# Response-act Guided Reinforced Dialogue Generation for Mental Health Counseling

Aseem Srivastava<sup>1</sup>, Ishan Pandey<sup>1</sup>, Md. Shad Akhtar<sup>1</sup>, Tanmoy Chakraborty<sup>2</sup> <sup>1</sup>IIIT-Delhi, India; <sup>2</sup>IIT Delhi, India

 $\{aseems, is han 20304, shad. akhtar\} @iiitd. ac. in; tanchak@iitd. ac. in and a shad a shad$ 

## ABSTRACT

Virtual Mental Health Assistants (VMHAs) have become a prevalent method for receiving mental health counseling in the digital healthcare space. An assistive counseling conversation commences with natural open-ended topics to familiarize the client with the environment and later converges into more fine-grained domain-specific topics. Unlike other conversational systems, which are categorized as open-domain or task-oriented systems, VMHAs possess a hybrid conversational flow. These counseling bots need to comprehend various aspects of the conversation, such as dialogue-acts, intents, etc., to engage the client in an effective and appropriate conversation. Although the surge in digital health research highlights applications of many general-purpose response generation systems, they are barely suitable in the mental health domain - the prime reason is the lack of understanding in the mental health counseling conversation. Moreover, in general, dialogue-act guided response generators are either limited to a template-based paradigm or lack appropriate semantics in dialogue generation. To this end, we propose READER - a REsponse-Act guided reinforced Dialogue genERation model for the mental health counseling conversations. READER is built on transformer to jointly predict a potential dialogue-act  $d_{t+1}$  for the next utterance (aka response-act) and to generate an appropriate response  $(u_{t+1})$ . Through the transformer-reinforcement-learning (TRL) with Proximal Policy Optimization (PPO), we guide the response generator to abide by  $d_{t+1}$  and ensure the semantic richness of the responses via BERTScore in our reward computation. We evaluate READER on HOPE, a benchmark counseling conversation dataset and observe that it outperforms several baselines across several evaluation metrics - METEOR, ROUGE, and BERTScore. We also furnish extensive qualitative and quantitative analyses on results, including error analysis, human evaluation, etc.

#### **1** INTRODUCTION

Virtual Mental Health Assistants (VMHAs) are the backbone of the new-age digital healthcare industry. More than 60% of therapies conducted in the past three years are via virtual assistants. This massive spike in the number of users using VMHAs to gain mental health assistance is due to the ease and safety of access to AI-based therapist-bots [1]. Numerous potential platforms, *viz.* Weobot<sup>1</sup>, Wysa<sup>2</sup>, etc. in the digital health space are developing practical and effective ways for the common public. More popular than ever, VMHAs are now becoming an instant solution to millions of clients struggling with mental health issues<sup>3</sup>.

**Limitations of existing methods.** Many such conversational agents fail to (a) understand the directives of the client with whom

<sup>2</sup>https://www.wvsa.io/



Figure 1: A sample counseling conversation along with associated dialogue-acts. The proposed model – READER takes utterance- and dialogue-act context to predict response-act and subsequently generate a response.

they are in active conversation, and (b) take the conversation in the required direction<sup>4</sup>. This is resemblant to the fact that even human therapists find it impossible to reply to something they do not understand from the help-seeker. Therefore, clients' directives directly impact the response generation capability. Current open domain conversational systems *viz*. XiaoIce [36] and GPT-3-based systems [33] generate semantically and grammatically rich responses. However, these open-domain counseling systems lack contextual understanding in the response generation process, which includes being unable to respond with the intended dialogue-act. Therefore, modeling this problem using open-domain dialogue systems cannot suffice the task of goal-oriented dialogue systems. To mitigate the issue in the mental healthcare domain, there is a need to harmonize VMHA's dialogue with individual intentions to be useful for clinical practice. A very generic solution to this is to design a model that

<sup>&</sup>lt;sup>1</sup>https://woebothealth.com/

<sup>&</sup>lt;sup>3</sup>https://psychnews.psychiatryonline.org/doi/10.1176/appi.pn.2022.05.4.50

<sup>&</sup>lt;sup>4</sup>https://www.bbc.com/news/technology-46507900

gauges the dialogue context and predicts the next dialogue-act (*aka* response-act), which collectively helps generate the next utterance.

**Our approach.** Our work focuses on response generation by exploiting response-acts. To understand the problem better, Figure 1 shows an example of a counseling conversation. As we observe, the dialogue contains both therapist's and client's utterances, each possessing a dialogue-act that is critical in maintaining the flow of the conversation. Evidently, the dialogue-acts of the utterances generally form a pattern. For instance, the dialogue-act of the third utterance from the therapist is information-request, which in succession is followed by *information-delivery* in the fourth utterance by the client. Earlier approaches [3, 16, 22] exploited dialogue-act and context to build rich representation for several tasks on dialogue system. Another work proposes a dialogue management strategy in order to improvise on response generation task exploiting fine-grained belief states [10]. These fine-grained belief states are task-specific, and their proposed system, SimpleTOD, needs relatively more information (specific slots) in order to generate a response. At the same time, exploiting the slot-filling task to generate responses supports the dialogue system in most goal-oriented cases. However, counseling conversations cannot be categorized either into open-ended or goal-oriented dialogue and hence needs a separate focus on the hybrid conversational pattern. On the other hand, several studies utilize other guiding factors such as keyword, target, etc. for the response generation task [9, 27]. In our work, we predict the dialogue-act of the next utterance aka response-act and take advantage of state-of-the-art language models to generate relevant responses. At the same time, contextual information in the conversation plays an essential role in developing a full-fledged conversational system. To this end, we propose a response-act guided dialogue generation model, named, READER. It comprises a foundation language model, on top of which we deploy three unique heads, namely, the response-act head (RAC-Head), the language model head (LM-Head) and the value head (V-Head). These three heads jointly learn to optimize the reinforced loss and primarily perform the response generation task. READER learns by optimizing Proximal Policy Optimization (PPO), for which we curate a unique reward function.

**Evaluation.** We benchmark READER on the HOPE dataset [14], which is a dyadic counseling conversation dataset containing 13k utterances from therapist and client. We observe that READER outperforms several baselines across three relevant quantitative metrics -- METEOR, ROUGE, and BERTScore, with improvements in the range of 0.82 - 11.53%. In addition, we also present an extensive qualitative and quantitative analyses of the performance, error analysis and human evaluation. Furthermore, to evaluate the generalizability of the READER, we benchmark it over the Switchboard Dialogue-act corpus (SWDA) [25] and obtain better results than baselines by 0.1 - 9.4%.

Major Contributions. Below, we summarize the contributions:

• We exploit future dialogue-acts (*aka* response-acts) in guiding the response generation model to generate the intended response and maintain the flow of counselling conversation in the mental-health domain. To the best of our knowledge, ours is one of the first attempts that exploits response-acts to generate precise responses in VMHAs or any other dialogue systems.

- We propose a novel transformer-reinforcement-learning (TRL) driven response-act guided model, READER to generate response in mental health counseling conversations.
- Our evaluation on the HOPE dataset shows significant improvements in the performance of response generation over several competing baselines. We also perform extensive ablation analysis and justify the choice of various components of READER.
- We conduct a through and qualitative human evaluation on the generated responses and establish that the proposed approach is qualitatively efficient as well.
- We also show the effective generalizability of READER on another dataset, i.e., the Switchboard Dialogue-act dataset.

We have open-sourced the code for READER and a sample of the dataset on an anonymous link<sup>5</sup>.

#### 2 RELATED WORK

To bring more clarity in understanding the role of dialogue-acts, we present relevant studies in two broad areas – (i) dialogue-act classification, and (ii) dialogue/response generation. We intend to comprehend how dialogue-acts could bring effective innovation in building a conversational system for a dedicated task.

**Dialogue-act Classification.** Earlier studies by Budzianowski et al. [2] and Su et al. [26] employ a sparse representation of each dialogue-act in the form of triple vectors (domain-action-slot); this triple vector is represented as a one-hot encoding. However, acts become very large with the use of such sparse representations. Later, Chen et al. [5] addressed the issue by considering dialogue-act structures. Further, the authors represented dialogue-acts considering the act structures with level-wise vectorization on a one-hot scale where a binary classifier predicts each dimension of vectors. Their methods are further improved in a recent work by Pei et al. [18]. The authors exploited a separate expert decoder for different areas and dialogue-acts to fuse them with a main *chair* decoder. A recent work applies a fusion approach to fuse their language model with a next utterance generation decoder [15]. Several other studies use reinforcement learning to generate dialogue responses [37].

**Response Generation.** Studies on dialogue generation [6, 19] showed improved performance by leveraging data corpus size, which in turn resulted in learning better context-sensitive features from large language models. Yang et al. [32] extended this idea further by deploying models with large parameters. They used a similar idea on XLNet, a generalized autoregressive pretrained model, in order to (i) maximizing the expected likelihood over all permutations of the factorization order allowing learning of bidirectional contexts, and (ii) coping up with the drawbacks of BERT by leveraging the proposed approach's autoregressive formulation.

Later Radford et al. [21] explored their hypotheses of the zeroshot learning capacity of large language models as multi-task learners on the task of response generation using GPT-2. The authors also showed an intuitive qualitative analysis of a sample to fetch quality insights. The analysis shows the reflection of coherent responses to prompts. The result presents a better path toward building a response generation system that learns to perform the task from their

<sup>&</sup>lt;sup>5</sup>Code and dataset sample: https://bit.ly/3CqpcrK. We commit to publicly release the source codes and datasets upon acceptance of the paper.

naturally occurring demonstrations. A recent study on transformerbased models has been fine-tuned for dialogue modeling through various data modification techniques. This includes methods such as adding information about the user's persona, masking, etc. [29].

At the same time, studies by Xu et al. [30] control responses using meta-words and manually controlled features (viz. length of response, specificity, etc.). They defined a meta-word as an organized record. The authors further described the response attributes. This allows them to model the relationship (one-to-many) within taskindependent conversations and execute the problem of generating a response in an explainable and controllable manner. Hosseini-Asl et al. [10] proposed a simpler architecture which relies on the belief-states generated by the dialogue management module. These belief states are similar to fine-grained intents and slots, exploiting which the authors aimed for the dialogue-generation task. Further, Khalifa et al. [11] proposed a distributional method for handling text generation in a controllable manner by exploiting language models. This method allows point-wise specification of details and distributional constraints on the target language model in one standard framework. Their work is the first effort into this concept while minimizing relative entropy from the earlier proposed language model distribution. They uniquely defined the optimal target distribution as an explicit EBM (Energy-Based Model) representation. Moreover, using those optimal representations, we train a target-controlled autoregressive language model through an adaptive distributional variant of the policy gradient. They conducted experiments on point-wise constraints and showed the advantages of their method over traditional fine-tuning methods. Furthermore, one of the studies on dialogue modeling [13] propose to combine the merits of template-based and corpus-based DRGs by introducing a prototype-based, paraphrasing neural network, called P2-Net, which aims to enhance quality of the responses in terms of both precision and diversity. Instead of generating a response from scratch, they generate system responses by paraphrasing template-based responses. Their approach learns to separate a response into its semantics, context influence, and paraphrasing noise, and to keep the semantics unchanged during paraphrasing.

#### **3 PROPOSED APPROACH: READER**

In a regular conversation, dialogue-acts of the interlocutors tend to form a pattern. For instance, if person A seeks some clarification from person B, the most probable response from B would be to elucidate the clarification raised by A. Therefore, leveraging the above connotation, we propose to utilize the next dialog-act (or response-act) in the response generation task. Formally, we formulate the problem as follows:

Given a counseling dialogue containing utterances and their corresponding dialogue-acts as  $U \in \{u_0, u_1, ..., u_{t-1}, u_t\}$  and  $DA \in \{d_0, d_1, ..., d_{t-1}, d_t\}$  respectively, where t is the time step, our twofold jointly-learned tasks are – (a) to predict the response-act  $d_{t+1}$  (auxiliary), and (b) to generate a response  $u_{t+1}$  in the dialogue abiding by the predicted response-act  $d_{t+1}$  (primary).

To this end, we propose READER, a novel response-act guided reinforced response generation model. The architecture of READER is presented in Figure 2. READER leans on the joint transfer-reinforcementlearning (TRL) paradigm for generating response-acts and responses. Our method of transformer reinforcement learning takes inspiration from an earlier work [37]. Moreover, we train the foundation language model with Proximal Policy Optimization (PPO) [23]. We define a vocabulary  $\Sigma$  and the foundation language model  $\theta$  (in our case, GPT2) that defines a probability distribution over sequences of tokens.

On top of the foundation language model, we place three taskcum-learning specific heads. First, the language model head (LM-Head) is generalized for text generation tasks. Secondly, we introduce a response-act classification head (RAC-Head), an encoderonly model to classify response-acts. At last, we have a value head (V-Head) to compute the reward to send back to the foundation model. Next, we train the model jointly to generate responses from LM-Head and predict response-acts from RAC-Head simultaneously. Subsequently, V-Head computes the reward considering the scores of LM-Head and RAC-Head, which in turn is optimized via PPO. We furnish details related to each head and the reward computation in subsequent sections.

**RAC-Head.** Dialogue-acts play an essential role in articulating dialogue flow. RAC-Head is a transformer-based encoder-only module on top of the foundation language model that learns to predict the future response-act. The head exploits the last hidden representations of the foundation language model. We feed the hidden representations to a GRU to exploit the contextual pattern of the dialog. In parallel, we obtain linear projections of the hidden representation. Next, these contextually-rich representations are passed through a multi-head attention module in which we treat the GRU representations as the *query* and the linear projections as the *key* and *value*. Finally, we apply softmax to classify a response-act. The prediction calibrates READER to adapt the PPO optimization through the RAC-Head's logits, thus allowing LM-Head to generate an appropriate response.

**LM-Head.** We use GPT- $2^6$  as our foundation language model. It has been established as one of the preferred models for a variety of generative tasks [7, 8, 12, 31].

#### 3.1 Reference Models for Reward Computation

We aim to augment the response by inheriting adequate semantics and response-acts. To maintain the stability of the reward function, we deploy state-of-the-art reference models to compare the outcomes for both tasks. For the language model head (LM-Head), we employ the pre-trained GPT-2 model as the reference model, whereas, SPARTA [14] is used for the response-act head (RAC-Head). Subsequently, we compute ROUGE (R), BERTScore (BS), and relative entropy (RE) between the proposed and the reference language model's outputs. Unlike primitive methods of RL-training with a standard reward function where the model deviates to learn biased features in order to maximize the reward, where for instance, the model may start copying text from reference text to maximize ROUGE, Our approach employs each metric to calculate the reward function and tracks the relative entropy with the performance of reference model in parallel. It ensures that READER's prediction does not deviate significantly and leverages the semantic richness of the pre-trained reference language model. We calculate the relative

<sup>&</sup>lt;sup>6</sup>https://openai.com/blog/better-language-models/



Figure 2: Architecture of READER. It contains three heads on top of the foundation language model, GPT-2: (a) RAC-Head classifies the response-act trained on context-aware representations, (b) LM-Head generates the response, and (c) V-Head calculates the final reward and initiates Proximal Policy Optimization (PPO).

entropy as follows:

$$RE = \mathbb{E}_{z \sim P_{lm}} \left[ \log P_{lm_p}(z) - \log P_{lm_{ref}}(z) \right]$$
(1)

where z is sampled from  $P_{lm}$ , and  $lm_p$  refers to the proposed language model; whereas  $lm_{ref}$  refers to the reference model. A lower *RE* score demonstrates better generations; therefore, we employ *RE* as a direct parameter in the reward computation.

Similarly, we utilize SPARTA [14] to compute the logit values for the predicted dialogue-act and apply mean-pooling for the reward computation.

**V-Head.** The value head (V-Head) is responsible for accumulating the reward parameters from other heads to yield the reward and subsequently, use it to reinforce the READER.

For our reward function, we use metrics including BERTScore and ROGUE Score. Along with these, we use known response-acts to train a reward model (SPARTA), and then optimize that reward model.

Our proposed reward function accumulates the weighted Rouge score (*R*), BERTScore (*BS*), the relative entropy (*RE*), and the DAC-Head's logit value ( $\rho$ ). The former three components (*R*, *BS*, *RE*) offer feedback on the semantic and syntactic richness of the current state, while the last component ( $\rho$ ) guides the model towards the desired response, exhibiting the predicted response-act. We compute the reward as follows:

$$Reward = [\lambda_1(R) + \lambda_2(BS) + \lambda_3(\rho) - \lambda_4 RE]$$
(2)

where  $\lambda_1$ ,  $\lambda_2$ ,  $\lambda_3$ , and  $\lambda_4$  are hyperparameters and tuned to optimize and maximize the reward. Subsequently, we reinforce the yielded reward to optimize the current state using PPO.

#### 3.2 Training and Proximal Policy Optimization

Similar to the optimization policy explored by Ziegler et al. [37] on a general-purpose task, the training of GPT-2 with PPO in READER is a three-step process:

- Initiate RAC-Head and LM-Head: Given  $u_t$ ,  $d_t$  along with the context {<  $u_{t-k}$ ,  $d_{t-k}$  >, ..., <  $u_{t-1}$ ,  $d_{t-1}$  >}, where k is the context size, READER generates a response-act and the response.
- <u>Evaluate Outcomes</u>: In this step, we calculate the log-probability distribution of logits from the active component (trainable model) of LM-Head and RAC-Head. Subsequently, we obtain the difference in the log probability distribution of reference model which is used to impose penalty and ensure coherency of the outputs.
- *PPO Optimization*: We choose ROUGE, BERTScore, and Relative entropy to assess the quality of the generated response and the max-logit scores in case of the response-act classification task. We receive the reward score from V-Head (c.f. Equation 2). In order to optimize READER, we first compute the relative entropy from LM-Head. At the same time, LM-Head and RAC-Head yield the remaining reward parameters. At last, V-Head accumulates and computes the reward from each head as per Equation 2. We perform optimization that subsequently allows READER to learn to penalize/reward the foundation language model.

This approach is extended from an earlier work [37]. The authors initialized a policy  $\pi = \theta$ , and then fine-tuned  $\pi$  to operate on downstream tasks using PPO. If the task is defined by a reward function  $(r : X \times Y \rightarrow R)$ , then the authors used PPO to optimize the expected reward. In their algorithm, PPO utilizes clipped surrogate objective, and the model maximizes a surrogate objective. Another study Ziegler et al. [37] exploited the usage of PPO algorithm to

Table 1: Statistics of the HOPE dataset [14]. The dyadic counseling conversational dataset contains a total of 12.8k utterances, each associated with one of the 12 dialogue-act labels.

HOPE	Train	Validation	Test	Total
Dialogue Sessions	149	21	43	212
Client Utterances	4668	595	1119	6382
Therapist Utterances	4751	599	1122	6472
#Total Utterances	9419	1194	$\bar{2}2\bar{4}1$	12854

further define the downstream task to optimize the main objective function. The authors opted for minimum of the clipped and unclipped objective. Hence the final objective is lower bound (i.e., a pessimistic bound) on the unclipped objective. With this scheme, we observe that only probability ratio is ignored when it improves the objective.

As a result, we then exploit the above mentioned PPO method to optimize our PPO algorithm [37] with the following equation.

$$R(x, y) = r(x, y) - \beta \cdot \log \pi(y|x) \cdot \theta(y|x)$$
(3)

where *r* and  $\theta$  represent reward function and foundation language model, respectively. In our case, we experiment with a constant as well as dynamic  $\beta$  to achieve a favorable value of  $RE(\pi, \theta)$ . The relative entropy plays the role of an entropy bonus; it prevents the policy from moving too far from the range where *r* is valid. We rely on the relative entropy to sync with the fine-tuned reference model's coherent responses.

## 4 EXPERIMENTS

In this section, we first discuss the counseling dataset, HOPE. We then define the baseline systems and evaluation metrics which we use to compare the performance of the proposed model and baselines.

#### 4.1 Dataset

We use HOPE [14], a mental health counseling conversation dataset. It contains 12.8K utterances from 212 dyadic counseling sessions between therapists and clients, publicly available on a video sharing platform. The conversation encompasses diverse demographic groups with distinct mental health discussions. Malhotra et al. [14] extracted transcriptions of the utterances and processed them to remove any noise and/or transcription issues. The collected dialogues are dyadic in nature, i.e., clients and therapists are the only interlocutors. Each utterance in the HOPE dataset is annotated with one of the twelve dialogue-acts - information-delivery (ID), informationrequest (IRQ), yes/no-question (YNQ), clarification-request (CRQ), opinion-request (ORQ), clarification-delivery (CD), positive-answer (PA), negative-answer (NA), opinion-delivery (OD), greeting (GT), acknowledgment (ACK), general chit-chat (GC). A detailed statistics of the HOPE dataset is presented in Table 1. Furthermore, we demonstrate the relation between the dialogue-acts of current and next utterances in the HOPE dataset in Appendix (c.f. Figure 6). Evidently, the dataset shows a high correlation between certain pairs of dialogue- and response-acts. For instance, an utterance

requesting-information (labelled IRQ) is mostly followed by an utterance delivering the information (labelled IRD).

#### 4.2 **Baselines and Evaluation Metrics**

We compare READER's performance with various competitive baselines in the domain of dialogue generation. Moreover, to have a fair comparison with READER, we choose systems which leverage and exploit the dialogue context for the response generation. To the best of our knowledge, no other systems have reinforced the responseact for the dialog generation. We choose the following baselines in this work. DialoGPT [34] is a pretrained transformer model dedicated for response-generation task. GPT-2 [21] is a decoder only model trained on a large corpora. A vanilla finetuned version of GPT-2 works well in our use case. DialogVED [4] introduces continuous latent variables into the encoder-decoder pre-training framework to increase the relevance and diversity of responses. ProphetNet-Dialog [20] focuses on pretraining of dialogue specific corpus to generate coherent response. HRED [24] is based on generative modeling to develop conversational response containing hierarchical encoder-decoder paradigm. It is trained on a large dialogue corpus for the utterance generation task. HRED with Speaker and Utterance Encoder [35] adds speaker and utterance level information to the hierarchical encoder-decoder (HRED) setup. It leverages the personalization parameters in a dialogue system. It is also trained on a large dialogue corpus. VHCR [17] uses variational hierarchical RNNs for the conversation-only setup. It is trained on a large conversation corpus for the dialogue modeling task.

For evaluating the performances of READER and other comparative systems, we employ **ROUGE**, **METEOR**, and **BERTScore** as evaluation metrics. We use *py-rouge*<sup>7</sup>, *nltk-meteor*<sup>8</sup>, and *Hugging Face - BERTScore*<sup>9</sup> for computing the scores.

#### 5 RESULTS AND ANALYSIS

In this section, we discuss the results obtained from the READER model and aforementioned baselines. Table 2 summarizes the comparative and ablation results on the HOPE dataset.

#### 5.1 Performance Comparison

Our evaluation shows superior performance of READER across a majority of the metrics. Evidently, there is a significant increase in the recall of the ROUGE-2 score – our model receives a ROUGE-2 recall of 13.67, which is +15.50% as compared to the second best performer, DialoGPT (11.83). At the same time, our model yields 43.93, 40.82, and 76.66 scores of ROUGE-1 recall, ROUGE-L recall, and METEOR, respectively, with an increase of +3.45, +2.22, and + 0.63 points as compared to the best baseline, i.e. DialoGPT. On the other hand, to evaluate the linguistic properties in the generated utterances, we calculate METEOR on READER's generations. Similar to the earlier cases, READER reports an improved BERTScore of 0.2103, +4.05% points better than DialoGPT.

**Ablation on Foundation Model.** Among all baselines, DialoGPT performs the best on average with GPT-2 closely competing with it.

<sup>&</sup>lt;sup>7</sup>https://pypi.org/project/py-rouge/

<sup>&</sup>lt;sup>8</sup>https://www.nltk.org/api/nltk.translate.meteor\_score.html

<sup>&</sup>lt;sup>9</sup>https://huggingface.co/spaces/evaluate-metric/bertscore

Table 2: Results obtained on the HOPE dataset. We show ROUGE (1, 2, L), BERTScore (BS), and METEOR to assess the perfor-
mance of the READER. $Rew(x)$ is the reward function, where x is the parameter.

						_						
			R1			K2			RL			METEOR
		Р	R	F1	Р	R	F1	Р	R	F1		
	DialoGPT [34]	12.34	40.48	15.72	2.92	11.83	4.42	12.23	38.60	15.76	0.7603	0.2021
	GPT2 [21]	12.70	32.63	14.98	3.08	7.92	3.51	13.74	32.05	15.87	0.7445	0.1754
nes	DialogVED [4]	12.48	31.74	12.8	0.98	2.45	1.22	12.45	31.11	14.46	0.7189	0.2000
seli	ProphetNet [20]	12.15	34.29	14.48	3.30	10.41	4.17	12.24	33.12	15.18	0.6707	0.1901
Bae	VHCR [17]	11.29	21.33	11.81	2.66	3.49	3.00	10.01	19.72	10.99	0.5953	0.1041
	HRED [24]	11.52	21.51	10.72	1.89	6.42	2.92	12.12	24.36	13.56	0.6259	0.1425
	HRED w/ Sp. Utt. Encoder [35]	11.77	28.63	10.08	1.29	4.19	2.06	12.25	21.27	12.72	0.6171	0.1801
ş	RagRes w/ DialoGPT	12.41	43.91	16.12	3.70	13.72	4.98	11.92	41.02	16.30	0.7656	0.2098
Jul	READER – RAC-Head	12.64	41.48	15.78	3.60	11.83	4.58	12.3	38.64	15.90	0.7628	0.2039
0	READER	12.82	43.93	16.15	3.77	13.67	4.93	12.51	40.82	16.32	0.7666	0.2103
	– <i>Rew</i> (R)	11.73	38.82	14.65	2.28	8.45	2.96	11.21	35.76	14.53	0.7561	0.1840
ons	-Rew(RAC)	12.36	40.71	15.43	3.13	11.12	4.06	11.91	37.63	15.40	0.7609	0.2000
lati	-Rew(RAC + R)	11.92	38.06	14.70	2.43	8.26	3.11	11.40	34.98	14.58	0.7530	0.1874
Ab	-Rew(R + BS)	12.48	41.13	15.57	3.52	11.85	4.47	12.22	38.29	15.77	0.7527	0.2092
	-Rew(RAC + BS)	12.01	40.45	15.18	2.72	9.93	3.52	11.46	37.05	14.97	0.7577	0.1908
	$\Delta_{READER-BEST}(\%)$	↑ 0.94	↑ 8.5	↑ 2.73	↑ 14.24	↑ 15.50	↑ 11.53	↓ 8.90	↑ 5.69	↑ 2.83	↑ 0.82	↑ 4.05

However, in our case, we find it suitable to choose GPT-2 as the foundation language model due to the marginally better performance in READER. We also experiment by swapping it with DialoGPT and report the results in Table 2. We observe that READER with GPT-2 performs better on recall scores of R1 (+0.41), R2 (+0.02), RL (+0.2), BS (+0.0139) as compared to READER with DialoGPT.

**Model Component Ablation Study.** One of the prime contributions of this work involves the role of the RAC-Head. READER relies on the RAC-Head to determine the response-act of the generated utterances. Further, RAC-Head gradually allows the response generation to adapt according to the predicted response-acts during the PPO optimization. We perform ablation on RAC-Head and present the results in Table 2. We observe that READER without RAC-Head scores 41.48, 11.83, 38.64 on ROUGE-1, 2, L (recall scores), respectively. The final model performs relatively better with an increased score (+2.45, +1.84, +2.18) on the same metrics as compared to the READER without RAC-Head.

**Discussion on Reward Selection and Reward Ablation.** We meticulously conduct experiments on several hypotheses to design a reward function that optimizes the PPO policy and penalizes the model for every shortcoming. While experimentation, we consider several metric scores as a parameter to the reward function (c.f. Equation 2). However, most of the parametric configurations deteriorate the results. We show various possible ablations on the final set of parameters, i.e., ROUGE, BERTScore, and RAC-Head's logits in the lower half of Table 2. We observe that a combination of RAC-Head along with BERT Score, ROUGE scores, and relative entropy yields the best result. In addition, using only BERTScore or ROUGE scores in the reward function deteriorates the results significantly. We also observe a decrease in the metrics after detaching RAC-Head. This justifies the contribution of both the heads of READER toward the generation task. Moreover, Figure 3 shows



Figure 3: The increment flow of reward in the PPO optimization of READER.

the incremental graph of the reward function during the PPO optimization. Evidently, the plot demonstrates the progressive learning curve considering the mean reward score, and supports our claim that the model improves with the increasing step.

#### 5.2 Qualitative Analysis

To further assess the quality of the generated responses of READER, we present a qualitative analysis in Table 3. In comparison with the reference utterance, we observe that semantics and grammar are well established in the generated response. Additionally, we observe that the response-act of the generated response is in accordance to the intended act. It suggests the effectiveness of RAC-head in reward computation. We also show generated utterances for the two best performing baselines (DialoGPT and GPT). Though the outputs are syntactically correct, they are mostly incoherent with the dialogue context.

**Human Evaluation** We also perform human evaluation on a subset of model outcomes on linguistic ground. We use four linguistic parameters, namely, *relevance, consistency, fluency*, and *coherence,* to perform the human evaluation [28]. We define these parameters as follows: **Fluency** demonstrates the linguistic quality of the

Context	Next utterance	RAC			
<b>Therapist:</b> Oh great, which is a little different. But yeah, that's great. That's a really good goal.	<b>Gold:</b> Okay, so you're getting A's and B's in really good numbers. So what did you discover about this?	CRQ			
Client: Yeah, thanks.	<b>READER:</b> Okay. Okay. What classes are you not getting A's and B's in?	CRQ			
Therapist: It's hard work to get into law school. Are you doing well in school? What kind of grades you get?	<b>GPT2:</b> Anyway, I should mention I'm probably going to get through that anyway. That might not be fun.	-			
Client: I'm doing okay. I'm getting mostly A's and B's so I'm pretty good.	DialoGPT: Are you going to law school?	-			
Client: My employer just said I wasn't a good fit.	Gold: My anxiety is really bad.	ID			
<b>Therapist:</b> wasn't a good fit. So this so these symptoms have caused you some real problems.	<b>READER:</b> Oh, I get really anxious. just scared that something's going to happen and your anxiety is going to be costly.	ID			
Client: Yeah.	<b>GPT2:</b> That's it. Lerner. It'is a honest fact and it is one piece of information about your mind. Lerner	-			
Therapist: With employment and how about with your anxiety level?	DialoGPT: I'm not sure if you're joking or not.				

#### Table 3: An example showing the generated response along with the reference response.

Table 4: Human evaluation on the responses generated from READER when compared to the top two best performing baselines. We observe that the performance of READER across all metrics is up to the mark and slightly better than the bestperforming dialogue models.

Model	Relevance	Consistency	Fluency	Coherence
DialoGPT	2.11	2.42	2.90	2.30
GPT2	2.70	3.00	3.01	2.44
READER	2.85	3.05	3.05	2.95

generated responses; **Coherence** shows the structure and organization of the generated responses; **Relevance** shows the selection of relevant content in the generated response considering the reference utterance; and **Consistency** evaluates the factual alignment between the generated response and the source utterance.

In total, we take 50 randomly-selected instances and ask 10 human evaluators to assign a score on a scale of [1, 5] to each of the four parameters, where 5 represents the best outcome. All human evaluators are linguistic experts, aged between 20 to 35. For comparison, we repeat the exercise for DialoGPT and GPT2 as well. Finally, we compute the average score and report the findings in Table 4. Our analysis shows that READER's outputs are also qualitatively better than baselines in each dimension.

#### 5.3 Application of READER: Dialogue Generation

In this section, we present the application of READER for generating counseling dialogues. To do so, we adopt two setups: **a**) **Natural**: an end-to-end conversation between a client and an agent (READER<sub>Therapist</sub>); and **b**) **Synthetic**: an end-to-end conversation between two agents, i.e., READER<sub>Therapist</sub> and READER<sub>Client</sub>. The first setup is a natural configuration for VMHAs, when deployed at the application stage, it generates therapist utterances to interact with real-time clients having mental health issues. To do so, at every step *i* of the response generation, we provide actual client inputs and the previously-generated READER's outputs for therapist ( $\{i - n, \dots, i - 2, i - 1\}$ ) as the recurring context to READER. On the other hand, the second setup is an analysis configuration to assess the effectiveness of READER in handling diverse inputs (e.g.,

generated by an agent). Moreover, this can also be viewed as a data augmentation technique to generate synthetic dialogues. In this setup, we provide READER's generated outputs for both client and therapist as context.

Furthermore, in both setups, we assume that a context is present to instigate the conversation, such that the agent (or READER in our case) understands the dynamics of the conversation and starts generating responses that are aligned with the conversation. This approach is similar to existing VMHAs, like WoeBot<sup>10</sup>, where the agent collects initial information from the client in terms of template-based questions and propels the conversation further with the provided details. A snippet of the generated dialogue for the two setups are presented in Figure 4 and Figure 5, respectively. Evidently, we observe that the proposed model is able to comprehend the context of the conversation in both setups and generates aligned responses.

### 5.4 Generalizability

READER outperforms several baselines across most of the metrics on the HOPE dataset. Further, to assess the model's generalizability, we extend our experiments and evaluate READER on the Switchboard Dialog-act corpus [25]. We observe that READER improves the performances of two best performing baselines (DialoGPT and GPT2) by 0.1% - 9.4% in 10 out of 11 metrics. In particular, we observe a significant improvement of 9.4% in BERTScore; thus suggesting that READER's outputs are semantically richer than other baselines along with the marginal improvements in textual similarity. We argue that in the presence of the information of dialogue-acts, READER harnesses the context in an efficient way for generating semanticallyricher responses. In conclusion, we posit that READER generalized well over other domains as well. Due to the space constraints, we furnish the results along with the baseline's performance on the Switchboard dataset in Appendix (c.f. Table 6).

#### 6 DISCUSSION

**Societal Impact and Deployment.** Our work acts as a support to the mental health community and ongoing research by leveraging the advancements in AI-based dialogue systems for counseling.

<sup>10</sup> https://woebothealth.com/

#### WWW '23, April 03-May 04, 2023, Texas, USA



Figure 4: Application of READER – Natural setup. Given a context, at each step, READER generates an output for the therapist. This align with the natural configuration of VMHAs, where a client seeks help from a bot or a virtual agent.

Such advancements in the mental health domain are likely to bring a high social impact. Further, to put this paper's ideas into practice, we are in active collaboration with a prominent mental health service provider. Collaborators have verified the model's applicability in the real world and agreed to extend READER on a bigger corpus and commercialize it. The results of the A/B testing are suppressed due to company's privacy issues.

Ethical Considerations and Future Work. Considering the severity of the research area, we make sure that at each step, we maintain the privacy of the personal data of clients. In future, we plan to extend our work in the expansion of Virtual Mental Health Assistants (VMHAs) modules and scale the idea of including dialogue components such as empathetic understanding.

### 7 CONCLUSION

The continuous need to face the shortage in the number of mental health experts is becoming a significant challenge every coming year. With new AI-based therapist-bots coming into the picture, clients receive much support with ease of access. However, one





Figure 5: Application of READER – Synthetic setup. Given a context, at each step, READER takes turn to generates outputs for the therapist and the client. This setup is an analysis configuration to assess the effectiveness of READER in handling diverse inputs (e.g., generated by an agent).

of the critical tasks for such conversational agents is to generate an accurate yet effective response for the clients possessing intended dialogue-act towards the client. To this end, we proposed a novel response-act guided dialogue generation model, READER. We designed a unique reward function that exploits several linguistic properties to train the model using transformer-reinforcement learning (TRL) and further improvised the PPO optimization. We added three heads on top of the foundation language model: RAC-Head, Value-Head, and LM-Head, which collectively curate the reward. We compared the performance of READER with several baselines. Our model outperformed several baselines across five metrics: ROUGE (1, 2, & L), METEOR, and BERTScore. At last, we Response-act Guided Reinforced Dialogue Generation for Mental Health Counseling

demonstrated an extensive ablation study and concluded the paper with a discussion on ethical considerations and generalizability.

#### ACKNOWLEDGMENTS

The authors acknowledge the support of ihub-Anubhuti-iiitd Foundation set up under the NM-ICPS scheme of the DST.

#### REFERENCES

- Alaa A Abd-Alrazaq, Mohannad Alajlani, Nashva Ali, Kerstin Denecke, Bridgette M Bewick, and Mowafa Househ. 2021. Perceptions and Opinions of Patients About Mental Health Chatbots: Scoping Review. J Med Internet Res 23, 1 (13 Jan 2021), e17828. https://doi.org/10.2196/17828
- [2] Paweł Budzianowski, Tsung-Hsien Wen, Bo-Hsiang Tseng, Iñigo Casanueva, Stefan Ultes, Osman Ramadan, and Milica Gašić. 2018. MultiWOZ - A Large-Scale Multi-Domain Wizard-of-Oz Dataset for Task-Oriented Dialogue Modelling. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing. Association for Computational Linguistics, Brussels, Belgium, 5016– 5026. https://doi.org/10.18653/v1/D18-1547
- [3] Chi Hsiang Chao, Xi Jie Hou, and Yu Ching Chiu. 2021. Improve Chit-Chat and QA Sentence Classification in User Messages of Dialogue System using Dialogue Act Embedding. In Proceedings of the 33rd Conference on Computational Linguistics and Speech Processing (ROCLING 2021). The Association for Computational Linguistics and Chinese Language Processing (ACLCLP), Taoyuan, Taiwan, 138–143. https: //aclanthology.org/2021.rocling-1.19
- [4] Wei Chen, Yeyun Gong, Song Wang, Bolun Yao, Weizhen Qi, Zhongyu Wei, Xiaowu Hu, Bartuer Zhou, Yi Mao, Weizhu Chen, Biao Cheng, and Nan Duan. 2022. DialogVED: A Pre-trained Latent Variable Encoder-Decoder Model for Dialog Response Generation. In Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers). Association for Computational Linguistics, Dublin, Ireland, 4852–4864. https://doi.org/10. 18653/v1/2022.acl-long.333
- [5] Xiuyi Chen, Jiaming Xu, and Bo Xu. 2019. A Working Memory Model for Taskoriented Dialog Response Generation. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics. Association for Computational Linguistics, Florence, Italy, 2687–2693. https://doi.org/10.18653/v1/P19-1258
- [6] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers). Association for Computational Linguistics, Minneapolis, Minnesota, 4171–4186. https://doi.org/10.18653/v1/N19-1423
- [7] Saket Dingliwal, Ashish Shenoy, Sravan Bodapati, Ankur Gandhe, Ravi Teja Gadde, and Katrin Kirchhoff. 2021. Prompt Tuning GPT-2 language model for parameter-efficient domain adaptation of ASR systems. https://doi.org/10.48550/ ARXIV.2112.08718
- [8] Shai Gretz, Yonatan Bilu, Edo Cohen-Karlik, and Noam Slonim. 2020. The workweek is the best time to start a family – A Study of GPT-2 Based Claim Generation. https://doi.org/10.48550/ARXIV.2010.06185
- [9] Prakhar Gupta, Harsh Jhamtani, and Jeffrey Bigham. 2022. Target-Guided Dialogue Response Generation Using Commonsense and Data Augmentation. In *Findings of the Association for Computational Linguistics: NAACL 2022.* Association for Computational Linguistics, Seattle, United States, 1301–1317. https: //doi.org/10.18653/v1/2022.findings-naacl.97
- [10] Ehsan Hosseini-Asl, Bryan McCann, Chien-Sheng Wu, Semih Yavuz, and Richard Socher. 2020. A Simple Language Model for Task-Oriented Dialogue. In Advances in Neural Information Processing Systems, H. Larochelle, M. Ranzato, R. Hadsell, M.F. Balcan, and H. Lin (Eds.), Vol. 33. Curran Associates, Inc., 20179–20191. https://proceedings.neurips.cc/paper/2020/file/ e946209592563be0f01c844ab2170f0c-Paper.pdf
- [11] Muhammad Khalifa, Hady Elsahar, and Marc Dymetman. 2021. A Distributional Approach to Controlled Text Generation. https://openreview.net/forum?id= jWkw45-9AbL
- [12] Weizhe Lin, Bo-Hsiang Tseng, and Bill Byrne. 2021. Knowledge-Aware Graph-Enhanced GPT-2 for Dialogue State Tracking. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing. Association for Computational Linguistics, Online and Punta Cana, Dominican Republic, 7871–7881. https://doi.org/10.18653/v1/2021.emnlp-main.620
- [13] Phillip Lippe, Pengjie Ren, Hinda Haned, Bart Voorn, and Maarten de Rijke. 2020. Diversifying Task-oriented Dialogue Response Generation with Prototype Guided Paraphrasing. *CoRR* abs/2008.03391 (2020). arXiv:2008.03391 https: //arxiv.org/abs/2008.03391
- [14] Ganeshan Malhotra, Abdul Waheed, Aseem Srivastava, Md Shad Akhtar, and Tanmoy Chakraborty. 2022. Speaker and Time-Aware Joint Contextual Learning for Dialogue-Act Classification in Counselling Conversations. In *Proceedings*

of the Fifteenth ACM International Conference on Web Search and Data Mining (Virtual Event, AZ, USA) (WSDM '22). Association for Computing Machinery, New York, NY, USA, 735-745. https://doi.org/10.1145/3488560.3498509

- [15] Shikib Mehri, Tejas Srinivasan, and Maxine Eskenazi. 2019. Structured Fusion Networks for Dialog. 165–177. https://doi.org/10.18653/v1/W19-5921
- [16] Bill Noble and Vladislav Maraev. 2021. Large-scale text pre-training helps with dialogue act recognition, but not without fine-tuning. In Proceedings of the 14th International Conference on Computational Semantics (IWCS). Association for Computational Linguistics, Groningen, The Netherlands (online), 166–172. https: //aclanthology.org/2021.iwcs-1.16
- [17] Yookoon Park, Jaemin Cho, and Gunhee Kim. 2018. 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). Association for Computational Linguistics, New Orleans, Louisiana, 1792–1801. https://doi.org/10.18653/v1/N18-1162
- [18] Jiahuan Pei, Pengjie Ren, Christof Monz, and Maarten de Rijke. 2019. Retrospective and Prospective Mixture-of-Generators for Task-oriented Dialogue Response Generation. CoRR abs/1911.08151 (2019). arXiv:1911.08151 http: //arxiv.org/abs/1911.08151
- [19] Matthew E. Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, and Luke Zettlemoyer. 2018. Deep Contextualized Word Representations. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers). Association for Computational Linguistics, New Orleans, Louisiana, 2227–2237. https://doi.org/10.18653/v1/N18-1202
- [20] Weizhen Qi, Yeyun Gong, Yu Yan, Can Xu, Bolun Yao, Bartuer Zhou, Biao Cheng, Daxin Jiang, Jiusheng Chen, Ruofei Zhang, Houqiang Li, and Nan Duan. 2021. ProphetNet-X: Large-Scale Pre-training Models for English, Chinese, Multi-lingual, Dialog, and Code Generation. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing: System Demonstrations. Association for Computational Linguistics, Online, 232–239. https: //doi.org/10.18653/v1/2021.acl-demo.28
- [21] Alec Radford, Jeff Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. 2019. Language Models are Unsupervised Multitask Learners. OpenAI blog (2019).
- [22] Tulika Saha, Dhawal Gupta, Sriparna Saha, and Pushpak Bhattacharyya. 2020. Emotion Aided Dialogue Act Classification for Task-Independent Conversations in a Multi-modal Framework. *Cognitive Computation* (2020), 1–13.
- [23] John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, and Oleg Klimov. 2017. Proximal Policy Optimization Algorithms. https://doi.org/10.48550/ARXIV. 1707.06347
- [24] Iulian V. Serban, Alessandro Sordoni, Yoshua Bengio, Aaron Courville, and Joelle Pineau. 2016. Building End-to-End Dialogue Systems Using Generative Hierarchical Neural Network Models. In Proceedings of the Thirtieth AAAI Conference on Artificial Intelligence (Phoenix, Arizona) (AAAI'16). AAAI Press, 3776–3783.
- [25] Andreas Stolcke, Klaus Ries, Noah Coccaro, Elizabeth Shriberg, Rebecca Bates, Daniel Jurafsky, Paul Taylor, Rachel Martin, Carol Van Ess-Dykema, and Marie Meteer. 2000. Dialogue act modeling for automatic tagging and recognition of conversational speech. *Computational Linguistics* 26, 3 (2000), 339–374. https: //aclanthology.org/J00-3003
- [26] Pei-Hao Su, David Vandyke, Milica Gaši ´c, Dongho Kim, Nikola Mrkši ´c, Tsung Hsien Wen, and Steve Young. 2015. Learning from Real Users: Rating Dialogue Success with Neural Networks for Reinforcement Learning in Spoken Dialogue Systems. https://doi.org/10.21437/Interspeech.2015-456
- [27] Jianheng Tang, Tiancheng Zhao, Chenyan Xiong, Xiaodan Liang, Eric Xing, and Zhiting Hu. 2019. Target-Guided Open-Domain Conversation. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics. Association for Computational Linguistics, Florence, Italy, 5624–5634. https://doi.org/10.18653/v1/P19-1565
- [28] Chris van der Lee, Albert Gatt, Emiel van Miltenburg, and Emiel Krahmer. 2021. Human evaluation of automatically generated text: Current trends and best practice guidelines. *Computer Speech & Language* 67 (2021), 101151. https: //doi.org/10.1016/j.csl.2020.101151
- [29] Thomas Wolf, Victor Sanh, Julien Chaumond, and Clement Delangue. 2019. TransferTransfo: A Transfer Learning Approach for Neural Network Based Conversational Agents. ArXiv abs/1901.08149 (2019).
- [30] Can Xu, Wei Wu, Chongyang Tao, Huang Hu, Matt Schuerman, and Ying Wang. 2019. Neural Response Generation with Meta-words. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*. Association for Computational Linguistics, Florence, Italy, 5416–5426. https://doi.org/10.18653/ v1/P19-1538
- [31] Yunyi Yang, Yunhao Li, and Xiaojun Quan. 2020. UBAR: Towards Fully End-to-End Task-Oriented Dialog Systems with GPT-2. https://doi.org/10.48550/ARXIV. 2012.03539
- [32] Zhilin Yang, Zihang Dai, Yiming Yang, Jaime Carbonell, Ruslan Salakhutdinov, and Quoc V. Le. 2019. XLNet: Generalized Autoregressive Pretraining for Language

Understanding. Curran Associates Inc., Red Hook, NY, USA.

- [33] Min Zhang and Juntao Li. 2021. A commentary of GPT-3 in MIT Technology Review 2021. Fundamental Research 1, 6 (2021), 831–833. https://doi.org/10.1016/ j.fmre.2021.11.011
- [34] Yizhe Zhang, Siqi Sun, Michel Galley, Yen-Chun Chen, Chris Brockett, Xiang Gao, Jianfeng Gao, Jingjing Liu, and Bill Dolan. 2020. DIALOGPT : Large-Scale Generative Pre-training for Conversational Response Generation. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics: System Demonstrations. Association for Computational Linguistics, Online, 270–278. https://doi.org/10.18653/v1/2020.acl-demos.30
- [35] Tianyu Zhao and Tatsuya Kawahara. 2019. Effective Incorporation of Speaker Information in Utterance Encoding in Dialog. https://doi.org/10.48550/ARXIV. 1907.05599
- [36] Li Zhou, Jianfeng Gao, Di Li, and Heung-Yeung Shum. 2020. The Design and Implementation of XiaoIce, an Empathetic Social Chatbot. *Computational Linguistics* 46 (01 2020), 1–62. https://doi.org/10.1162/COLI\_a\_00368
- [37] Daniel M. Ziegler, Nisan Stiennon, Jeffrey Wu, Tom B. Brown, Alec Radford, Dario Amodei, Paul F. Christiano, and Geoffrey Irving. 2019. Fine-Tuning Language Models from Human Preferences. *CoRR* abs/1909.08593 (2019). arXiv:1909.08593 http://arxiv.org/abs/1909.08593

Response-act Guided Reinforced Dialogue Generation for Mental Health Counseling

## APPENDIX

### A DISCUSSION ON OPTIMIZATION

Our model, READER is a result of numerous experiments on the selection of rewards and other hyper-parameters. To scale this model's applicability in the real world, it is equally crucial to understand what worked and what didn't. In this section, we analyze the model's behavior for different configurations. **Learning Rate** (**Ir**): READER behaves unstably with higher learning rate and often causes the reward to collapse significantly. Consequently, we observe that both the convergence rate and the stability of the model start deteriorating.

After fine tuning lr to  $2 \times 10^{-7}$ , we find an optimal tradeoff point between the convergence of the model and the model's stability. **Batch-size**: We observe that a large batch size helps with the model's stability for a continuous action space without collapsing the reward. **Relative Entropy (RE)**: We also scaled down the RE value by a factor of 1000 for the reward computation against the standard recommended<sup>11</sup> values of *subjective responses* and *highest metrics*.

**Reward.** a) Employing the ROUGE-1 score explicitly as a reward is highly prone to the collapse, and as a consequence, the text generation deteriorates through a repetition of similar phrases. b) At the same time, if we use BERTScore only, READER becomes unstable and starts generating arbitrarily long responses. c) Using an external reference classifier (i.e., SPARTA) to supplement the reward shows significant improvement in generation quality and benchmark metrics. It ensures that the generated responses are consistent with the response-acts gold labels.



Figure 6: Inspired by the work of Malhotra et al. [14], we take their proposed relationship among dialogue-act classes. Here, the directed path  $U_t^x \rightarrow U_{t+1}^y$  demonstrates the current dialogue-act and response-act pair. Note: We use this diagram directly from their work.

Table 5: The table demonstrate the results of RAC-Head on the response-act classification task. The comparision of the head is three-fold: a) reference model (SOTA) vs gold dialogue-act labels, b) RAC-Head's prediction vs gold labels, and c) RAC-Head's prediction vs reference model (SOTA). We show the accuracy along with weighted precision, recall, and F1 scores.

Model	Precision	Recall	F1	Accuracy
SOTA vs Gold Labels	0.69	0.55	0.52	0.55
RAC-Head vs Gold Labels	0.49	0.49	0.42	0.49
RAC-Head vs SOTA	0.50	0.45	0.41	0.45

# **B** EXPERIMENTAL SETUP

We perform numerous experiments using various combinations of the autoregressive language modeling loss, the dialogue-act loss, the value loss, and the policy loss. Moreover, we conduct extensive hyper-parameter tuning to correctly optimize the PPO trainer and scaling of the relative entropy reward. Further, we extensively experimented with the reward function and observe that Rouge, BERTScore, and RAC-Head's logits along with the relative entropy (*RE*) contribute towards most optimal policy learning.

We perform all experiments on an Nvidia A6000 GPU. We tune our hyperparameters to find the optimal configurations. We utilize the learning rate of  $2x10^{-6}$ , batch size of 128, which we run for 4 PPO-epochs. We use the Adam optimizer and train the reference READER for 50 epochs. We also perform hyperparameter tuning on values of  $\lambda$  in Equation 2 and observe that READER works best with  $\lambda_1 = 0.5$ ;  $\lambda_2 = 0.15$ ;  $\lambda_3 = 0.15$ ;  $\lambda_4 = 0.2$ .

# C PERFORMANCE OF RAC-HEAD

We deploy RAC-Head to perform the task of response-act classification on the HOPE dataset. RAC-Head and LM-Head jointly learns to optimize the READER. Further, to analyze the performance of RAC-Head, we present the results in Table 5.

# D ANALYSIS

We present a detailed analysis of responses generated by READER in Table 7. We see the model is able to correctly incorporate the context. Further observations shows that the quality of the generations is up to the mark and READER is capable to carry out full-fledged counseling. However, considering the severity of the matter, we never intend to eliminate the human in the loop.

# E GENERALIZABILITY

We discuss the generalizability of our proposed model, READER on the Switchboard Dialogue-act Corpus for the response-generation task. We present the results in the Table 6. The results show that the performance of the model is better on majority of the metrics.

# F REPRODUCIBILITY CHECKLIST

We upload our code in a zip file to reproduce the results of READER. In this section we show the directory structure. The root directory consist of modified trl sub directories consisting of model file named *gpt2.py*, ppo trainer file named *ppo.py* along with additional

<sup>&</sup>lt;sup>11</sup>https://github.com/lvwerra/trl

Table 6: Results obtained on the Switchboard Dialogue-act dataset. We show Rouge (1, 2, L), BERTScore (BS), and Meteor to assess the generalizability of the READER on datasets similar to HOPE.

	R1		R2				RL		BertScore	Meteor	
	Р	R	F1	Р	R	F1	Р	R	F1		
DialoGPT GPT2	21.64 22.25	27.16 27.95	23.87 24.14	11.41 11.89	14.43 14.49	12.47 12.75	19.53 20.12	23.78 24.76	21.46 21.80	0.6615 0.6608	0.1836 0.1822
READER	22.32	27.92	24.18	11.97	14.49	12.79	20.20	24.76	21.84	0.7295	0.1850
$\Delta_{\text{READER}-BEST}(\%)$	↑ 0.3	↓ 0.1	↑ 0.1	↑ 0.6	↑ 0.0	<b>↑ 0.3</b>	<b>↑ 0.3</b>	↑ 0.0	<b>↑ 0.1</b>	↑ 9.4	↑ 1.5

helper functions in *core.py* file. The training program is stored in *Train.py* file and the latest saved checkpoint can be located in

*model\_train\_final.pt*. Further details can be found in an enclosed README.md file.