PEPDS: A Polite and Empathetic Persuasive Dialogue System for Charity Donation

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Abstract

Persuasive conversations for a social cause often require influencing other person’s attitude or intention that may fail even with compelling arguments. The use of emotions and different types of polite tones as needed with facts may enhance the persuasiveness of a message. To incorporate these two aspects, we propose a polite, empathetic persuasive dialogue system (PEPDS). First, in a Reinforcement Learning (RL) setting, a Maximum Likelihood Estimation loss based model is fine-tuned by designing an efficient reward function consisting of five different sub rewards viz. Persuasion, Emotion, Politeness-Strategy Consistency, Dialogue-Coherence and Non-repetitiveness. Then, to generate empathetic utterances for non-empathetic ones, an Empathetic transfer model is built upon the RL fine-tuned model. Due to the unavailability of an appropriate dataset, by utilizing the PERSUASION-FORGOOD dataset, we create two datasets, viz. EPP4G and ETP4G. EPP4G is used to train three transformer-based classification models as per persuasiveness, emotion and politeness-strategy to achieve respective reward feedbacks. The ETP4G dataset is used to train an empathetic transfer model. Our experimental results demonstrate that PEPDS increases the rate of persuasive responses with emotion and politeness acknowledgement compared to the current state-of-the-art dialogue models, while also enhancing the dialogue’s engagement and maintaining the linguistic quality 1.

1 Introduction

A persuasive message can be initially analyzed by distinguishing between the cause or stimulus the persuadee is being persuaded for and the associated attitude shown during persuasion. The message is first presented to the persuadee; s/he pays attention to it and comprehends its contents. A persuadee’s response depends partly on the information provided in the message and how one perceives or interprets it. Empathy plays a crucial role in mediating the persuasive effects as it evokes cognitive and emotional processing conducive to persuasion. Similarly, use of different polite tones as per context may establish a better connection with the persuadee and engage them for a longer time in the ongoing conversation. Therefore, for persuasion to be effective, cause or stimulus of persuasion can be encoded with empathy and politeness, ensuring interactiveness, empathetic connection, right tone as well as user engagement in a persuasive message.

Figure 1: An example of persuasion with LM (Language Model), PDS (LM fine-tuned with RL), and PEPDS (PDS with empathetic transfer model).

A persuasive message consists of some form of directives, hence having the potential for disagreement or dissatisfaction thus may threaten the face of recipients. Hence, messages employing different politeness strategies such as positive politeness and negative politeness as per user’s mood and message content may emphasize users’ freedom to get persuaded or not. For an example, in Figure 1, the strike through response is persuasive but also consists of forceful language. Whereas, the
green box response connects with the user empathetically and also gives him/her freedom of choice by adopting positive politeness strategy (i.e. by using non-imposing, face-saving language). Further, to acknowledge underlying emotion in the content an empathetic transfer model can transfer the non-empathetic messages to empathetic messages as shown in orange box of Figure 1.

Paucity of available data poses a challenge to model a persuasive dialogue system in a supervised learning (SL) setting. Further, modelling persuasion considering different attributes such as politeness and empathy brings a greater challenge due to its different dynamics with different users. Therefore, a model which can learn from user interactions itself in an ongoing dialogue is required. Recently, researchers had widely used reinforcement learning (RL) to reinforce dialogue agents to approximate better policy as per user’s feedbacks (Singh et al., 1999; Li et al., 2016; Chen et al., 2019; Mesgar et al., 2021; Mishra et al., 2022). Hence, to induce both, a consistent politeness-strategy and empathy, we utilize goodness of both the frameworks i.e. RL and SL, and propose a novel Polite-Empathetic Persuasive Dialogue System (PEPDS).

To ensure persuasiveness, politeness-strategy consistency, right emotion, dialogue coherence and non-repetitiveness, a maximum likelihood estimation loss (MLE) language based model is fine-tuned with an RL loss considering five rewards viz. Persuasion, Emotion, Politeness-strategy Consistency, Dialogue-coherence and Repetitiveness. In case the generated persuasive messages are found to be non-empathetic, a sequence-to-sequence (seq2seq) based style transfer model is employed to make them empathetic. In order to achieve this goal, we prepare a new dataset named as ETP4G from the EPP4G dataset. To obtain persuasion, emotion and politeness-strategy consistency reward feedbacks, first, we annotate PERSUASIONFORGOOD dataset (Wang et al., 2019) with the required emotion and politeness-strategy labels, and obtain a new dataset named as EPP4G. Then, considering these three aspects, we fine-tune three RoBERTa-large (Liu et al., 2019) based respective classifiers.

Recently, to generate persuasive responses, an MLE-loss based language model is fine-tuned by Shi et al. (2021) with an RL-loss without using any user simulators. To persuade the persuadee, they penalized the generation of repetitive and inconsistent utterances. Our work differs from them in three aspects. Firstly, we consider new aspects of politeness-strategy consistency and emotion acknowledgement to force the dialogue agent to be consistent as well as empathetic. Second, a new reward function is designed to ensure right persuasion strategy, emotion acknowledgement, politeness-strategy consistency, dialogue-coherence in an ongoing dialogue and non-repetition of similar responses. Third, to connect with the user empathetically, we transfer the non-empathetic responses to empathetic ones. Lastly, we perform automatic and human evaluation to assess the persuasiveness, politeness-strategy consistency, empathy, response-length, fluency, adequacy, consistency and non-repetitiveness of the generated responses for our proposed PEPDS. Following are the key contributions we present in this paper:

1. To have PERSUASIONFORGOOD dataset utterances with politeness-strategy and empathy information, we manually annotate it with three different labels to obtain EPP4G and ETP4G datasets, respectively.

2. We build an empathetic transfer model by utilizing pre-trained and fine-tuned transformer models.

3. We propose a polite empathetic persuasive dialogue system (PEPDS) by designing an efficient reward function to ensure politeness-strategy consistency, persuasiveness, emotion acknowledgement, dialogue-coherence and non-repetitiveness.

4. We perform detailed empirical evaluation considering automatic and human evaluation to demonstrate robustness of our proposed system PEPDS.

2 Related Work

Recent research on personalised conversational agents shows that incorporating various human-oriented conversational strategies can have a significant impact on the user responses and make the conversations more engaging (Mazare et al., 2018; Kocaballi et al., 2019; Wang et al., 2019; Dutt et al., 2020; Song et al., 2021). These dialogue agents can better acknowledge the user’s state to adapt themselves as per user’s need. For instance, Bertro et al. (2016) tries to recognize user emotions in real-time in an interactive dialogue system. Shi
and Yu (2018) builds an effective dialogue system considering user’s sentiment information, whereas Firdaus et al. (2020) utilizes multimodal information to generate sentiment and emotion controlled responses. Golchha et al. (2019) induces courteous behaviour in customer care responses. Similarly, Mishra et al. (2022) designed three politeness based rewards to reinforce polite responses in an ongoing task-oriented dialogue. Due to subtle dependency between these user-targeted personalization techniques such as politeness-strategy, empathy or sentiment, and persuasion, we focus on incorporating politeness-strategy consistency and empathy to generate more persuasive and engaging utterances.

Historically, different persuasion models have been proposed, such as Petty and Cacioppo’s Elaboration Likelihood Model (ELM) (Petty and Cacioppo, 1986) and Friestad and Wright’s Persuasion Knowledge Model (PKM) (Friestad and Wright, 1994). This indicates that a person’s persuasion may depend on several factors, such as the content of the message, context, common sense knowledge and scientific knowledge. Similarly, Dijkstra (2008) states that personal factor consideration with informative content can enhance the quality of persuasive messages. Bohner et al. (2002); Sparks and Areni (2002, 2008) point out that the language employed in persuasive messages can impact both perceptions of the persuader as well as the message conveyed. Similarly, Brown and Levinson (1978); Brown et al. (1987) in their politeness theory points out that persuasive messages in the absence of indirect or face-saving language may commensurate threat in the face of recipients.

Recent research studies have started focusing on building persuasive dialogue agents by considering different aspects, such as persuasion strategies (Wang et al., 2019) and resistive strategies (Dutt et al., 2021). Shi et al. (2020) conducted an online study considering 790 participants to check if they can be persuaded or not by a chatbot. Further, the availability of transformer based pre-trained language models has led the researchers to train style transfer even in the absence of parallel data (Yang et al., 2018; Xu et al., 2018; He et al., 2020; Goyal et al., 2021; Lai et al., 2021; Malmi et al., 2020; Jin et al., 2022). Our current method of transferring non-empathetic utterance to empathetic is based on the prior technique proposed in (Krishna et al., 2020).

Recently, two MLE-loss based language models - one for persuadee and one for persuader are jointly trained to generate persuasive responses (Wu et al., 2021). Shi et al. (2021) fine-tunes a language model in RL-setting to persuade with non-repetitive and consistent responses. In contrast to the fact that persuasion encompasses a vast domain space with different associated attitudes, these research studies either concentrated on predicting persuasion strategy or generating persuasive responses alone. Persuasion alone cannot ensure user engagement; a dialogue agent should be able to adapt to different associated attitudes as per rapport built with the user. Therefore, our work here focuses on adapting different politeness strategies as per user attitudes and generating empathetic and engaging persuasive dialogues. To the best of our knowledge, no previous study has incorporated politeness strategies to build a persuasive dialogue system.

3 Methodology

A persuasive dialogue \( d \) = \( \{ u_{1r}^e, u_{1e}^e, u_{2r}^e, u_{2e}^e, \ldots, u_{T-1r}^e, u_{T-1e}^e \} \) consists of \( T - 1 \)-turns, where \( u_i^r \) and \( u_i^e \) represents the persuader’s and persuadee’s utterance, respectively, at \( i \)th turn \((1 < i < T - 1)\). Considering this ongoing dialogue as a context, our goal is to generate an adequate dialogue coherent persuader’s utterance \( u_T^{ee} \) = \( \{ t_1, t_2, \ldots, t_r \} \) at turn \( T \) with \( r \) number of tokens. To achieve this goal, first, an MLE-loss based language model is fine-tuned with an RL-loss by designing an efficient reward function to generate rich emotion acknowledged and politeness-strategy consistent persuasive responses. On generating the non-empathetic utterances, it is passed through an empathetic transfer model to transfer to an empathetic utterance.

3.1 Classifiers

All the four classifiers, viz. persuasion strategy, emotion, politeness-strategy and empathy are built by fine-tuning RoBERTa-large (Liu et al., 2019) pre-trained model. Persuasion strategy, Emotion and Politeness strategy classifiers are used to provide reward feedbacks, whereas empathy classifier is used to inform if the generated utterance is empathetic or non-empathetic. In a dialogue, for \( m \) number of persuader’s utterance, each utterance has four labels, viz. politeness-strategy \( pos = \{ pos_1^l, pos_2^l, \ldots, pos_m^l \} \), emotion \( emo = \{ emo_1^l, emo_2^l, \ldots, emo_m^l \} \) and per-
While non-coherent and repetitive utterances are penalized. The model is trained in an end-to-end fashion in a sequence-to-sequence problem, where the input text corresponds to a non-empathetic utterance and the output corresponds to an empathetic utterance. The model is trained in an end-to-end fashion in two steps. First, the input text is corrupted using an arbitrary noising function. Second, it optimizes a reconstruction loss i.e. cross-entropy between the decoder’s output and the ground truth output.

3.2 Empathetic Transfer Model

We build the Empathetic Transfer (ET) model, based on BART (Lewis et al., 2020), following a standard seq2seq transformer based architecture. It comprises of a bidirectional encoder (like, BERT) and a left-to-right decoder (like, GPT). As in seq2seq transformers, each layer of BART’s decoder performs cross-attention over the final hidden layer of the encoder. To build our model, we fine-tune the pre-trained BART-large (Lewis et al., 2020). As BART comprises of an auto-regressive decoder, it can be directly fine-tuned in the form of a sequence-to-sequence problem, where the input text corresponds to a non-empathetic utterance and the output corresponds to an empathetic utterance. The model is trained in an end-to-end fashion.

3.3 Reinforcement Learning Fine Tuning

An MLE-based language model generates candidate responses for a given input. These candidates are evaluated in terms of quality with respect to gold human response using the designed reward function. The candidates with the right persuasion, emotion, and politeness strategies are rewarded, while non-coherent and repetitive utterances are penalized. The RL-system is trained using the proximal policy optimization (PPO) (Schulman et al., 2017) method to achieve optimal policy.

**Reward:** To capture each aspect of the persuasion, underlying emotion, politeness-strategy consistency, dialogue-coherence and non-repetitiveness, a single reward function $R$ is designed consisting of all the four sub-rewards: $R_1$ for persuasion, $R_2$ for emotion, $R_3$ for politeness-strategy consistency, $R_4$ for dialogue coherence and $R_5$ for non-repetitiveness. The reward, $R$ can be expressed as a weighted sum of all these four sub-rewards.

$$R = \gamma_1 R_1 + \gamma_2 R_2 + \gamma_3 R_3 + \gamma_4 R_4 + \gamma_4 R_5$$  \hfill (1)

**Persuasion, Emotion and Politeness-Strategy Consistency:** Persuasion strategy ($R_1$), emotion ($R_2$) and politeness-strategy ($R_3$) reward feedbacks are achieved by passing generated utterance $u_T^r$ through persuasion strategy, emotion and politeness-strategy classifiers, respectively. Then, each of the three predicted labels is compared with the respective gold human response label, and the candidates with matching label are rewarded.

$$R_1 = \mathcal{P}_{ps}(u_T^r) - \beta \sum_{i \in S} \mathcal{P}_{ps_i}(r_T)$$  \hfill (2)

$$R_2 = \mathcal{P}_{emo}(u_T^r) - \beta \sum_{i \in S} \mathcal{P}_{emo_i}(r_T)$$  \hfill (3)

$$R_3 = \mathcal{P}_{pos}(u_T^r) - \beta \sum_{i \in S} \mathcal{P}_{pos_i}(r_T)$$  \hfill (4)

where $\mathcal{P}_{ps}(u_T^r)$, $\mathcal{P}_{emo}(u_T^r)$ and $\mathcal{P}_{pos}(u_T^r)$ denote the persuasion, emotion and politeness-strategy probabilities of the gold response $u_T^r$. The $\mathcal{P}_{ps_i}(r_T)$, $\mathcal{P}_{emo_i}(r_T)$ and $\mathcal{P}_{pos_i}(r_T)$ denotes the predicted persuasion, emotion and politeness-strategy probabilities of the generated response $r_T$, and $i \in S$ with $S = \{l_1, l_2, ..., l_n\}$ is the set of all the classes respective to persuasion strategy and politeness-strategy. $\beta$ is a scalar value acting as a penalization factor, i.e. increasing $\beta$ will result into greater penalization of the generated response.

**Dialogue-coherence Reward:** In order to force the agent to generate human-like responses in an ongoing dialogue, the Meteor score (Banerjee and Lavie, 2005) is calculated between the generated response $u_T^r$ (hypothesis) and the gold human response $p_{gr_T}$ (reference). The more the meteor score is the more the generated utterance is semantically similar to the gold human response.

$$R_A = MET(u_T^r, p_{gr_T})$$  \hfill (5)

Meteor score is selected as it shows high correlation with human judgement in machine translation tasks (Banerjee and Lavie, 2005) by leveraging WordNet, in case an exact match of tokens is not found (Castillo and Estrella, 2012). This leads to better generalization as language model tend to generate semantically similar responses but different in terms of morphemes.

$\beta$The value of $\beta$ is taken as greater than or equal to 1
Repetitiveness Reward: It is found that repetitions usually happen only on the lexical level in this task (Shi et al., 2021). Therefore, to penalize the repetitions of same responses in a dialogue we use Jaccard similarity score between the previous generated \( r_{T-1} \) and current generated response \( r_T \).

\[
R_5 = \frac{r_{T-1} \cap r_T}{r_{T-1} \cup r_T} \tag{6}
\]

Policy: In an RL framework, a policy models the agent’s action selection as a probability mapping function. Hence, policy \( P_\theta \) representing the probability of generating an utterance \( r \) consisting of \( L \) tokens can be formulated as:

\[
P_\theta(r_1:L|x) = \prod_{l=0}^{L} P_\theta(r_l|y_{<l}, x) \tag{7}
\]

Proximal Policy Optimisation: To ensure low variance, proximal policy optimisation (PPO) method (Schulman et al., 2017) is chosen to update the policy at each step. It updates an existing policy to seek improvement on certain parameters such that the old policy is not too different from the new policy. Policy optimisation mainly comprises of three steps. First, to maximize the expected reward, gradient ascent is applied on loss function \( J(\theta) \).

\[
\nabla_\theta J(\theta) = \mathbb{E}_{r \sim P_\theta} [\nabla_\theta \log P_\theta(r) \hat{A}_r] \tag{8}
\]

Second, PPO restricts large deviations from the old policy in the above equation, by replacing the log term with an importance sampling term with clipping to prevent catastrophic forgetting. Here, the clipped variant of PPO neither have any KL-divergence term in the objective function nor any constraint instead, it relies on specialized clipping in the objective function. It is formulated as given below:

\[
L_{CLIP}(\theta) = \mathbb{E}\{\min(pr_r(\theta)\hat{A}_r, \text{clip}(pr_r(\theta), 1-\epsilon, 1+\epsilon)\hat{A}_r)\}
\]

Here, \( pr_r(\theta) = \frac{P_{\text{new}}(\theta)}{P_{\text{old}}(\theta)} \) denotes the probability ratio of generating a response between the new and old policies. \( \hat{A}_r \) gives the estimated advantage which, here equals to the normalized rewards and \( \epsilon \) represents the clipping range. Lastly, parameters are updated using the following steps:

\[
\theta_{k+1} = \arg\max_{\theta} \mathbb{E}_{s,a \sim P_{\theta_k}} [L_{CLIP}] \tag{9}
\]

3.4 Proposed Method

We employ the attributes of emotion and politeness-strategy consistency to control the agent to generate engaging, polite, emotionally acknowledged, and persuading responses. First, we fine-tune an MLE-based language model, ARDM, in an RL setting considering five rewards. Then, we use this trained model to generate responses at inference time which are transferred to empathetic responses by an auto-regressive seq2seq model. The overall architecture of the proposed system is shown in Figure 2.
Table 1: Data statistics of all datasets. Here, train, eval and test correspond to the number of utterances used to train, validate and test the respective models. Further '-' signifies that either persuadee or persuader’s role is not considered or that role’s utterances are absent in the dataset.

| Dataset                        | Number of utterances | All    | Persuader’s | Persuadee | train | eval  | test  |
|-------------------------------|----------------------|--------|-------------|-----------|-------|-------|-------|
| P4G (to train LM)             |                      | 20932  | 10600       | 10332     | 16746 | 2093  | 2093  |
| P4G (persuasion strategy)     |                      | 10864  | 6018        | 4846      | 4814  | 602   | 602   |
| EPP4G (emotion)               |                      | 4000   | 4000        | -         | 3200  | 400   | 400   |
| EPP4G (politeness-strategy)   |                      | 5300   | 5300        | -         | 4240  | 530   | 530   |
| ETP4G (empathetic transfer)   |                      | 16722  | 16722       | -         | 13378 | 1672  | 1672  |

3.4.1 Baselines

We define the following baselines in our current work.

**ARDM**: To model both persuadee and persuader separately, ARDM jointly trains two GPT-2 (Radford et al., 2019) models. This model has reported to have achieved good performance levels (Wu et al., 2021). The RL-model is initialized with $p$ parameters of the ARDM model.

**RFI**: To learn policy directly from the data, it fine-tunes the ARDM in an RL-framework. Then using the response filter, response detector and response imitator, it selects the best response out of all the available candidate responses (Shi et al., 2021). RFI achieved state-of-the-art results considering ARDM as baseline. (Shi et al., 2021).

4 Datasets and Experiments

The datasets utilised in our studies are introduced in Section 4.1. In Section 4.2, implementation details of the proposed RL-based system are discussed. Due to space constraints, the classifiers’ and empathetic transfer model’s implementation details are provided in Section A.3 of the appendix. Finally, Section 4.3 describes the specifics of automatic and human evaluation metrics.

4.1 Datasets

To design our experiments, we use PERSUASION-FO RGGOOD (P4G) dataset. It consists of 1,017 persuasive conversations for donation to a charity organization Save the Children. These conversations are carried out between two humans, where one acted as a persuadee and the other as persuader. Each of the persuader’s utterances in P4G dataset is grounded in one of the 11 persuasion strategies. To have emotion and politeness strategy information for all utterances in PERSUASION-FO RGGOOD, we annotate it with both of these aspects and name it as EPP4G dataset. Then, we prepare a empathetic transfer dataset - ETP4G utilising the annotated EPP4G dataset. Due to space restrictions, annotation details for both the datasets are provided in Section A.2 of appendix. All the datasets statistics can be found in Table 1.

We also use the P4G dataset to train two classifiers: a persuasion strategy classifier and a persuasive binary classifier. While the former is used to provide persuasion reward, the latter is used to evaluate persuasiveness of generated utterance.

4.2 Implementation Details

To model both the persuader and the persuadee, GPT-2 medium model (Radford et al., 2019) is employed to train the language model. This language model is fine-tuned in an RL-setting, by experimenting with different candidate responses i.e. $n = 2, 3, 4, 5, 10$. Finally, $n = 2$ is chosen as the final value. Further, the generated candidates are decoded adopting nucleus sampling (Holtzman et al., 2019) with temperature $T = 0.8$ and probability $p = 0.9$. To train the proposed RL system $human\_reward = 10$, $max\_candidate\_length = 50$, and AdamW (Loshchilov and Hutter, 2017) optimizer is chosen with a learning rate of $\alpha = 2e-05$ and $\varepsilon = 0.2$. After performing several experiments with different values of the reward weights, 0.3, 0.3, 0.2, 0.1, 0.1 are chosen as the final weights for $\gamma_1$, $\gamma_2$, $\gamma_3$, $\gamma_4$ and $\gamma_5$, respectively (detailed weight optimization is given in Section A.4 of the appendix). Lastly, for persuasion, emotion and politeness-strategy consistency rewards, the penalization factor $\beta$ is set to 2.

4.3 Evaluation Metrics

We evaluate our proposed system considering both automatic and human evaluation metrics.

All the four classifiers are evaluated in terms of Weighted Accuracy (W-ACC) and Macro-F1 (to account for imbalanced class distribution). Further, empathetic transfer model is evaluated in terms of
Perplexity (PPL) (Brown et al., 1992), Bleu score (BLEU) (Papineni et al., 2002), METEOR score (MET) (Banerjee and Lavie, 2005), Rogue-2 F-1 score (R-2-F1) (Lin and Hovy, 2003), NIST score (Doddington, 2002) (NIST) and Empathy Accuracy (EM-ACC). The Empathetic Transfer Model is a sequence-to-sequence model, hence its performance has also been assessed using the BLEU metric, which measures how well the expected response correlates with the actual response. The anticipated response might be semantically same, but it might differ from the ground truth response in terms of the words that are true. To be sure of this, we additionally incorporate the METEOR score while evaluating the model.

Since the goal of the proposed system is to generate a persuasive response effectively, we evaluate our system in terms of four metrics, viz. PerStr - percentage of the utterances generated with persuasion strategy. PolSt - percentage of utterances generated with consistent politeness strategy as per ongoing dialogue, Emp - percentage of empathetic utterance generated, PPL - perplexity of the dialogue agent and LEN - number of tokens generated in an utterance. PerStr and Emp are evaluated by building two binary classifiers, i.e. a persuasive classifier predicts if a response comprises of persuasion strategy or not, and empathy classifier predicts if it is empathetic or not. In contrast to the persuasion strategy classifier, which predicts one of the 11 persuasion strategies, the binary persuasive classifier predicts the persuasiveness of the response as 0 or 1. PolStr is evaluated by comparing the predicted politeness strategy with the gold response politeness strategy.

We perform human evaluation by engaging three human experts (regular employees in our research group) with postgraduate experience and having proficiency in a similar task. They were asked to evaluate 40 generated persuasive dialogues in terms of Per, Emp - checking persuasiveness and empathy of the generated dialogue; DonPr - computing percentage of time people donated; Const, Adeq, Fluen and N-Rep to evaluate if the generated utterances are consistent (with the dialogue context), adequate, linguistically fluent and non-repetitive in nature.

Lastly, in order to take politeness-strategy consistency into account, we also evaluate our proposed model based on Pol-Con - denoting politeness-strategy consistency of persuader in an ongoing dialogue on 1-3 scale. To get final values for each of the evaluation metric, the average of all three ratings given by human evaluators is taken.

5 Results and Analysis

We first analyse the results of our sub-modules used in our proposed system viz. all the four classifiers and the empathetic transfer model. Then, we analyse our proposed system by comparing it with two baselines: ARDM (MLE loss based model) (Wu et al., 2021) and RFI (DialGAIL with response filter and response imitator) (Shi et al., 2021). Automatic and human evaluation results of our proposed system are shown in Table 4 and Table 5, respectively.

Classifiers: Evaluation results of all the four classifiers are shown in Table 2. It can be observed that all the four classifiers achieve significantly good scores in terms of both W-ACC and Macro-F1. Further, it is also observed that RoBERTa-large (Liu et al., 2019) performs better than BERT-large (Kenton and Toutanova, 2019) on both the metrics.

Empathetic transfer model: Evaluation results of our proposed empathetic transfer model are shown in Table 3. It can be seen that BART-large (Lewis et al., 2020) performs better in terms of EM-ACC with a margin of 3% as compared to BERT-BERT seq2seq model. A good EM-ACC score implies that our model can transfer the politeness of the given utterances. Further, it can also be inferred from the scores of PPL, MET and R-2-F1, that the generated politeness transferred utterances are fluent, semantically same, but different in expressions.

Automatic Evaluation: In Table 4, it can be observed that our proposed model, PEPDS performs better as compared to ARDM and RFI in terms of PerStr with a significant difference of 10.72 and 8.78 points, respectively. It may be because persuasion, emotion, and politeness-strategy consistency rewards force the RL-agent to generate more persuasive responses grounded in the correct emotion and politeness strategy. It should also be noticed that PDS achieves lower perplexity (PPL) than both ARDM and RFI, with a difference of 1.39 and 1.32 points, respectively, showcasing the better performance.

\footnote{All metrics were calculated on 1-5 scale, denoting low to high such as Per = 1 denotes not-persuasive.

\footnote{1 denotes politeness strategy inconsistent response, 2 denotes acceptable response, 3 denotes politeness-strategy consistent response.

\footnote{An inter-annotator agreement ratio of 73.7\% is found between all three human evaluators.}
### Table 2: Evaluation results of the Classifiers

| Classifier         | W-ACC | Macro-F1 | W-ACC | Macro-F1 |
|--------------------|-------|----------|-------|----------|
| Persuasion-strategy | 0.718 | 0.602    | 0.732 | 0.623    |
| Emotion            | 0.647 | 0.640    | 0.671 | 0.670    |
| Politeness Strategy| 0.870 | 0.852    | 0.901 | 0.889    |
| Empathy            | 0.833 | 0.830    | 0.851 | 0.846    |

### Table 3: Evaluation results of empathetic transfer model

| Model             | EM-ACC | PPL  | BLEU | NIST | MET  | R-2 F1 |
|-------------------|--------|------|------|------|------|--------|
| BERT-BERT         | 0.862  | 9.82 | 0.032| 0.164| 0.401| 0.281  |
| BART-large        | 0.894  | 8.71 | 0.041| 0.182| 0.442| 0.310  |

### Table 4: Results of automatic evaluation. Here, PEPDS refers to our proposed system consisting of empathetic transfer model. Here, PDS refers to only the fine-tuned RL-system on rewards.

| Model             | PerStr | PolSt | Emp  | PPL  | LEN  |
|-------------------|--------|-------|------|------|------|
| ARDM (Wu et al., 2021) | 49.2%  | -     | -    | 12.45| 15.03|
| RFI (Shi et al., 2021)   | 51.2%  | -     | -    | 12.38| 19.36|
| PDS                | 59.98% | 41.117%| 67.26%| 11.06| 15.73|
| PEPDS              | 59.98% | 41.117%| 78.1% | 11.06| 16.87|

### 5.1 Ablation Study

To find the importance of each of the rewards, we experiment with various sets of weights ($\gamma_1$, $\gamma_2$, $\gamma_3$, $\gamma_4$ and $\gamma_5$) by excluding one reward at a time. These rewards are validated on a 10% held out data. The ablation study to showcase the importance of each weight is shown in Table 6. It can be observed from the table that better perplexity is obtained when all the five rewards are considered, whereas each of its removal affects the perplexity value (i.e. increase in the value). It is also to be noted that persuasion reward $\gamma_1$ helps achieve better perplexity when considered with emotion $\gamma_2$ and politeness-strategy consistency rewards $\gamma_3$. It can be because aspects of politeness and emotion force the agent to generate more engaging utterances with right tone.
| Model   | Per | Emp | Pol-St | DonPr | Const | Fluen | Adeq | N-Rep |
|---------|-----|-----|--------|-------|-------|-------|------|-------|
| ARDM    | 2.33| -   | -      | 0.50  | 4.17  | 4.17  | -    | 3.17  |
| RFI     | 2.98| -   | -      | 0.61  | 4.41  | 4.41  | -    | 3.50  |
| PDS     | 3.39| 3.91| 3.86   | 0.64  | 4.48  | 4.65  | 3.51 | 3.72  |
| PEPDS   | 3.77| 4.21| 4.03   | 0.67  | 4.56  | 4.78  | 3.84 | 3.78  |

Table 5: Results of human evaluation

| ABLATION STUDY | $\gamma_1$ | $\gamma_2$ | $\gamma_3$ | $\gamma_4$ | $\gamma_5$ | PPL    |
|----------------|------------|------------|------------|------------|------------|--------|
| 0              | 0          | 0          | 0.5        | 0.5        | 11.3100    |
| 0              | 0          | 0.8        | 0.1        | 0.1        | 11.2830    |
| 0              | 0.8        | 0          | 0.1        | 0.1        | 11.3123    |
| 0.8            | 0          | 0          | 0.1        | 0.1        | 11.1164    |
| 0.3            | 0.3        | 0.2        | 0.1        | 0.1        | 11.0671    |

Table 6: Ablation study to showcase the effectiveness of all the five sub-rewards

6 Conclusion

In persuasive conversations, even responses with factual arguments and the right cause may not be able to persuade due to a lack of polite and empathetic tone. Therefore, to ensure these two aspects in persuasive messages, we first fine-tune an MLE loss language model with an RL-loss function consisting of five rewards viz. persuasion, emotion, politeness-strategy consistency, dialogue-coherence, and non-repetitiveness. Then generated non-empathetic utterances are transferred using an auto-regressive seq2seq model to empathetic utterances. Detailed empirical evaluation concerning both automatic and human evaluation metrics demonstrate that our proposed model, PEPDS can achieve state-of-the-art performance compared to the existing baselines and can retain both the aspects of emotion and politeness-strategy consistency at par in an ongoing dialogue. Our results also conclude that adding the empathetic transfer model helps the proposed model better facilitate empathy in persuasive responses.

We would like to see more into the personalization aspects in the future to model persuasion, such as likeness, authority, demography, etc.

7 Ethical considerations

In this work, persuasion is modelled using a publicly available dataset. We adhered to the policies of the dataset and have not violated any copyright issues. Dataset which has been used to model empathetic persuasion will be made available only with an official agreement with restriction that data would be used only for research works. The dataset is annotated by recruiting three annotators who were paid as per our university norms. We have also got our data annotation process verified by our university review board. Further, persuasion is an intricate process which can be used for personal gain. Therefore, to develop a persuasive conversational AI an ethical intention must be taken into account. In this work, we choose to style persuasive dialogue generation with politeness and empathy for social work of donation to a charity organization utilizing PERSUASIONFORGOOD dataset.

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A APPENDICES

A.1 Classifiers

To train the classifiers, first contextual representations \( c_{<s>} \) are obtained by feeding sampled batches of persuader’s utterances to the classifier. These contextual representations \( c_{<s>} \) are then passed through a feed forward network to output a vector containing a scalar value for each of the considered classes. Lastly, a softmax is applied on this vector to obtain the resultant vector having probability values for each class. The highest probability value in the resultant vector represents the predicted class for each of the utterances.

A.2 Dataset Annotation Details

EPP4G: First, we annotate the P4G dataset with emotions. To achieve this task we used EMPATHETIC_DIALOGUES (ED) (Rashkin et al., 2019) dataset consisting of approximately 25k conversations grounded in 32 emotions. Due to imbalanced class distribution in EMPATHETIC_DIALOGUES dataset, we first boil down the 32 labels to 23 labels by merging similar emotion labels. Details of the merged emotion labels can be seen in Table 7. Then, we train a RoBERTa-large (Liu et al., 2019) based classifier which is used to predict emotion labels for PERSUASONFORGOOD dataset. These predicted labels are cross-verified manually for a sample of 4000 utterances by three annotators proficient in English communicative skills. They check the trueness of the predicted emotion labels in persuasive context following the EMPATHETIC_DIALOGUES dataset guidelines to infer their definitions. All three annotators annotate the mis-classified utterances with right emotion labels for each utterance. A reliable multi-rater Kappa (McHugh, 2012) agreement ratio of 72.1% is found between all three annotators annotations.

In order to avoid inevitable face threatening acts, persuader may adopt any one of the different politeness strategies viz. positive politeness, negative politeness or off-record (Brown et al., 1987). We ask same three annotators to annotate the approximatey 5300 persuader’s utterances with one of these three politeness strategies. Positive politeness strategies are generally used to make the persuadee feel good about themselves or their interests with a implicit known friendly or equal relationship between persuadee and persuader. Negative politeness strategy try to avoid imposition on the persuadee and presume that there is no known relationship between persuadee and persuader. Off-record strategy tries to give some general information or uses indirect language and relies on the persuadee’s interpretation for the information that has been conveyed. Annotators were asked to follow these definitions as per guidelines of Brown and Levinson’s politeness theory (Brown et al., 1987) to annotate all the 5300 persuader’s utterances. Lastly, for each utterance, maximum voted politeness strategy is chosen out of three labels. In these annotations also, a good multi-rater kappa agreement ratio of 78% is found. We name this P4G dataset annotated with right emotion and politeness strategy labels as EPP4G dataset.

| Emotion_1 | Emotion_2 | Merged_Emotion |
|-----------|-----------|----------------|
| angry     | turuous   | angry          |
| sad       | devastated| sad            |
| afraid    | terrified | afraid         |
| guilty    | ashamed   | guilty         |
| apprehensive | anticipating | apprehensive |
| sentimental | nostalgic   | sentimental    |
| surprised | excited   | surprised      |
| annoyed   | disgusted  | annoyed        |
| trusting  | faithful   | trusting       |

Table 7: Emotion classes after merging

EPP4G: To build empathetic transfer model, we required a seq2seq dataset consisting of non-empathetic-to-empathetic utterances. To prepare such a dataset, we follow (Krishna et al., 2020) approach. First, we ask the same three annotators to boil down these 23 emotion labels to only two labels i.e. empathetic and non-empathetic. We ask them to analyse all the 23 emotion labels in EPP4G dataset utterances and discriminate the empathetic and non-empathetic labels to annotate them with respective label. Second, all empathetic utterances are now filtered. It is found that out of 4000 utterances only 817 were non-empathetic and rest 3181 utterances were empathetic. This led to highly imbalanced class distribution. Hence, we oversample each of the non-empathetic utterance using forward-backward machine translation (English → Chinese → English) with two corresponding similar responses. Hence now, we have 847 × 3 = 2451 non-empathetic utterances and 3181 empathetic

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6The emotion classifier with 32 and 23 labels gives the accuracy scores of 58.17% and 67.44% respectively.

7All three annotators were post-graduate qualified and were paid as per our university norms.

8A RoBERTa-large (Liu et al., 2019) based empathetic classifier trained on this highly imbalanced dataset yielded the accuracy of 82.5% and macro-f1 of 73.0%.
### Table 8: Empathetic transfer model dataset statistics and details

| Dataset | #Utterances | Oversampling Details |
|---------|-------------|----------------------|
| EMP4G   | 5632        |                      |
|         |             | 1. Oversample non-empathetic utterances  |
|         |             | 2. Use forward-backward machine translation to get more number of utterances  |
|         |             | 3. #non-empathetic utterances : $817 \times 3 = 2451$ utterances  |
| ETP4G   | 16722       |                      |
|         |             | 1. Train a seq2seq paraphrase transformer based model on PARANMT-filtered (Krishna et al., 2020)  |
|         |             | 2. Filter the empathetic utterances from empathetic P4G dataset.  |
|         |             | 3. Through forward-backward machine translation increase the size of empathetic utterances: $3181 \times 3 = 9543$.  |
|         |             | 4. Pass these 9543 empathetic utterances to seq2seq paraphrase transformer based model and get corresponding non-empathetic utterances.  |
|         |             | 5. Out of 9543 approx utterances, 3287 generated utterance were non-empathetic.  |
|         |             | 6. Increase the 3287 utterances employing forward-backward machine translation.  |
|         |             | 7. First, obtain two similar candidates for non-empathetic utterances keeping corresponding empathetic utterances as the same, hence #seq2seq non-empathetic-to-empathetic utterances: $3287 \times 3 = 9861$. Second, keep non-empathetic utterances same and obtain corresponding two similar candidates of empathetic utterances. Hence, #utterances: $3287 \times 5 = 16722$.  |

We call this dataset as ETP4G dataset whose details are shown in Table 8. Lastly, these non-empathetic utterances are considered as input and corresponding empathetic utterances as output to train the empathetic transfer model.

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A RoBERTa-large (Liu et al., 2019) based empathetic classifier trained on this balanced empathetic dataset gave the accuracy of 85.1% and macro-f1 of 84.6%

A.3 Implementation Details

We first used three models: persuasion strategy, emotion and politeness-strategy classifiers to design reward feedback for our RL-agent and then at inference time we use three models: empathetic classifier and empathetic transfer model to generate empathetic utterance.

A.3.1 Classifiers

All four classifiers are trained using transformer based BERT-large: 24-layer, 1024-hidden units, 16-heads and 340M parameters (Kenton and Toutanova, 2019) and Roberta-large: 24-layer, 1024-hidden units, 16-heads and 355M parameters (Liu et al., 2019). For both the architectures, we used batch size = 16 (experimented with 8, 16 also), epochs=2 learning_rate = 4e-5, optimizer = AdamW, attention_dropout = 0.1 and activation = gelu.

A.3.2 Empathetic Transfer Model

We use two seq2seq generation models: BERT-BERT considering encoder and decoder both as BERT (Kenton and Toutanova, 2019) and BART-large having a BERT like encoder and GPT-2 like decoder (Lewis et al., 2020). BART consists of
24 layers, 1024 hidden units, 16 heads and 406M parameters. We followed following configuration to train our BART-based model: optimizer = AdamW, learning_rate = 4e-5, activation = gelu, attention_dropout = 0.1, repetition_penalty = 1.0 and max_seq_length = 128.

A.3.3 Device configurations details
To train transformer based classifiers, empathetic transfer model and PEPDS, we used following device configurations:

- GPU: A100-PCIE-40GB.
- CUDA Support: CUDA 11.x (or later).
- Memory clock: 1215 MHz.
- Total board power: 250 W.
- GPU clocks: Base: 765 MHz, Boost: 1410 MHz.
- Memory Size: 40 GB.
- Memory Type: HBM2.
- Bus Width: 5120 bits.

A.4 Weight Optimization
In order to find the right combination of weights for the reward function, we investigate with various sets of weights ($\gamma_1$, $\gamma_2$, $\gamma_3$, $\gamma_4$ and $\gamma_5$). These rewards are validated on a 10% held out data. Finally, the weight combination giving the highest perplexity is chosen. Considered weights for optimization is shown in Table 9. It can be observed from table that better perplexity is obtained when balance between all five rewards viz. persuasion, emotion, politeness-strategy consistency, dialogue-coherence and non-repetitiveness is taken into account showcasing the importance of each of the rewards used. It can also be inferred that when emotion and persuasion reward kept constant with keeping a balance between all three rewards, the PPL score varied near 11.07, showcasing the dependency between all three rewards: persuasion, emotion and politeness-strategy consistency. Whereas when any of these three rewards are not taken into account an abrupt drop in PPL score is seen.

| REWARD WEIGHT OPTIMIZATION | PPL  |
|-----------------------------|------|
| $\gamma_1$ | $\gamma_2$ | $\gamma_3$ | $\gamma_4$ | $\gamma_5$ |   |
| 0     | 0     | 0     | 0.5 | 0.5 | 11.3100 |
| 0     | 0     | 0.8   | 0.1 | 0.1 | 11.2830 |
| 0.8   | 0     | 0.1   | 0.1 | 0.1 | 11.3123 |
| 0.3   | 0.2   | 0.1   | 0.1 | 0.1 | 11.0671 |

Keeping Emotion constant
| 0.1 | 0.1 | 0.6 | 0.1 | 0.1 | 11.0785 |
| 0.3 | 0.1 | 0.4 | 0.1 | 0.1 | 11.0737 |
| 0.4 | 0.1 | 0.3 | 0.1 | 0.1 | 11.0740 |
| 0.5 | 0.1 | 0.2 | 0.1 | 0.1 | 11.0738 |

Keeping Persuasion constant
| 0.2 | 0.3 | 0.3 | 0.1 | 0.1 | 11.0662 |
| 0.2 | 0.2 | 0.4 | 0.1 | 0.1 | 11.0697 |
| 0.1 | 0.2 | 0.5 | 0.1 | 0.1 | 11.0711 |
| 0.1 | 0.4 | 0.3 | 0.1 | 0.1 | 11.0813 |

Table 9: Weight Optimisation using different values of $\gamma$

A.5 Discussion
An example of user’s interaction with proposed PEPDS and ARDM model is shown in Table 10. It can be seen that the user gave better ratings in terms of Per, Emp, Const, Fluen, Adeq, N-Rep to PEPDS than the ARDM. It is also observed that our proposed system is able to employ different persuasion strategies, such as Credibility Appeal, Emotional Appeal, Foot-in-the-Door, Task-related Enquiry and Self-Modelling as well as acknowledging the underlying emotion like caring, trusting, sentimental etc. Further, user gave score to the Pol-St metric as 3 which showcases that our model is able to adapt right politeness strategy as per the context of the dialogue. These results qualitatively shows that PEPDS is able to generate richer, coherent, engaging, right-emotion oriented and politeness-strategy consistent responses. Further, it can also be seen that once the non-empathetic response is generated by PDS, PEPDS is able to generate much more empathetic utterances utilising empathetic transfer model.

Some limitations are also observed such as in reply to utterances like ‘That’s good, do they take money orders or checks for donations?’, model replies that ‘You can choose any payment you’d like to make. Any amount from $0 to all your payment’. This can be due to the fact that defined reward function is not able to cover the crucial aspects of knowledge retention, and grounding of valuable information in utterances. Hence, we may need knowledge grounding to generate better utterances. Lastly, an another user interaction example with PEPDS examples is given in Table 11.
| Speaker | PEPDS model generated utterances (Per=5, Emp=3, Pol-St=5, Const=5, Fluem=5, Adeq=4 and N-rep=4) |
|---------|------------------------------------------------------------------------------------------------|
| PEPDS | Hi. How are you doing today? |
| USER | I am doing well! How about you? |
| PEPDS | I am doing pretty well. thanks for asking! Let’s talk about donation to a charity organization. |
| USER | Alright. What you want to talk about? |
| PEPDS | Good morning. Would you like to donate to a charity called Save the Children? |
| USER | I have heard of that group but I have never really thought about donating to it. |
| USER | Have you heard about a charity organization Save the Children? |
| PEPDS | Only in name. I haven’t heard too much about it though. Can you tell me more? |
| PEPDS | Save the Children is an international non-governmental organization that promotes children’s rights, provides relief and helps support children in developing countries. |
| USER | That sounds like a good charity. I prefer to keep things closer to home though. Are they active in India too? |
| PEPDS | Save the Children is a non-governmental organization that operates world wide raising funds through partners and donations to fight for children’s rights and provide relief and support for children in developing countries. |
| PEPDS(ET) | Sure, I can tell you about that. Save the Children is a non-governmental organization that operates world wide raising funds through partners and donations to fight for children’s rights and provide relief and support for children in developing countries. |
| USER | It sounds good. Still, I’ve to think about it. |
| PEPDS | Have you ever donated to any charities before? |
| PEPDS(ET) | That is understandable. Have you ever donated to any charity before? |
| USER | I have, I have been one for about 2 years now. I come on every once and a while and do it part time. I like to call it picking up nickels and dimes. How about yourself? |
| PEPDS | I have. I usually donate at least $2 every month. Do you feel the same way? |
| USER | Yes. monthly or yearly I try to donate. Can you provide more information about this organization? |
| PEPDS | The research team will collect all donations and send it to Save the Children. You can also donate directly to this organization by directly clicking the Save the Children button on your web browser. |
| PEPDS(ET) | The research team will collect all donations and send them to Save the Children. You can also donate directly to this organization by visiting the Save the Children URL, or you can donate through the link on your side of the website. |
| USER | That’s good, do they take money orders or checks for donations? |
| PEPDS | You can choose any payment you'd like to make. Any amount from $0 to all your payment. |
| USER | Ok, well I think I could donate half my earnings to this. |
| PEPDS | That’s a good idea. Thank you for your time and willingness to donate. |
| USER | I think I’ll donate $1. |
| PEPDS | Thank you so much. Have a nice day. |
| USER | Good to talk to you. |

| Speaker | ARDM model generated utterance (Per=2, Emp=2, Pol-St=2, Const=4, Fluem=4, Adeq=2 and N-rep=2) |
|---------|------------------------------------------------------------------------------------------------|
| ARDM | Hello |
| USER | Hello how are you doing? |
| ARDM | Good, have you heard of the Save the Children charity? |
| USER | No, I have not heard about them. |
| ARDM | Are you familiar with it? |
| USER | No I don’t know. Please tell me. |
| ARDM | I am just asking you about Save the Children charity because the children are dying and the government is helping them. |
| USER | Yes, I understand. That is very sad to hear. What we can do? |
| ARDM | Do you know about children’s charities? |
| USER | No, I do not know much about them. |
| ARDM | Do you like to help children? |
| USER | Definitely, I do like to help them. |
| ARDM | Do you know children’s charities? |
| USER | I have very little knowledge about them. |
| ARDM | Do you know about the save the children charity? |
| USER | Like I said very less. |
| ARDM | Are you familiar with the charity? |
| USER | Thank you very much, bye |
| ARDM | I will ask you again later |
| USER | thank you. |

Table 10: An example of user interaction with our proposed PEPDS and ARDM. Yellow highlighted responses show the responses with persuasion strategy.
Hello, How are You?

USER

PEPDS

We are going to talk about a charity called Save the Children.

USER

PEPDS

Can you tell me more about the charity?

USER

PEPDS

They help children in developing countries like Syria and Uganda.

USER

Can you tell me more about the charity?

PEPDS

Save the Children is an international non-governmental organization that promotes children’s rights, provides relief and helps support children in developing countries.

USER

Alright, Good, What would you like from me in this regard?

USER

PEPDS

Yes, we should help as much as possible.

USER

PEPDS

How much amount do you like to donate to the charity?

USER

PEPDS

Okay, Well, we could donate a portion of the payment you are going to get from this task to them.

PEPDS

Okay, well if you decide you would like to donate any of the proceeds from this task to them, we can donate a portion of the payment you will get from that portion.

USER

I think it is very important to help people in need whenever one can but is this organization legit?

USER

PEPDS

Yes, this organization is completely legit. They have been around for years and I have been working with them for the past two years now.

USER

Oh they are doing god’s work. Which countries do they operate in?

PEPDS

They help children in war torn areas with education, health care, safety, etc.

USER

Sure. What can we do to help these children?

PEPDS

We can donate. This organization has done quite a lot for the children in war torn areas. They help with education, health, safety, etc.

USER

We will talk about a charity called Save the Children. Have you heard of this charity before?

USER

PEPDS

Yes, I have probably not heard about them.

USER

PEPDS

They help children in developing countries like Syria and Uganda.

USER

Can you tell me more about the charity?

PEPDS

Save the Children is an international non-governmental organization that promotes children’s rights, provides relief and helps support children in developing countries.

USER

Alright, Good, What would you like from me in this regard?

USER

PEPDS

Yes, I do care a lot about them and love them.

USER

Sure, I’ll donate. I can think of donating some of my earnings with this task.

USER

PEPDS

That’s great, I appreciate your donation. Thank you again for your help.

USER

PEPDS

How much amount do you like to donate to the charity?

USER

PEPDS

Yes. Great. How much would you like to donate to charity now?

USER

PEPDS

Okay that’s great. Thanks again for your time. Have a wonderful day.