Generating Persona-Consistent Dialogue Responses Using Deep Reinforcement Learning

Mohsen Mesgar  Edwin Simpson*  Yue Wang  Iryna Gurevych
Ubiquitous Knowledge Processing Lab (UKP), Department of Computer Science
Technische Universität Darmstadt (TUDa)
https://www.ukp.tu-darmstadt.de

Abstract
Recent transformer-based open-domain dialogue agents are trained by reference responses in a fully supervised scenario. Such agents often display inconsistent personalities as training data potentially contain contradictory responses to identical input utterances and no persona-relevant criteria are used in their training losses. We propose a novel approach to train transformer-based dialogue agents using actor-critic reinforcement learning. We define a new reward function to assess generated responses in terms of persona consistency, topic consistency, and fluency. Our reference-agnostic reward relies only on a dialogue history and a persona defined by a list of facts. Automatic and human evaluations on the PERSONACHAT dataset show that our proposed approach increases the rate of persona-consistent responses compared with its peers that are trained in a fully supervised scenario using reference responses.

1 Introduction
Open-domain dialogue generation aims at producing informative and fluent dialogue responses to a given dialogue history, i.e., a sequence of utterances exchanged between dialogue partners. Despite the impressive success of recent neural end-to-end agents (Ritter et al., 2011; Serban et al., 2016; Li et al., 2016b; Zhao et al., 2017; Li et al., 2017; Ghazvininejad et al., 2018; Huang et al., 2018; Pan et al., 2019; Tang et al., 2019; Ko et al., 2019), they still express information about the speaker that is inconsistent with previous utterances in the same dialogue, for example, by contradicting earlier statements (Li et al., 2016a). This happens because these agents are trained on a huge number of dialogues that are inconsistent with one another as they are collected from various resources with different speakers’ personas, e.g. social media (Ritter et al., 2010) and movie scripts (Banchs, 2012).

A solution is to ground responses in a set of predefined facts that describe a speaker’s persona\(^1\) (Zhang et al., 2018; Dinan et al., 2019). So far only supervised models have been examined to achieve this goal (Li et al., 2016b; Zhang et al., 2018; Madotto et al., 2019). These models endow dialogue agents with factual aspects of a persona by conditioning responses on both a dialogue history and a speaker’s persona. However, generated responses are still not necessarily consistent with

\(^1\)In this paper, “persona” refers only to aspects of persona that can be captured by factual statements. We leave speaking style and other characteristics to future work.

---

Table 1: An example of a persona, dialogue history, and generated responses by a transformer-based agent trained in a supervised (SupL-Trans) and in a DeepRL scenario (DeepRL-Trans). SupL-Trans’s response is inconsistent with the previous response and the facts that are marked with an asterisk. The response from our method, DeepRL-Trans, is consistent.

| Persona (B) |
| i visit europe twice a year . |
| i ’ m a descendant of christopher columbus . |
| i love to cook paella . |
| i ’ ve a weakness for fish and chips . (*) |
| i am an art major in college . |

| Dialogue History |
| A: i am not sure , what is that ? i am a farmer myself . love driving the tractor . |
| B: it is a fish stew with rice , very good . i can make it for you . |
| A: interesting , i ’ m not sure if i ’ d like it . but i ’ ll try ! |
| B: i also love fish and chips , (*) |
| A: lol yum . my sister often has those at her shows . |
| B: ? |

| Response |
| SupL-Trans: i ’ m not sure if i ’ d like that . |
| DeepRL-Trans: i like to cook and i ’ ve a weakness for chips |

---
the speaker’s persona because the fully supervised objective function used in these approaches, i.e., cross entropy, lacks supervision signals for assessing persona consistency. Table 1 shows an example dialogue with two final utterances produced by different systems, the first of which is inconsistent with the defined persona and previous utterances.

We propose a novel approach to train dialogue agents with deep reinforcement learning (DeepRL). Although DeepRL has previously been used to train dialogue agents (Li et al., 2016b; Zhao and Eskenazi, 2016; Sankar and Ravi, 2019), existing methods do not attempt to ensure persona consistency. Methodologically, most RL-based approaches to dialogue generation use naïve Monte Carlo algorithms, i.e., REINFORCE (Williams, 1992), for training sequence-to-sequence (seq-to-seq) models (Li et al., 2016b). In contrast, we adopt the actor-critic method (Mnih et al., 2016) for the first time to open-domain dialogue agents, and use it to train a transformer-based (Vaswani et al., 2017) dialogue agent. The actor-critic method converges faster and requires less training data than REINFORCE (Mnih et al., 2016). Compared to seq-to-seq, transformer-based models achieve higher performance on many benchmark text understanding and generation tasks (Vaswani et al., 2017) and are able to consider longer dialogue histories when generating a response (Radford et al., 2019).

The core of any DeepRL approach is its reward function (Sutton and Barto, 1998). We define a novel reward function that combines three sub-rewards: persona-consistency, topic-consistency, and fluency. Recent research (Welleck et al., 2019; Dziri et al., 2019) shows that a major challenge in the persona-consistency problem is the content consistency, which can be characterized as a Natural Language Inference (NLI) problem. Building upon this finding, for our persona-consistency sub-reward we introduce a new NLI model to automatically assess the consistency of a generated response with a given speaker’s persona. Two other sub-rewards are required to ensure the quality of generated responses. We use an embeddings-based similarity metric between a generated response and its previous dialogue utterance as a proxy for topic-consistency to assess dialogue coherence. We estimate the fluency of a response using both the probability of the response given a language model fine-tuned on dialogue utterances and the frequency of repetitive words in the response.

We evaluate our agent on PERSONACHAT as a benchmark open-domain dialogue corpus (Zhang et al., 2018), in which utterances are associated with their speakers’ personas. Besides the automatic metrics used for dialogue evaluation (Dinan et al., 2019), e.g., perplexity, F1, and BLEU, we introduce a novel automatic metric to assess responses in terms of their consistency with personas using our NLI model. Our reference-agnostic metric quantifies to what extent responses generated by our agent are entailed from and contradict personas. We also conduct a human study for comparing our DeepRL-based agent and its supervised counterpart in terms of persona consistency and fluency.

Our core contributions are: (1) a new DeepRL method combining actor-critic with transformer-based models; (2) a reward function that ensures persona consistency as well as fluency; (3) empirical evaluation with automatic metrics for language quality, a new metric for persona consistency, and human evaluation, showing that our DeepRL approach outperforms the state-of-the-art supervised system (Wolf et al., 2018).

2 Dialogue Generation Method

Our goal is to generate a persona-consistent and fluent response consisting of $m$ tokens, $r = \{r_1, ..., r_m\}$, to a dialogue history, $d$, given a speaker’s persona, $p$. An example is shown in Table 1. A dialogue history consists of utterances exchanged between dialogue partners until turn $T−1$, $h = \{u_0, u_1, ..., u_{T−1}\}$. We refer to the last utterance in a dialogue history, $u_{T−1}$, as the query. A persona contains a set of facts, $p = \{f_1, ..., f_k\}$, about the speaker, our dialogue agent, expressed by short sentences.

2.1 DeepRL Formulation

We first formulate the dialogue generation task as a deep reinforcement learning (DeepRL) problem and then solve it by training a transformer-based dialogue agent (Trans) with our actor-critic method. We refer to our complete approach as DeepRL-Trans.

State The environment state consists of a persona, $p$ and a dialogue history, $d$. We represent $d$ conditioned on $p$ using the Generative Pre-
trained Transformer (GPT) model (Radford et al., 2018), which has three main benefits for our agent. First, since GPT uses transformers, it utilises the most salient information in its inputs to generate text. Second, since GPT is pretrained on a large amount of data (the BooksCorpus dataset), it has learned to encode linguistic properties such as semantic relations between words (Radford et al., 2018; Jawahar et al., 2019; Alt et al., 2019). Third, each word in the input text to GTP, which is a concatenation of the facts in p appended by utterances in d, is conditioned only on its preceding words using its transformers. This allows our model to encode the dialogue history and persona as its context.

Agent Our transformer-based agent transforms the state vector, which consists of p and d, into a probability distribution over a response, r:

\[
\mathcal{P}_\theta (r|d, p) = \prod_{t=1}^{m} \mathcal{P}_\theta (r_k | r_{<k}, d, p), \quad (1)
\]

where \( r_k \) is the kth token in the response and \( r_{<k} \) is the sequence of tokens prior to k.

Action An action in our formulation is to generate a word for a response. To do so, the output vector of the transformer decoder is fed into a dense layer to compute the probability distributions in Equation 1 for each token position, k, in a response. Following Radford et al. (2019), we retain the words for which the commutative probabilities are greater than a threshold. At the end of a response generation episode, we choose a word sequence that has the maximum probability.

Reward Our transformer-based agent should ideally generate responses consistent with the speaker’s persona as well as the dialogue history. While we could train the agent with a supervised approach using reference responses, this does not guarantee such consistency as it is not explicitly considered by the learning objective. Thus, we propose a multi-objective reward function with four sub-rewards: \( R_1 \) ensures consistency with the speaker persona, \( R_2 \) accounts for consistency with the dialogue history, and \( R_{3,1} \) and \( R_{3,2} \) reinforce fluency. The final reward, which is used as the training signal, is a weighted sum of the sub-rewards:

\[
R = \gamma_1 R_1 + \gamma_2 R_2 + \gamma_{3,1} R_{3,1} + \gamma_{3,2} R_{3,2}, \quad (2)
\]

where \( \gamma_1 + \gamma_2 + \gamma_{3,1} + \gamma_{3,2} = 1 \). These weights can be tuned to control the properties of the agent’s responses. A key benefit of our reward function is that it does not evaluate responses based on their similarity to reference responses, meaning that it can more fairly assess novel or creative responses. Furthermore, since the final reward is the linear combination of sub-rewards, which encode different aspects of a high-quality response, the agent does not become biased towards any of these sub-rewards.

Persona consistency sub-reward (\( R_1 \)) This sub-reward measures to what extent a generated response is entailed from a given persona. To do so, we train a natural language inference (NLI) model to predict the relationship (entailment, neutral, contradiction) between a response and a fact in a persona. We use this model to compute a sub-reward function that penalises an agent if its generated response contradicts a fact in the speaker’s persona, and rewards the agent if its response entails a fact. We define a BERT-based NLI model as follows:

\[
\begin{align*}
    h_{cls}^{i}, [h_1^{i}, \ldots, h_{f_i}^{i}], [h_1^{r}, \ldots, h_{r_i}^{r}] &= BERT(f_i, r) \\
    [s_e, s_c, s_n] &= \text{FeedForward}(h_{cls}) \\
    [P_{e}^{NLI}, P_{c}^{NLI}, P_{n}^{NLI}] &= \text{Softmax}([s_e, s_c, s_n])
\end{align*}
\]

where \( f_i \) is a fact of a given persona and \( r \) is a response, \( h_{cls}^{i} \) is the hidden vector representation provided by BERT, which is shown to be effective for classifying the semantic relationship between input sentences (Devlin et al., 2018). \( \text{FeedForward} \) is a dense neural layer that maps \( h_{cls}^{i} \) to the scores \( s_e, s_c \) and \( s_n \), for the entailment, contradiction, and neutral classes, respectively. \( P_{e}^{NLI}, P_{c}^{NLI} \) and \( P_{n}^{NLI} \) denote the respective class probabilities. We calculate the persona consistency sub-reward according to:

\[
R_1 = \sum_{f_i \in p} P_{e}^{NLI}(f_i, r) - 2 \sum_{f_i \in p} P_{c}^{NLI}(f_i, r), \quad (4)
\]

where \( P_{e}^{NLI} \) and \( P_{c}^{NLI} \) are the entailment and contradiction probabilities of the relationship between a fact in a persona \( f_i \) and a generated response \( r \).

Persona consistency alone is not sufficient to generate meaningful dialogue, as the agent can maximise consistency merely by repeating the facts in the persona and jumping between topics. The following sub-rewards prevent such behavior and improve the fluency of responses.
**Topic consistency sub-reward (R2)** As shown by See et al. (2019), the semantic relatedness of responses to dialogue history is important for engaging, human-like dialogue. Therefore, we define the topic consistency sub-reward by computing the cosine similarity, as a proxy for semantic relatedness, between the vector representations of a response, \(v_r\) and a query, \(v_q\). We obtain the vector representations from a pretrained BERT model as sub-reward \(R_2\):

\[
R_2 = \cos(v_r, v_q),
\]

where \(v_r\) and \(v_q\) are obtained by averaging the second-to-last hidden layer of the pretrained BERT model for a query \(q = u_{T-1}\) and a generated response \(r\), respectively. \(R_2\) encourages the agent to generate a response that is semantically related to the given query.

**Fluency sub-rewards (R3.1 and R3.2)** Given only the persona and topic consistency sub-rewards, the agent could repeat the vocabulary from its persona and dialogue history. Therefore, we add further sub-rewards to our reward function that promote fluency and deter repetition. The first fluency sub-reward employs a language model trained on a set of human-human dialogues to estimate whether a given response is likely in a realistic conversation. We fine-tune a pretrained OpenAI GPT model (Radford et al., 2019), which is a transformer-based language model, on dialogue utterances (details in Section 3.3), to adapt the model to the language style used in dialogue. We use the log-probability of a generated response estimated by our language model as a gauge of its fluency:

\[
R_{3.1} = -\frac{1}{m} \sum_{k=1}^{m} \log P^{LM}(r_k| r < k),
\]

where \(P^{LM}\) indicates the probability of generating token \(r_k\) given its preceding tokens in response \(r\). The log probability is normalized by response length \(m\) to ensure that longer responses are not discouraged.

See et al. (2019) show that repeated tokens in an utterance correlate highly negatively with the fluency and humanness of responses perceived by human judges. We therefore define another language quality sub-reward using the frequency of repeated tokens:

\[
R_{3.2} = 1 - \frac{\# \text{uni.grams}}{m},
\]

While trivial responses such as “I don’t know” have high fluency, they would lead to low-quality conversations. However, the agent is prevented from generating such responses by the other sub-rewards, which give such responses low rewards.

**Weight optimization** In combination, the sub-rewards reinforce consistency with the persona and across responses in a dialogue, as well as fluent, non-repetitive language. The weights must be selected to ensure a suitable balance between the sub-rewards. We apply a grid-search approach over the weights and choose the values with the best performance on the validation set.

**2.2 DeepRL: Actor-Critic**

The goal of training a dialogue agent by reinforcement learning is to learn a policy that maximises the expected reward of responses sampled from the agent’s policy:

\[
\max_{\theta} \mathcal{L} = \max_{\theta} \mathbb{E}_{(d,p) \in D} \left[ R(r, (d, p)) \right]
\]

where \((d, p)\) is a pair of a dialogue history and a persona for which we want to generate a response. We optimise function \(\mathcal{L}\) by policy gradient methods, where the gradient of \(\mathcal{L}\) is:

\[
\frac{\partial \mathcal{L}}{\partial \theta} = \mathbb{E}_{(d,p) \in D} \left[ R(r, (d, p)) \frac{\partial \log P_\theta(r|(d, p))}{\partial \theta} \right].
\]

Previous RL-based dialogue agents use the REINFORCE method (Williams, 1992) to approximate the above gradient. However, since REINFORCE estimates rewards by sampling from an exponential number of possible actions (the sequence of subsequent words), the estimated rewards have very high variance. Therefore, we propose to combine our transformer-based dialogue agent with the actor-critic learning method (Mnih et al., 2016). This approach reduces the variance in the estimated gradient by sampling a single response \(r \sim P(d,p)\) and computing the difference between its reward \(R(r, (d, p))\) and the reward predicted by a critic, \(\eta(r < k)\), for the actions up to position \(k\). The gradient in Equation 9 is now approximated as follows:

\[
\frac{\partial \mathcal{L}}{\partial \theta} \approx \sum_{k=1}^{m} (R(r, (d, p)) - \eta(r < k)) \frac{\partial}{\partial \theta} \log P_\theta(r_k),
\]

where \(\eta(r < k) = w^T h_k\), \(w\) is trainable parameters of our critic and \(h_k\) is the response decoder.
state representation at position \( k \). We train the critic by minimising the error between the future reward estimated by the critic and the delayed reward:

\[
L^{cr} = \mathbb{E}_{x \in D} \sum_{y \sim P(x)} (\eta(y < t) - R(y, x))^2. \tag{11}
\]

Compared to naïve Monte Carlo reinforcement learning methods such as REINFORCE used by previous work on dialogue systems (Li et al., 2016b), actor-critic reduces sampling biases for large action spaces (Mnih et al., 2016). The \( \eta \) model is robust to biases caused by rare response words that appear in few personas, as those words have very small probabilities, so consequently have a small effect on the expectation in Equation 11. The other advantage of the above method is that the critic has only a small number of parameters for training (the size of the state representation, \( h_k \)). Consequently, a small number of samples are needed for training.

3 Experiments

First, we validate the models that we use for the sub-rewards (defined in Section 2) on their relevant datasets (Section 3.2 and Section 3.3). Then, we assess to what extent our complete DeepRL approach, which uses the complete reward, leads a dialogue agent to generate consistent and fluent responses compared with its fully-supervised counterpart (Section 3.4). Finally, we perform a human evaluation and error analysis on responses generated by these models (Section 3.5).

3.1 The PERSONACHAT Dataset

Our three experiments make use of datasets built upon the PERSONACHAT dataset (Zhang et al., 2018), which consists of dialogues, in English, with 6 to 8 utterances between pairs of human crowd-workers. The workers were assigned short text facts representing personas and instructed to talk to their dialogue partner naturally to discover each other’s persona. We choose this dataset because of its size, the breadth of topics it covers, and its focus on promoting engaging conversations by grounding conversation in the facts presented in personas. We use the standard splits of the version of PERSONACHAT made available in ParlAI as the benchmark dataset for the ConvAI2 challenge (Dinan et al., 2019) to train and evaluate our agent. The numbers of dialogues in the training and validation sets are 17,878, and 1,000, respectively. The test set is hidden for the competition, so we compare our model with the winner of the competition (Wolf et al., 2018) on the validation set. The dataset contains 1,155 personas, among which 200 personas are used only for the dialogues in the validation set and never used for training. On average each persona description has 8.3 unique dialogues. Table 1 shows a speaker persona and an example dialogue with that persona.

3.2 Exp1: NLI for Persona Consistency

In this experiment, we investigate the choice of NLI model for sub-reward \( R_1 \) by comparing several recent NLI models for predicting entailment labels.

Dialogue NLI dataset We train NLI models for sub-reward \( R_1 \) on the dialogue NLI dataset (Welleck et al., 2019), which consists of a set of fact-utterance or fact-fact pairs and their human-annotated language inference relationships, i.e., entailment, contradiction, and neutral. The facts and utterances were extracted from the PERSONACHAT dataset. Two examples of a fact and utterance pair from the dataset are: “My dad is a priest.” contradicts “Since my dad is a mechanic we had mostly car books.”; “I like playing basketball” entails “I prefer basketball. Team sports are fun.”.

This dataset contains 310,110 training pairs, 16,500 validation pairs and 16,500 test pairs. Besides the standard test set, which was annotated by one crowd-worker, there is also a gold-standard test set (Test Gold) containing 12,376 of the test pairs, which was annotated by three crowd-workers.

Experimental settings We use bert-base-uncased (Devlin et al., 2018) as the core of our NLI model for \( R_1 \). The maximum input sequence length is 128. The training and evaluation batch sizes are 32 and 8, respectively. We set the learning rate to \( 5 \times 10^{-5} \) and train the model for 3 epochs.

We compare our BERT-based NLI model with (1) the majority class as a baseline; (2) Enhanced Sequential Inference Model (ESIM) (Chen et al., 2017), an LSTM-based NLI model with intersentence attentions; (3) InferSent (Conneau et al.,
Table 2: The accuracy of different NLI models on the dialogue NLI dataset.

| Model                  | Validation | Test | Test Gold |
|------------------------|------------|------|-----------|
| Majority               | 33.33      | 34.54| 34.96     |
| InferSent w/o response | 55.98      | 57.19| 51.52     |
| InferSent pre-trained  | 47.86      | 46.36| 47.03     |
| InferSent              | 85.82      | 85.68| 89.96     |
| ESIM                   | 86.31      | 88.20| 92.45     |
| Our NLI model          | 86.84      | 89.50| 93.60     |

Table 2, an utterance encoder using a bidirectional LSTM followed by a max-pooling over the output states; (4) **InferSent with pretraining** (Gururangan et al., 2017), which is identical to InferSent but is pretrained on the SNLI dataset (Bowman et al., 2015); and (5) **InferSent w/o response** (Poliak et al., 2018), which is InferSent with pretraining without response inputs during evaluations.

**Evaluation metric** Following Welleck et al. (2019), we compare NLI models using accuracy.

**Results** Table 2 shows the accuracy of different NLI systems for the persona consistency task. Our persona-based NLI model outperforms all other models tested and defines a new state-of-the-art for this task. This supports the use of our proposed NLI model for computing sub-rewards $R_1$.

### 3.3 Exp2: Fluency Estimation

Sub-reward $R_{3.1}$ requires a language model to measure the quality of a generated response. In this experiment, we investigate if fine-tuning a pretrained, non-dialogue language model on dialogue utterances improves its performance for assessing responses.

**Dataset** We train and evaluate the language model on the training set of PERSONACHAT by uniformly sampling 90% of utterances ($\approx 236,588$) from the PERSONACHAT training set to train our dialogue language model, then evaluating on the remaining 10% ($\approx 26,288$ utterances).

**Experimental settings** We fine-tune the OpenAI-GPT language model for three epochs on the sampled training set. The training and validation batch sizes are 8 and 16, respectively. The learning rate is $6.25 \times 10^{-5}$. We compare (1) **Non-Dialogue LM**, which is the OpenAI-GPT language model with no fine-tuning; and (2) **Dialogue LM**, which is the OpenAI-GPT language model fine-tuned on dialogue utterances.

**Evaluation metric** Following previous work, we use perplexity (PPL). Lower PPL scores are better.

**Results** Table 3 shows the impact of fine-tuning the language model on dialogue utterances. We observe a substantial improvement in perplexity, showing that the fine-tuned language model better captures the type of language used in dialogue utterances. This suggests that fine-tuning the language model on in-domain dialogue data could lead to a more suitable model for sub-reward $R_{3.1}$.

| Model        | PPL  |
|--------------|------|
| Non-Dialogue LM | 108.29 |
| Dialogue LM   | 10.01 |

Table 3: The perplexity (PPL) of the pretrained GPT language model (Non-Dialogue LM) substantially improves after fine-tuning on dialogue utterances.

### 3.4 Exp3: Dialogue Generation Assessment

Here, we study to what extent our proposed deep reinforcement learning method leads a dialogue agent to generate persona-consistent and fluent responses.

**Experimental settings** We refer to our agent described in Section 2 as **DeepRL-Trans**. In this agent, the transformer that represents the state and generates actions is the pretrained OpenAI-GPT model. Inspired by Ranzato et al. (2016), we initialise our DeepRL-Trans agent using a general response generation policy learned from a fully supervised setting. We train our model on the PERSONACHAT training set for three epochs in the fully supervised scenario, and then perform one epoch DeepRL training on the 90% of the training set. We use the rest of the training set to choose the weights of sub-rewards in Equation 2 based on the performance of the model (F1). The weights are $\gamma_1 = 0.4$, $\gamma_2 = 0.16$, $\gamma_3 = 0.22$ and $\gamma_4 = 0.22$. The list of all examined weight sets is in the Appendix.

On the PERSONACHAT validation set, we compare our method to the following dialogue agents.

**Seq2Seq+Att** This dialogue agent encodes a persona and a dialogue history using an LSTM encoder and then utilises an LSTM decoder with attention to generate a response. This model is
trained using supervised learning with reference responses.

**SupL-Trans** This agent is the generative dialogue model of the TransferTransfo agent (Wolf et al., 2018). This agent performs the best in terms of automatic evaluation and the second-best in human evaluation among 26 participants in the ConvAI2 competition. TransferTransfo consists of a generative and a ranking dialogue model. The former model addresses the response generation task and the latter deals with the response ranking task. The agent is optimised to achieve the best scores for both competition tasks by combining the respective loss functions. Since we focus on generative dialogue agents, following Wolf et al. (2018) we train the agent for both tasks, and then use its generative model for evaluations.

**Evaluation metrics** Following ConvAI2 (Dinan et al., 2019), we report perplexity (PPL), F1, and BLEU to assess the quality of generated responses compared with reference responses. Alongside these, we introduce the persona-consistency metric, PC, to measure the consistency of generated responses with facts in personas:

\[
PC = 100 \frac{N_e - N_c + N_n}{N},
\]

where \(N_e\), \(N_c\), and \(N_n\) are the numbers of entailment, contradiction, and neutral inference relations between responses generated by an agent and the facts describing the persona of the agent. \(N\) is the total number of response-fact pairs. To compute \(N_e\), \(N_c\), and \(N_n\), we use our NLI model (used for \(R_1\) in Section 2) to assign inference relations between each response in the generated dialogue and each fact in the persona. However, as human dialogue partners do not have perfect persona consistency themselves, we take the PC score of the model relative to the human PC score to give the relative PC metric, rPC:

\[
rPC = 1 + \frac{1}{100} (PC^{model} - PC^{human}).
\]

Higher rPC scores indicate higher persona consistency.

**Results** Table 4 shows the performance of different dialogue agents in dialogue response generation.

| Model       | PPL | F1  | BLEU | PC     | rPC  |
|-------------|-----|-----|------|--------|------|
| Seq2Seq+Att | 35.07 | 16.82 | 0.062 | 94.97  | −0.93 |
| SupL-Trans  | 21.31 | 17.06 | 0.065 | 96.36  | +0.46 |
| DeepRL-Trans| 22.64 | 17.78 | 0.067 | 96.49  | +0.59 |
| Human       | -   | -   | 1.0  | 96.89  | 1.0   |

Table 4: Dialogue quality metrics for three agents, showing that involving persona information improves persona consistency.

DeepRL-Trans outperforms the alternative methods on all metrics except PPL, including the PC and rPC scores. Looking at persona consistency in detail, we find that the percentage of responses that are entailed from personas increases with DeepRL-Trans compared to SupL-Trans from 11.14% to 14.81%. Importantly, the percentage of contradicting responses reduces from 1.82% to 1.75%, while the percentage of responses with neutral relations also reduces from 87.04% to 83.43%. These results confirm the validity of our DeepRL approach for generating persona-consistent responses.

Table 1 shows an example persona, dialogue history and the responses generated by the SupL-Trans and DeepRL-Trans agents. We observe that DeepRL-Trans generates a response that is not only related to the persona but also to the topics in the dialogue history. In its response, the DeepRL-Trans agent connects their response to the previous topic of conversation (“i’ve a weakness for chips”) then reveals some related information about themselves from the persona (“i love to cook”). In contrast, SupL-Trans states facts that contradict both the persona and their previous utterances.

3.5 Exp4: Human Evaluation and Error Analysis

Finally, we conduct a human evaluation between the SupL-Trans and DeepRL-Trans agents. We randomly select 100 samples, where each sample consists of a sub-sequence of utterances from a dialogue history, a speaker’s persona, and the responses generated by these agents. We ask seven human judges (two native and five fluent English speakers) to rate the fluency of each sampled response with a score ranging from 1 to 5, encompassing grammatical correctness, low repetitiveness, and coherence of the generated responses. The human judges are able to see both the dialogue history up to the response as well as the persona facts. We also ask the judges to assign a consis-
tency label from \{consistent, neutral, contradicting\} to the response concerning the facts in the speaker’s persona (for full instructions, please see the Appendix).

| Consistent | Neutral | Contradicting |
|------------|---------|---------------|
| SupL-Trans | 43.71   | 38.58         | 17.71         |
| DeepRL-Trans | 52.71   | 33.29         | 14.00         |
| ∆          | 9.00↑   | 5.29↓         | 3.71↓         |

Table 5: The average percentages (%) of the consistency labels between responses generated by the SupL-Trans and DeepRL-Trans agents and personas. ∆ presents the differences between the numbers in the first and the second rows.

| DeepRL-Trans label | Consistent | Neutral | Contradicting |
|--------------------|------------|---------|---------------|
| SupL-Trans Consistent | 57.46     | 27.73   | 14.82         |
| Trans Neutral      | 46.87     | 44.99   | 08.14         |
| Label Contradicting | 52.48     | 22.05   | 25.47         |

Table 6: Each row corresponds to the samples in the human evaluation for which SupL-Trans received a particular consistency label. The values in each row show the percentages of consistency labels for DeepRL-Trans for the same data points.

Results Table 5 shows the average fraction (%) of consistency labels in the responses generated by SupL-Trans and DeepRL-Trans. The number of consistent responses increases by 9% when DeepRL is used, while the number of contradictions decreases by 3.71%, confirming that our proposed DeepRL method reduces the persona inconsistency problems compared to supervised approaches. The number of neutral responses also decreases when DeepRL is used. As most neutral responses are generic and could be used with different personas and dialogue histories, a decrease in neutral responses shows that DeepRL-Trans generates more persona-specific responses than its supervised peer.

Table 6 presents the distributions of consistency labels for DeepRL-Trans’s responses given the consistency labels for SupL-Trans’s response. For the majority of samples whose SupL-Trans responses are contradictory or neutral, DeepRL-Trans generates consistent responses, confirming the appropriateness of our approach. DeepRL-Trans generates contradictory responses for some samples whose SupL-Trans responses are consistent with their personas. This may be due to errors in the NLI model’s predictions of entailment, hence a more accurate NLI model may improve the quality of the reward function and consequently the consistency of responses. Alternatively, these contradictory responses may receive high rewards from the topic consistency and fluency sub-rewards, which could override R1.

Table 7 shows that the human raters found DeepRL-Trans’s responses more fluent than SupL-Trans’s responses, showing the advantage of our fluency and topic-consistency sub-rewards over learning from reference responses.

| Model     | Fluency |
|-----------|---------|
| SupL-Trans | 3.33    |
| DeepRL-Trans | 3.50   |

Table 7: The average fluency scores assigned by human judges. Higher is better.

4 Related Work

In the literature, there are two types of approach to grounding dialogue models in a speaker’s persona. The first category includes approaches that learn speaker-level vectors from dialogues produced by a particular speaker. For example, Li et al. (2016a) learn a vector representation for each speaker, which they use in the response decoding phase of a seq-to-seq dialogue generating model. Similarly, Madotto et al. (2019) learn persona vectors to eliminate the need for the explicit definition of persona. These approaches depend on the availability of suitable dialogues performed by the speaker whose persona we wish to imitate. If those dialogues do not reveal the persona information, then models cannot learn the speaker’s persona. A major limitation of these approaches is that the model cannot be adapted to new, explicitly defined speaker personas at test time, since the speaker vectors must be learned from training data.

The second category includes approaches that rely on an explicit list of facts about the speaker’s persona. For example, Zhang et al. (2018) propose a key-value memory neural model to encode those facts and then use this memory in the response decoding phase of a seq-to-seq model.

Persona consistency was also a topic of the ConvAI dialogue generation competition (Dinan et al., 2019), which uses the dataset and baseline models proposed by Zhang et al. (2018). Several participants used transformers to generate and rank
responses, including the top-performing Transfer-transfo agent (Wolf et al., 2018), whose generative model, SupL-Trans, was tested in our experiments. However, to date all entrants have relied on supervised techniques rather than reinforcement learning. Our experiments showed that reinforcement learning methods can improve persona consistency by explicitly accounting for it in the reward function.

DeepRL has been extensively used for training a policy for task-oriented dialogue agents, which aim to fulfill a goal-oriented request such as booking a table in a restaurant (Su et al., 2016; Nogueira and Cho, 2017; Liu et al., 2018). Unlike task-based dialogue, incorporating personas is a less well-defined task as there is no easily measurable outcome to test whether the goal has been achieved.

Recent research has also used DeepRL to train open-domain dialogue agents (Li et al., 2016b; Li and Jurafsky, 2017), but unlike our work, it has not explored the benefits of DeepRL for making generated responses consistent with given personas. Additionally, previous work uses the REINFORCE algorithm to train dialogue agents, which is known for being slow, unstable, and with high-variance when rewards are sparse and delayed until the end of a task episode, as in dialogue response generation (Mnih et al., 2016). In this paper we showed how to adopt the actor-critic method (Bahdanau et al., 2016) to overcome these weaknesses.

5 Conclusions

We proposed a novel method for reinforcing information about a speaker’s persona into responses while maintaining topic consistency and fluency. Our method employs a new reference-agnostic reward function to train an agent using an actor-critic reinforcement learning approach. Both automatic and human evaluations on the PERSONACHAT dataset confirm that our deep reinforcement learning approach increases the rate of persona-consistent responses compared to a state-of-the-art, fully supervised approach. Furthermore, the responses of our reinforcement learning-based agent are perceived to be more fluent than those generated by the fully supervised agent. In the future, we plan to investigate whether speakers with certain personas have a specific language style, and if so, how to incorporate this information when training our agent. Future work may also consider alternative methods for choosing the sub-reward weights. While we found grid search effective, more precise optimization may lead to further performance gains.

Acknowledgments

This work was supported by the German Research Foundation through the German-Israeli Project Cooperation (DIP, grant DA 1600/1-1 and grant GU 798/17-1).

References

Christoph Alt, Marc Hübner, and Leonhard Hennig. 2019. Fine-tuning pre-trained transformer language models to distantly supervised relation extraction. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), Florence, Italy, 28 July – 2 August 2019, pages 1388–1398.

Dzmitry Bahdanau, Philemon Brakel, Kelvin Xu, Anirudh Goyal, Ryan Lowe, Joelle Pineau, Aaron Courville, and Yoshua Bengio. 2016. An actor-critic algorithm for sequence prediction. In The 5th International Conference on Learning Representations (ICLR 2017), Toulouse, France, 24–26 April 2017.

Rafael E. Banchs. 2012. Movie-DiC: A movie dialogue corpus for research and development. In Proceedings of the 50th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers), Jeju Island, Korea, 8–14 July 2012, pages 203–207.

Samuel R. Bowman, Gabor Angeli, Christopher Potts, and Christopher D. Manning. 2015. A large annotated corpus for learning natural language inference. In Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, Lisbon, Portugal, 17–21 September 2015, pages 632–642.

Qian Chen, Xiaodan Zhu, Zhen-Hua Ling, Si Wei, Hui Jiang, and Diana Inkpen. 2017. Enhanced LSTM for natural language inference. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), Vancouver, Canada, 30 July – 4 August 2017, pages 1657–1668.

Alexis Conneau, Douwe Kiela, Holger Schwenk, Loïc Barrault, and Antoine Bordes. 2017. Supervised learning of universal sentence representations from natural language data. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, Copenhagen, Denmark, 7-11 September 2017, pages 670–680.
Jacon Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. BERT: pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805.

Emily Dinan, Varvara Logacheva, Valentinn Malykh, Alexander H. Miller, Kurt Shuster, Jack Urbanek, Douwe Kiela, Arthur Szlam, Silvan Serban, Ryan Lowe, Shriraj Prabhumoye, Alan W. Black, Alexander I. Rudnicky, Jason Williams, Joelle Pineau, Mikhail Burtsev, and Jason Weston. 2019. The second conversational intelligence challenge (ConvAI2). CoRR, abs/1902.00998.

Nouha Dziri, Ehsan Kamalloo, Kory Mathewson, and Osmar Zaiane. 2019. Evaluating coherence in dialogue systems using entailment. 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), Minneapolis, Minnesota, 2–7 June 2019, pages 3806–3812.

Marjan Ghazvininejad, Chris Brockett, Ming-Wei Chang, Bill Dolan, Jianfeng Gao, Wen-Tau Yih, and Michel Galley. 2018. A knowledge-grounded neural conversation model. In Proceedings of the 53rd Conference on Artificial Intelligence, New Orleans, Louisiana, 2–7 February 2018, pages 5110–5117.

Suchin Gururangan, Swabha Swayamdipta, Omer Levy, Roy Schwartz, Benjamin Bowman, and Noah A. Smith. 2017. Annotation artifacts in natural language inference data. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), New Orleans, Louisiana, 1–6 June 2018, pages 107–112.

Chenyang Huang, Osman Zaiane, Amine Trabelsi, and Nouha Dziri. 2018. Automatic dialogue generation with expressed emotions. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 2 (Short Papers), New Orleans, Louisiana, 1–6 June 2018, pages 49–54.

Ganesh Jawahar, Benoît Sagot, and Djamé Seddah. 2019. What does BERT learn about the structure of language? In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), Florence, Italy, 28 July – 2 August 2019, pages 3651–3657.

Wei-Jen Ko, Greg Durrett, and Junyi Jessy Li. 2019. Linguistically-informed specificity and semantic plausibility for dialogue generation. 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), Minneapolis, Minnesota, 2–7 June 2019, pages 3456–3466.

Jiwei Li, Michel Galley, Chris Brockett, Georgios Spithourakis, Jianfeng Gao, and Bill Dolan. 2016a. The second conversational intelligence challenge (ConvAI2). CoRR, abs/1902.00998.

Jiwei Li, Will Monroe, Alan Ritter, and Dan Jurafsky. 2017. Neural net models of open-domain discourse coherence. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, Copenhagen, Denmark, 7–11 September 2017, pages 198–209.

Jiwei Li, Will Monroe, Tianlin Shi, Sébastien Jean, Alan Ritter, and Dan Jurafsky. 2017. Adversarial learning for neural dialogue generation. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, Copenhagen, Denmark, 7–11 September 2017, pages 2157–2169.

Bing Liu, Gokhan Tür, Dilek Hakkani-Tür, Pararth Shah, and Larry Heck. 2018. Dialogue learning with human teaching and feedback in end-to-end trainable task-oriented dialogue systems. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), Melbourne, Australia, 15–20 July 2018, pages 2060–2069.

Andrea Madotto, Zhaojiang Lin, Chien-Sheng Wu, and Pascale Fung. 2019. Personalizing dialogue agents via meta-Learning. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), Florence, Italy, 28 July – 2 August 2019, pages 5454–5459.

Volodymyr Mnih, Adria Puigdomenech, Badia Mehdri Mirza, Alex Graves, Timothy Lillicrap, Tim Harley, David Silver, and Koray Kavukcuoglu. 2016. Asynchronous methods for deep reinforcement learning. In Proceedings of The 33rd International Conference on Machine Learning, New York, New York, 20–22 Jun 2016, pages 1928–1937.

Rodrigo Nogueira and Kyunghyun Cho. 2017. Task-oriented query reformulation with reinforcement learning. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, Copenhagen, Denmark, 7–11 September 2017, pages 574–583.

Zhufeng Pan, Ke Bai, Yan Wang, Lianqiang Zhou, and Xiaojiang Liu. 2019. Improving open-domain dialogue systems via multi-turn incomplete utterances. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing.
A Weight optimization

We examine various weight sets \( (\gamma_1, \gamma_2, \gamma_3, \gamma_4) \) to balance the contribution of sub-rewards in the complete reward function on the validation set. Table 8 shows the those weights.

| \(\gamma_1\) | \(\gamma_2\) | \(\gamma_3\) | \(\gamma_4\) | F1   |
|----------|----------|----------|----------|------|
| 0.00     | 0.00     | 0.00     | 0.00     | 02.04|
| 1.00     | 0.00     | 0.00     | 0.00     | 16.34|
| 0.00     | 1.00     | 0.00     | 0.00     | 16.12|
| 0.00     | 0.00     | 1.00     | 0.00     | 12.77|
| 0.00     | 0.00     | 0.00     | 1.00     | 17.91|
| 0.70     | 0.00     | 0.30     | 0.00     | 16.37|
| 0.65     | 0.00     | 0.35     | 0.00     | 19.90|
| 0.60     | 0.00     | 0.40     | 0.00     | 16.98|
| 0.50     | 0.25     | 0.25     | 0.25     | 18.27|
| 0.60     | 0.20     | 0.00     | 0.20     | 15.54|
| 0.40     | 0.20     | 0.20     | 0.20     | 20.57|
| 0.40     | 0.16     | 0.22     | 0.22     | 20.75|
| 0.45     | 0.13     | 0.17     | 0.20     | 19.98|
| 0.47     | 0.12     | 0.17     | 0.20     | 19.95|
| 0.47     | 0.10     | 0.17     | 0.21     | 20.33|
| 0.47     | 0.10     | 0.19     | 0.19     | 19.73|
| 0.50     | 0.10     | 0.16     | 0.20     | 19.10|
| 0.40     | 0.16     | 0.22     | 0.22     | 19.56|
| 0.40     | 0.20     | 0.15     | 0.20     | 19.34|
| 0.43     | 0.20     | 0.12     | 0.20     | 20.22|
| 0.45     | 0.20     | 0.12     | 0.20     | 20.13|
| 0.45     | 0.25     | 0.00     | 0.25     | 17.40|
| 0.40     | 0.10     | 0.25     | 0.25     | 18.93|
| 0.40     | 0.15     | 0.20     | 0.20     | 19.80|
| 0.40     | 0.20     | 0.20     | 0.15     | 20.44|
| 0.45     | 0.17     | 0.21     | 0.17     | 18.85|
| 0.50     | 0.15     | 0.15     | 0.15     | 20.25|
| 0.47     | 0.13     | 0.20     | 0.15     | 19.97|
| 0.50     | 0.15     | 0.20     | 0.15     | 17.64|
| 0.55     | 0.15     | 0.15     | 0.10     | 19.15|

Table 8: The examined sub-reward weights and their corresponding F1 on the validation set.

B Human Evaluation

For each sample, we show to each participant a set of facts describing a persona, a dialogue history, and the response generated by one of the SupL-Trans and the DeepRL-Trans to each participant. We instruct our participants to assess fluency according to the following objective definition: “grammatical correctness, lowest repetitiveness, and coherence”. The fluency rates are integer values between 1 and 5, where 5 is most fluent.

To measure persona consistency, we instruct participants as follows:

An answer is considered consistent if and only if

- it is relevant to any of the given persona description sentences

An answer is considered neutral:

- it **does not contradict** either the dialogue history or the persona description
- it **is not relevant** to any of the given persona description sentences.