not sure what you mean. Can you explain? I like pizza.

- **Yes**: the response is logical and easy to understand, and it presents a clear and organized train of thought.
  - I think that what you’re saying makes a lot of sense, and I agree with your point of view. Can you tell me more about your experience?

E Results on original DD dataset

In Table 4, we present the automatic evaluation results for response generation using non-pretrained, zero-shot and finetuned baselines and our proposed models separately for the original DD dataset. For our proposed models, we present variants based on (1) reward function (BERT/ESIM), (2) sample generation method (off-policy and mix-policy), (3) Random or Blenderbot initialization.

For our proposed CORAL models, we found \( m = 0.2 \) and \( p^+ = 0.6 \) for CORAL-ESIM and \( m = 0 \) and \( p^+ = 0.6 \) for CORAL-BERT as the best hyperparameters. Fig. 3 shows sensitivity analysis for \( p^+ \) and \( m \). Similar to DSTC7 and DD datasets, CORAL-based models outperform baselines by significant margins.

Table 4: Results for DailyDialog (DD) dataset: From the results, we can see that by optimizing the contextual \( R_3 \) score directly, using REINFORCE, the CORAL model is able to produce contextually relevant responses (as evident from MaUde and DEB). The average length is reported to make sure that the model is not resorting to short utterances, such as “I don’t think I know about [topic_word]”, just to be coherent. CORAL_x denotes a Seq2Seq model trained with CORAL loss. ‘x’ identifies the retrieval model used for the \( R_3 \) reward.

| Model                  | PT? | Size     | Lea | BLEU | METEOR | Dist-1 | Dist-2 | MaUde (MS) | MaUde (Reg) | DEB(a) | DEB(g) |
|------------------------|-----|----------|-----|------|--------|--------|--------|------------|------------|--------|--------|
| Ground Truth           |     |          |     |      |        |        |        |            |            |        |        |
| (A) No                 |     |          |     |      |        |        |        |            |            |        |        |
| pre-training           |     |          |     |      |        |        |        |            |            |        |        |
| Adalabel               | ✓   | 240M     | 7.9 | 0.062 | 0.084  | 0.037 | 0.149 | 0.622      | 0.500      | 0.655  | 0.812  |
| ALD-gen                | ✓   | 90M      | 11.6| 0.121 | 0.088  | 0.038 | 0.229 | 0.581      | 0.489      | 0.673  | 0.741  |
| (B) DialoGPT (ZS)      | ✓   | 93M      | 8.5 | 0.067 | 0.045  | 0.042 | 0.168 | 0.633      | 0.502      | 0.848  | 0.894  |
| Zero-shot              | ✓   | 345M     | 15.9| 0.081 | 0.053  | 0.027 | 0.119 | 0.652      | 0.606      | 0.854  | 0.871  |
| Blenderbot (ZS)        | ✓   | 365M     | 17.3| 0.105 | 0.077  | 0.022 | 0.098 | 0.636      | 0.632      | 0.964  | 0.965  |
| (C) DialoGPT (FT)      | ✓   | 93M      | 6.1 | 0.075 | 0.068  | 0.067 | 0.296 | 0.788      | 0.783      | 0.856  | 0.915  |
| Fine-tuned Blenderbot (FT) | ✓ | 345M | 16.5 | 0.107 | 0.098  | 0.035 | 0.179 | 0.809      | 0.832      | 0.934  | 0.948  |
| CORAL-ESIM (offp)      | ✓   | 93M      | 10.0| 0.191 | 0.173  | 0.046 | 0.284 | 0.740      | 0.847      | 0.825  | 0.871  |
| CORAL-ESIM (mixp)      | ✓   | 93M      | 11.0| 0.212 | 0.197  | 0.043 | 0.258 | 0.758      | 0.659      | 0.831  | 0.881  |
| CORAL-BERT (offp)      | ✓   | 93M      | 9.7 | 0.184 | 0.166  | 0.046 | 0.290 | 0.728      | 0.653      | 0.813  | 0.865  |
| Our Models             |     |          |     |      |        |        |        |            |            |        |        |
| CORAL-BBESIM (offp)    | ✓   | 93M      | 10.5| 0.224 | 0.208  | 0.045 | 0.276 | 0.742      | 0.669      | 0.816  | 0.870  |
| CORAL-BBESIM (mixp)    | ✓   | 365M     | 21.2| 0.128 | 0.112  | 0.037 | 0.197 | 0.904      | 0.871      | 0.988  | 0.985  |
| CORAL-BBESIM (offp)    | ✓   | 365M     | 20.5| 0.129 | 0.111  | 0.037 | 0.194 | 0.925      | 0.895      | 0.999  | 0.984  |
| CORAL-BBBERT (offp)    | ✓   | 365M     | 21.2| 0.129 | 0.115  | 0.037 | 0.195 | 0.865      | 0.875      | 0.982  | 0.982  |
| CORAL-BBBERT (mixp)    | ✓   | 365M     | 21.1| 0.131 | 0.114  | 0.033 | 0.179 | 0.889      | 0.896      | 0.999  | 0.983  |

F Ethical Considerations

Like many other pretrained language representation models, the proposed model may also have learned patterns associated with exposure bias. Interpretability associated with the output is rather limited, hence users should use the outputs carefully. The proposed model generates possible response candidates, and does not filter out any “problematic” candidates. Thus, for applications, where candidate responses could be problematic, (e.g., offensive, hateful, abusive, etc.), users should carefully filter them out before using the output from our model.
All the datasets used in this work are publicly available. We did not collect any new dataset as part of this work.

DailyDialog: The dataset was downloaded from http://yanran.li/dailydialog. DailyDialog dataset is licensed under CC BY-NC-SA 4.0.

DSTC7-Ubuntu: The dataset was downloaded from https://ibm.github.io/dstc-noesis/public/data_description.html#ubuntu. The dataset is available under MIT license.

G Limitations

We experimented with English datasets only. While we hope that these results will generalize to models trained on multi-lingual datasets; empirical validation needs to be done.