ABSTRACT
Maintaining a consistent persona is essential for building a humanlike conversational model. However, the lack of attention to the partner makes the model more egocentric: they tend to show their persona by all means such as twisting the topic stiffly, pulling the conversation to their own interests regardless, and rambling their persona with little curiosity to the partner. In this work, we propose COSPLAY (Concept Set guided Personalized Dialogue Generation Across both Party Personas) that considers both parties as a “team” expressing self-persona while keeping curiosity toward the partner, leading responses around mutual personas, and finding the common ground. Specifically, we first represent self-persona, partner persona and mutual dialogue all in the concept sets. Then, we propose the Concept Set framework with a suite of knowledge-enhanced operations to process them such as set aggregation, set expansion, and set distance. Based on these operations as medium, we train the model by utilizing 1) concepts of both party personas, 2) concept relationship between them, and 3) their relationship to the future dialogue. Extensive experiments on a large public dataset, Persona-Chat, demonstrate that our model outperforms state-of-the-art baselines for generating less egocentric, more human-like, and higher quality responses in both automatic and human evaluations.

CCS CONCEPTS
• Computing methodologies → Discourse, dialogue and pragmatics; Natural language generation; Knowledge representation and reasoning; • Information systems → Personalization.

KEYWORDS
Personalized Dialogue Generation; Knowledge Concept Set; Mutual Benefit; Common Ground Modeling; Reinforcement Learning.

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SIGIR `22, July 11–15, 2022, Madrid, Spain
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ACM ISBN 978-1-4503-8732-3/22/07 $15.00
https://doi.org/10.1145/3477495.3531957

1 INTRODUCTION
Building a more human-like dialogue system has been an important topic in artificial intelligence, where one of the main challenges is to maintain a consistent persona such as age, gender, occupation, etc. [11, 13, 20, 21, 26, 34, 46]. More recently, a more direct approach, defining the persona as several profile sentences, was proposed with a novel dataset Persona-Chat [41]. This task required models to generate responses consistent with several persona sentences (Formula 1) [41]. Due to the flexibility for users to describe complicated, compositional profile and to choose whoever they want to talk with, the dataset sparked a wide range of interest in developing methods on generating the persona-consistent responses [3, 5, 17, 29, 37, 40, 41, 44]. To better control the consistency, some additional work were made to further enhancing the persona understanding of the model [16, 27, 28]: Song et al. [27] introduced unlikelihood training with non-dialogue inference data to strengthen consistency understanding. Liu et al. [16] utilized a finegrained consistency reward model trained by negative sampling to reinforce consistency understanding of the model. Song et al. [28] integrated a matching model to detect and delete inconsistent words and further rewrite it to a persona-consistent one.

However, as an increasingly amount of efforts have been devoted to encourage persona-consistent responses, the agents tend to be more and more egocentric; they tend to demonstrate their own persona information by all means while show less interests about the partner’s. Here we take the examples in Figure 1 to further illustrate this phenomenon. In line 11, in response to the question “what is your family like?”, one baseline model replies “They are okay, but I like to sing in the park”. We can see that in order to express its own persona “I love to sing songs” eagerly, the model hastily and bluntly twists the topic by using an inappropriate transitional word “but”, resulting in an illogical response. Considering another answer “They like sing songs” where the baseline who even cannot be bothered to transit the topic just grafts its own persona “I love to sing songs” to their family, which indicates that over focusing its own persona instead makes the response inconsistent. There is another example in line 16. When a user says “Great! I like music too and that’s why I play guitar”, we, as human beings, can easily feel that he is very looking forward to further interacting and resonating with us in terms of his persona “music” and “guitar.”
The expected responses should be "That’s awesome to hear!" or "Do you play in a band?". However, the baselines ignore the user’s emotion and just pull the conversation to their own personas again by starting the response with first-person pronouns: "I love to sing songs" or "I have a friend" without showing any interests or further questions about the partner persona because giving the partner more opportunities to express "sacrifices" the chances to show its own persona. However, this also "sacrifices" the user experience and the model interactivity.

We argue that the key difference between the personalization and egocentrism lies in whether the self-persona expression sacrifices the partner’s. In everyday life conversations, referring to the examples in Figure 1 again, we do a great job in balancing self-expression, asking questions to the partner (e.g., "I just got back from Disney world. Do you like it?" in line 8) and giving the partner more opportunities to express persona (e.g., "Do you play in a band?" to respond "I play guitar" in line 18). In addition, with the partner’s persona acquired, we try to lead the conversation around both self and partner’s persona by bridging them (e.g., "My parents[← family] are very nice, but they do not like my singing[← sing songs]" in line 15) or finding the common ground between them (e.g., "music"/"guitar" ← band ← "sing"/"songs" in line 18), which shows that what we know from the partner’s persona decides what information to choose from our persona when building the response. From all examples above, we can see that giving enough attention to the partner’s persona plays an important role in generating less egocentric responses and making a big contribution to generate realistic conversations.

In this paper, we view self and partner as a "team" to capture this global consistency with the proposed model COSPLAY (COntent Set guided PersonaLized dialogue generation Across both party personas) that can 1) balance "answering" and "asking", expressing itself while being curious about the partner’s persona which gives the partner more opportunities to express, 2) balance "speaking" and "listening", leading responses around mutual personas and finding the common ground.

Motivated by this, our research starts by asking: How to encourage the model to ask question frequently and give the partner more chance to express persona in a generative way? Naively inserting general predefined question templates makes response stiff and unable to ask concrete questions in different context. What we only know is that if everyone is willing to give the partner more chances to express persona, then the persona information of both parties will be recalled in the future dialogue. Motivated by this, we train the model in a lookahead way. Specifically, we let the model interactivity by applying ConceptNet in the personalized dialogue generation and propose COSPLAY to achieve a new consistency paradigm: being curious about the partner, leading conversation around mutual personas, and finding the common ground.

Next, the second question is: How to fuse both party personas and automatically find the common ground? Supported by Concept Set, COSPLAY uses a concept copy mechanism trained to copy information from both sides (concepts of self-persona and the partner’s one shown in the context). Furthermore, to also explore and introduce concepts connecting them, Common Ground Reward is designed where we regard both party personas as two constraints and simultaneously minimize the concept set distances from the future dialogue to each of them in a geometrical way.

In summary, our key contributions are as follows:

- We take the first step towards addressing the problem of egocentrism by applying ConceptNet in the personalized dialogue generation and propose COSPLAY to achieve a new consistency paradigm: being curious about the partner, leading conversation around mutual personas, and finding the common ground.
- We explore a new way for the usage of ConceptNet and propose the Concept Set framework: modeling personas and dialogues across concept sets and using set operations to calculate their relationships. Driven by Concept Set, COSPLAY utilizes both concept set and concept set relationships to guide the model and
operates knowledge in parallel computing, without the need to construct a sub-graph, search in the whole graph, or do one or multi-hop reasoning during the generation.

- We find an efficient way to encourage dialogue agent to be curious about the partner by Mutual Benefit Reward that utilizes the concept relationship between the future generated dialogue and both party personas. Moreover, to encourage the model to find the common ground, we design Common Ground Reward by viewing both party personas as two constraints and make use of the concept relationship between them to train the model.
- Experiments on PersonA-Chat demonstrate that our model COSPLAY, by giving more attention to the partner, can generate less egocentric, more human-like, and higher quality responses.

2 RELATED WORK

2.1 Personalized Dialogue System

Open-domain dialogue systems have long been an important and challenging task in the field of AI. Although neural response generation models have achieved promising results [25, 42, 43], they are still unsatisfactory. One possible reason is that they lack a consistent personality. Li et al. [13] is the first to propose a personalized dialogue system for improving response consistency. Zhang et al. [41] introduced the PersonA-Chat. The dataset facilitated the training of chatbots with predefined textually described persona sentences and sparked a wide range of interest in developing both retrieval and generative based personalized dialogue models.

In the line of retrieval-based methods [7, 8, 41], a relevant work was done by Gu et al. [8]. They provide an empirical study on retrieval-based methods and find that it is helpful to utilize both persona sentences into response selection. However, the main drawback of this line of approaches is that selecting responses from a pre-constructed pool cannot satisfy different persona settings such as diverse combinations of occupation and location. Therefore, to produce an informative while consistent responses, a better way is to build generative dialogue models.

In the line of generative-based methods [2, 3, 5, 16, 29, 32, 37, 39–41], with the advancement of the pre-training [22, 23, 33], two-stage methods are applied for personalized dialogue generation such as fine-tuning a pre-trained model on the PersonA-Chat [3, 5, 16, 37]. Our work also follows this line where a relevant work was done by Liu et al. [16]. They train a receiver to reinforce the mutual persona understanding. Specifically, the receiver is trained by negative samples where self utterances are paired with partner persona to obtain fine-grained consistency understanding ability. We borrow the idea that incorporating the partner persona by self-play with several differences in motivation and methodology: 1) The partner persona sentences in their work are used as negative samples to enhance model consistency understanding while we incorporate both party personas as positive samples to alleviate model egocentrism; 2) Considering personas of both sides simultaneously (not separately) and equally (not as negative samples) enables us to further utilize the relationship between them; 3) We incorporate commonsense knowledge to calculate reward without training implicitly reward models.

2.2 Knowledge Enhanced Text Generation

Incorporating external knowledge is essential for text generation to augment the limited information in the context or better achieve tasks [9, 10, 14, 30, 38, 46, 47]. As one of the most common knowledge graphs, ConceptNet [30] is a large-scale multilingual semantic graph that describes general human knowledge in natural language. Each node can be a word or a phrase, and the edges represent the semantic relations between nodes with the confidence score as weights. To enhance emotion perception and expression, Li et al. [14] inject concepts with higher emotion intensity values from ConceptNet into the model in empathetic dialogue generation. Zhou et al. [46] employ graph attention embedding to encode sub-graphs which contains neighbor concepts on ConceptNet in dialogue generation.

Our work also follows this line where a relevant work was done by Liu et al. [16]. They train a receiver to reinforce the mutual persona understanding. Specifically, the receiver is trained by negative samples where self utterances are paired with partner persona to obtain fine-grained consistency understanding ability. We borrow the idea that incorporating the partner persona by self-play with several differences in motivation and methodology: 1) The partner persona sentences in their work are used as negative samples to enhance model consistency understanding while we incorporate both party personas as positive samples to alleviate model egocentrism; 2) Considering personas of both sides simultaneously (not separately) and equally (not as negative samples) enables us to further utilize the relationship between them; 3) We incorporate commonsense knowledge to calculate reward without training implicitly reward models.

In reinforcement fine-tuning phase (Figure 2b), we design two rewards based on the concept relationships to guide the model:
of the shortest path between the concept $v_i$ and the concept $v_j$. Note that the minimum value $d_{ij}$ is set as 0.001 because we distinguish it from zero (this is important when we do mask operation $\circ$ over $D$).

3.2.3 Set Expansion Operation. Set expansion operation (Figure 3b) uses the concepts in the original set $A$ (solid dots) to query their related ones (hollow dots). The process is formulated as follows:

$$\text{Expa}(A; k) = \text{topk}(\min((c^A)^T \circ D), k)$$

where $\circ$ (mask operation) denotes the element-wise multiplication with broadcasting and $\min$ denotes the min pooling operation on row dimension, which can be viewed as classifying each concept $v_i$ to its nearest cluster in the set $A$ by retaining the minimum distance. Finally, we obtain $k$ (parameter) concepts ordered by shortest distances in the final concept set.

3.2.4 Set Union Operation. The union of two concept sets (Figure 3c) contains all the elements stored in either set, which is same as the one in traditional set theory:

$$\text{Union}(A, B) = \lor(c^A, c^B)$$

where $\lor$ denotes the logical or operation over two logical vectors.

3.2.5 Set Intersection Operation. We define the intersection set of two concept sets as $A \cap B = \{v_i \in B \mid \exists v_j \in A \ni d_{ij} < r\}$. Note that this intersection set is not the traditional one in set theory because of the existence of parameter $r$ that enables non-exact matching (if $r \rightarrow 0$, then the operation will degenerate into the traditional intersection operation). Therefore, it is not commutative because we define this intersection as the subset of $B$. The intersection set $A \cap B$ is obtained by the concept set intersection operation (Figure 3d):

$$\text{Inter}(A, B; r) = \lor(0 < M < r)$$

where $M = c^A \odot D \odot (c^B)^\top$
where $M$ is the masked $D$, $r$ is a parameter as the threshold indicating the degree of similarity, and $\lor$ represents logical or operation on the column dimension of the logical matrix ($0 < M < r$).

### 3.2.6 Set Distance Operation
The distance operation (Figure 3e) is to measure the distance between any two concept sets:

$$\text{Dist}(A, B) = \frac{(c^A)^T \cdot D \cdot c^B}{||e^A||_1 \cdot ||e^B||_1}$$

where the intermediate result of $(c^A)^T \cdot D$ is the distance vector representing the distances from $A$ to each concepts. Then the dot product between this distance vector and the $\frac{c^B}{||e^B||_1}$ means that only the distances to the concepts in $B$ are considered.

### 3.3 Concept Set Guided Response Generation

#### 3.3.1 Context Modeling
We adopt the GPT-2 model [23], a $L$ transformer blocks stacked decoder with a classifier at the sequence tail. The input to the model is the concatenation of self-persona sentences $P^S$, history utterances $U_h$, target response $y = u^r_S$ and some special tokens: $(P^S, [SEP], U_h, [SEP], y, [CLS])$. At each time step, we compute the probability of the next token as follows:

$$e^t_0 = e_t + p_t,$$

$$h^t_{\text{Block}} = \text{Block}(W_{\text{LM}} \cdot h^t_{\text{Mask}} + b)$$

where $e_t$ and $p_t$ are the token embedding and the position embedding respectively, $\text{Block}$ is the transformer block with masked self-attention, and $h^t_{\text{Mask}}$ is the final hidden state at the $t$-th time step.

#### 3.3.2 Concept Attention
This module assigns attention probabilities over the expanded concept set. The expanded set is initially extracted from the persona text across both parties. That is, both of the self-persona sentences $P^S$ and the partner last utterance $u^p$ reflecting its persona information are collected (union operation) and expanded (expansion operation) by the concept set operations:

$$e^a = \text{Expa} (\text{Union}(e^{S^a}, e^{P^a}); k)$$

where $e^{S^a}$ and $e^{P^a}$ are two concept sets extracted from $P^S$ and $u^p$ respectively, $\text{Expa}$ (Eq. 2) and $\text{Union}$ (Eq. 3) are two Concept Set operations, and the expanded set $e^a$ with $k$ concepts serves as a utterance-level guide waiting to be copied. Note that though the concepts of both parties are fused into one set, our model will not confuse them since the self-persona sentences $P^S$ are still fed into the Context Modeling module ($\S$3.3.1). Next, in order to keep the generated text grammatically sound, the re-stemming/lemmatization operation first maps each element in set $e^a$ with basic form (explained in §3.2.1) to its correct form with the largest $P^L_{\text{LM}}$ (Eq. 8) in its word group (sing, singing) before being copied: $e^a_t = \text{re}(e^a_t, P^L_{\text{LM}})$. $e^a_t$ can be viewed as a stretched version $e^a$ over the GPT-2 vocabulary but with the same number of elements ($||e^a_t||_1 = ||e^a||_1$). Finally, the attention distribution $[1]$ over the stretched concept set $e^a_t$ at each time step $t$ is calculated as follows:

$$E^a_t = e^a_t \otimes E$$

$$P^c_t = \text{softmax}(\sum_{i=1}^{t} \text{re}(E^a_t, h^t_{i}))$$

where $E$ is the word embedding matrix and $h^t_i$ represents the decoder states (Eq. 8). Next, the distribution is used to produce the concept set states $h^t_{\text{Concept}}$, the weighted sum of its concept embeddings:

$$h^t_{\text{Concept}} = \sum_{i} (P^c_t)^i \cdot e^c_{i}$$

#### 3.3.3 Concept Copy
This module oversees the gate, letting concepts flow in at the appropriate time. Specifically, we use a soft gate probability $P^c_{\text{Gate}}$ which denotes whether to copy a concept from the set. The gate controls the weight of the two distributions, which is similar to the copy mechanism [6, 10, 24]:

$$P^c_{\text{gate}} = \sigma(W_1 \cdot h^c_f + W_2 \cdot h^t_{\text{Concept}} + b)$$

Finally the output distribution is the linear combination of LM distribution and the distribution over the concept set:

$$P_t = P^c_{\text{Gate}} \cdot P^c_t + (1 - P^c_{\text{Gate}}) \cdot P^L_{\text{LM}}$$
Future dialogue is scored as an example. The score can be viewed as a fraction of concepts in the union of self and partner persona concepts $S \cup P$ (closed dots) which are covered by the concepts in the future dialogue $F$ (open dots).

and the generation loss for the response is calculated as follows:

$$L_{gen} = - \sum_t \log P_t$$  \hfill (15)

Besides the generation loss, we further add two auxiliary losses: $L_{\text{gate}}$ to supervise the probability of selecting an element from the concept set or a generic word and $L_{\text{next}}$ provided by the classifier built on top of [CLS] trained by negative sampling to discriminate whether the response is the next utterance of the given context. Both auxiliary loss functions take the form of cross-entropy and the final loss is the combination of these three losses:

$$L = L_{gen} + \alpha_1 L_{\text{gate}} + \alpha_2 L_{\text{cls}}$$  \hfill (16)

3.4 Concept Set Guided Reinforcement:

Fine-Training

In supervised fine-tuning, copying concepts from both persona information (the response persona sentences and the partner persona shown in context) can be viewed as an entrance to fuse both-party concepts into the response, which is used to generate responses mentioning mutual persona information simultaneously. In this section, we further introduce two rewards build on the concept set relationships between self-persona, partner persona, and future generated dialogue. These rewards are used to fine-training, which completely improve the model’s attention to the partner while generating responses via reinforcement learning [35].

3.4.1 COSPLAY via Policy Gradient. In order to generate the future dialogue, we adopt the self-play [12, 16, 45]. That is, we randomly pair another COSPLAY as the partner to complete a dialogue together. The partner whose parameters are frozen starts the conversation, and the trainable one generates response (we call the trainable one as self in contrast to the partner). This process repeats $N$-turns keeping the conversation flowing (note that the first utterance is directly taken from the dataset and all $N$ self-utterances are optimized simultaneously). Three elements of reinforcement environment are defined as follows: (1) State: the input to the model $(U_n, P^S)$; (2) Action: the generated response $u_n^S$, (3) Policy: the self COSPLAY $P_n^S(u_n^S | U_n, P^S)$. Then the policy gradient [31] is used to optimize the self COSPLAY with the expected return:

$$J(\theta) = E_{u_n^S \sim P_n^S(u_n^S | U_n, P^S)} [R(u_n^S)]$$  \hfill (17)

With the log derivative trick, we get the gradient of the policy performance, namely expected return:

$$\nabla_{\theta} J(\theta) = E_{u_n^S \sim P_n^S(u_n^S | U_n, P^S)} \left[ \nabla_{u_n^S} \log P_n(u_n^S | U_n, P^S) R(u_n^S) \right]$$  \hfill (18)

3.4.2 Mutual Benefit Reward. This reward uses the combined effects of persona recall score and utterance coherent score to stimulate model curiosity about the partner and the willing to give the partner more opportunities to express. In addition, the recall score individually can also encourage the model to copy both persona concepts into the responses. We define the reward as follows:

$$R_{\text{mut}} = \gamma S_{\text{rec}} + (1 - \gamma) S_{\text{coh}}$$  \hfill (20)

The recall score of future dialogue is calculated as shown in Figure 4. We first get the intersection concept set of the future dialogue and both party personas by the intersection operation (Eq. 4):

$$S_{\text{rec}} = \frac{\|c^{F \cap (S \cup P)}\|_1}{\|c^{S \cup P}\|_1}$$  \hfill (22)

The coherent score is the mean of the scores following previous utterance and followed by later utterance given by the classifier:

$$S_{\text{coh}} = (C_{u_n^P} + C_{u_{n+1}^P}) / 2$$  \hfill (23)

$$C_{u_n^P} = \log P(\text{IsNext}|u_n^P, P^S, U_n)$$

$$C_{u_{n+1}^P} = \log P(\text{IsNext}|u_{n+1}^P, P^S, U_n, u_n^S)$$  \hfill (24)
Table 1: Automatic evaluation results on Persona-Chat. The best models are bold and second best ones are underlined within each metric. Baselines are categorized into retrieval based, generative based, and pre-training & fine-tuning based methods.

| Type               | Model                                      |Hits@1(%)| F1(%)| Perplexity |Hits@1(%)| F1(%)| Perplexity |
|--------------------|--------------------------------------------|---------|------|------------|---------|------|------------|
| Retrieval Based    | KV Profile Memory [41]                      |54.8     |14.25 | -          |38.1     |13.65| -          |
|                    | Dually Interactive Matching [7]             |78.8     | -    | -          |70.7     | -    | -          |
| Generative Based   |personaChat [41]                            |-       |16.30 |50.67       |-        |13.59|51.61       |
| Pre-training & Fine-tuning Based | TransferTransfo [37]              |82.1     |19.09 |17.51       |-        |-    |-          |
|                    | CODOSPLAY (Ours)                           |85.5     |20.16 |16.77       |74.4     |18.79|19.92       |

3.4.3 Common Ground Reward. This reward aims to encourage the model to find common interests, explore new concepts close to both parties, and maintain the topic around the common field. Specifically, the reward is designed from a geometrical perspective by viewing both personas as two constraints and simultaneously minimizing the concept set distances from the future dialogue to each of them. As shown in Figure 5, the distance from the concept set of future dialogue $F$ to the both persona sets ($S$ and $P$) can be calculated by the set distance operation (Eq. 5). Then the reward $R_{con}$ aims to minimize the sum of these two concept set distances:

$$
R_{con} = \frac{1}{\text{Dist}(c^{F}, c^{S}) + \text{Dist}(c^{F}, c^{P})}
$$

(25)

$$
\text{Dist}(c^{F}, c^{S}) = \frac{\langle c^{F} \rangle^T}{\|c^{F}\|_1} \cdot D \cdot \frac{c^{S}}{\|c^{S}\|_1}
$$

(26)

$$
\text{Dist}(c^{F}, c^{P}) = \frac{\langle c^{F} \rangle^T}{\|c^{F}\|_1} \cdot D \cdot \frac{c^{P}}{\|c^{P}\|_1}
$$

(27)

4 EXPERIMENTAL SETUP

4.1 Research Questions

We list the research questions we want to investigate in this paper:

- **RQ1**: Can COSPLAY make a good performance in both automatic and human evaluations by generating responses consistent with personas across both parties? (See §5.1)
- **RQ2**: How do different key components contribute to moving the generated responses towards the ground truth? (See §5.2)
- **RQ3**: How is COSPLAY guided by concept set during the generation? How do different modules work together to build responses? (See §5.3)
- **RQ4**: Can our rewards really stimulate the model’s curiosity and give the partner more chances to express? (See §5.4)
- **RQ5**: Can our rewards really improve the model’s attention to the partner when generating responses? (See §5.5)
- **RQ6**: What is the influence of generalization strength of concept sets (parameter $k$ and $r$) on the performance? (See §5.6)
- **RQ7**: What is the differences of response pattern between ours and baselines? (See §5.7)

We answer the above questions in the results and analysis section.

Table 2: Human evaluation Results

| Models         | Fluency | Engagement | Consistency | Avg. |
|----------------|---------|------------|-------------|------|
| TransferTransfo| 4.43    | 3.64       | 3.83        | 3.97 |
| p^2 Bot        | 4.57    | 3.98       | 4.31        | 4.29 |
| CODOSPLAY      | 4.52    | 4.35       | 4.37        | 4.41 |

4.2 Datasets

We conduct experiments on the Persona-Chat [41] where each persona is described with at least 5 profile sentences. The dataset contains 8,939/1,000 multi-turn dialogues conditioned on 1,155/100 personas for train/dev. We report all results on the dev set. We also present the automatic results on revised Persona-Chat where the original personas are rephrased, generalized, or specialized because there is a danger that during the dataset construction, humans will unwittingly copy persona information either verbatim or with significant word overlap. This may make the task less challenging and constrain the generalization ability of models [41].

4.3 Evaluation Metrics

4.3.1 Automatic Evaluation. Following Zhang et al. [41], three common metrics are used: F1, Hits@1/20 and Perplexity (PPL). F1 is calculated from the word-level precision and recall between the gold response and generated response. Hits@1 is the accuracy that measures whether the model distinguishes the gold from distracting ones. Here, 19 distracting responses are mixed with one gold response. PPL evaluates the generation quality of language models.

4.3.2 Human Evaluation. Three crowdsourcing workers are asked to evaluate Fluency (1-5), Engagement (1-5) and Consistency (1-5). For engagingness, 1 point means that the response is boring and general. 3 point means that it is an interesting, informative and unexpected but reasonable response. 5 means that it has all the properties of 3 points responses and at the meantime, the dialogue is conducted around the common ground with interactivity. Consistency measures whether the generated response is consistent with its own persona. 1 is not “consistent”, 3 is “consistent” and 5 represents the response is consistent with self-persona while also considers partners’ persona. That is, the response as a bridge
to mention both persons can achieve a good score. For example, when meeting a music student, a good response for a computer student should be “Hi, would you like to hear some music created by my computer programs?” instead of saying a lot of computer knowledge though these contents are consistent with self-persona.

4.4 Baseline Methods

We compare our model with three groups of highly correlated and strong baselines: retrieval, generative, and pre-training & fine-tuning based methods. Specifically, they are introduced as follows:

- **Retrieval Based**: KV Profile Memory is proposed by Zhang et al. [41], a key-value memory neural model by taking as input the dialogue history and calculate attention over the persona sentences along with the history; Dually Interactive Matching Network (DIM) proposed by Gu et al. [7] with interactive matching between the context and response as well as between the persona and response simultaneously.

- **Generative Based**: LSTM language model is trained by prepending persona to the input sequence. Generative Profile Memory Network is based on RNN to encode persona texts into memory representations. Both are proposed by Zhang et al. [41]. Seq2Seq Attention is built by the traditional attention-based method [1].

- **Pre-training & Fine-tuning Based**: GPT-2 [23] was fine-tuned on the dataset with concatenated persona and history as prefix. Lost in Conversation team [3] proposed a conversational model based on the transformer architecture and transfer learning, to pre-train the model on a separate large dataset and fine-tune for the Persona-Chat. Wolf et al. [37] proposed TransferTransfo, a multi-layer transformer [33] based on the Generative Pre-trained Transformer (GPT) [22], pre-trained and then fine-tuned with fully supervised learning (SL); P2Bot was proposed by Liu et al. [16] who fine-tuned a pre-trained language model by a receiver trained on negative sampling to enhance mutual persona understanding.

4.5 Implementation Details

All concept set operations are based on the matrix computations implemented by Pytorch [19]. Two parameters of set operations $k$ and $r$ are set to 250 and 0.2 respectively and the length of concept vocabulary $V$ is 2600. Our model is built on GPT-2 [23] of HuggingFace transformers [36] and run on one single NVIDIA V100 GPU. In addition, the self-play framework is modified from Miller et al. [18] and Liu et al. [16]. We also thank the open source codes from Zhong et al. [45] and Ji et al. [10] for references. For hyper-parameters, all $\alpha_1$, $\alpha_2$, $\beta_1$, $\beta_2$, $\beta_3$ are set as 1 and $\gamma$ as 0.5. Before we add all rewards together, we perform batch normalization to push them into the same 0-1 scale and batch standardization to only view a half rewards as positive ones to encourage and the others as negative ones. The number of turns of future dialogue is 3, the batch size is 10/6 for supervised fine-tuning/reinforcement fine-training, and the beam size is 2.

5 RESULTS AND ANALYSIS

5.1 Automatic and Human Evaluations (RQ1)

5.1.1 Automatic Evaluation. We present the automatic evaluation results in Table 1. We can see that in general, our model achieves either the best or the second best performance across all metrics and outperforms all baselines on original F1 and Hits@1 while presents competitive performance on PPL. The results indicate that by giving more attention to the partner, our model can generate more human-like responses (F1↑). In addition, based on the concept set framework, our model can better recognize the gold response among the distractors, even in situations where the persona is revised (8.5% improvement on Hits@1 against the strongest baseline).

5.1.2 Human Evaluation. As automated metrics are notoriously poor for evaluating dialogue [15], we also perform the human evaluation. We collect 384 generated responses for each model.
from 50 different sampled dialogues. We report the averaged scores of them and the results are shown in Table 2. Three models obtain similar scores on fluency while our model significantly (Wilcoxon signed-rank test [4]) is used with $p < 0.05$ outperforms all the baselines on engagingness and consistency.

### 5.2 Ablation Study (RQ2)

We conduct ablation study to verify how different components contribute to the performance as shown in Table 3. We use F1 and BLEU as metrics to measure how close between the generated responses and the ground truths. COSPLAY Base denotes the version of COSPLAY only fine-tuned by the supervised phase, with the gate control to copy concepts from both personas at the appropriate time. Dropping concept copy mechanism means we shut up the guide from the concept set, which results in deteriorated performance indicating the importance of the guidance from the concepts. In addition, Mutual Benefit Reward and Common Ground Reward contribute to the largest improvements in F1 and BLEU respectively, demonstrating that being curious about the partner, leading conversation around mutual personas, and finding the common ground plays an important role in pushing response towards the ground truth of how a conversation really goes.

### 5.3 Effectiveness of Concept Set Guided Response Generation (RQ3)

We demonstrate how COSPLAY is guided by the concept set during the generation in Figure 6 and give the following observations: 1) The concept copy module (§3.3.3) is able to find out the appropriate time to open the gate; 2) The concept attention module (§3.3.2) independently prepares the best concepts with the correct grammar even at the time step when the gate is closed (e.g. "do"); 3) COSPLAY is able to generate response across both personas by two ways. The first way is to bridge both-party concepts (e.g., parents, singing in Figure 6a). The other way is to copy common ground concepts which is not directly covered by both personas while bridges them (e.g., music/guitar $\rightarrow$ band $\leftarrow$ sing/songs in Figure 6b); 4) Not only across both parties, but COSPLAY is also able to copy concepts across multiple persona sentences (Fig 6c).

The above observations show the more human-like and sophisticated ability of COSPLAY to organize multiple information across both parties and multiple persona sentences into one response.

### 5.4 Effectiveness of Encouraging Curiosity for the Partner (RQ4)

To better observe whether our rewards can stimulate the model’s curiosity, we deliberately train the model with a specified episodes without early stopping (Figure 7). It’s clearly that the power of Mutual Benefit Reward is great. Without interruption, the COSPLAY tends to fuse question for every response through the RL in a generative way (Figure 7a). However, asking question too frequently can make the performance decrease (Figure 7b). After all in daily life, though frequently, people may not ask questions for every time. In addition, there is a delicate balance of question-asking and performance (Figure 7b). Hence we use F1 to early stop the reinforcement fine-training when the performance declines.

### 5.5 Effectiveness of Encouraging Balance of Attention between Both Parties (RQ5)

Two self-play dialogues in Figure 8 are compared to evaluate our rewards on the effect of improving the model’s attention to its
Figure 9: Performance with different values of operation parameters: $k$ of set expansion and $r$ of set intersection.

6 CONCLUSION

We propose COSPLAY with Concept Set framework to address the problem of egocentrism in the personalized dialogue generation. Concept Set framework enables us to model personas and dialogues all in the form of concept sets, as well as using a suite of knowledge-enhanced concept set operations to calculate their relationships. Based on Concept Set, the concepts of both party personas, the concept relationships between them, and their relationships to the future dialogues are all used to train the model in the supervised fine-tuning and reinforcement fine-training phases, in order to give more attention to its partner and give partner more opportunities to express persona during generating responses. Experiments on PERSONA-CHAT demonstrate that COSPLAY is capable of generating less egocentric, more human-like, and higher quality responses.

7 ACKNOWLEDGMENTS

We thank the anonymous reviewers whose suggestions helped clarify this work. This research is supported in part by the National Natural Science Foundation of China (Grant No. 62106105). We would like to thank Dr. Fijii Li and Prof. Chuangbai Xiao for insightful suggestions and careful mentoring. We also want to thank Dr. Yan Wang, Dr. Wei Bi, and other members of the NLP group at Tencent AI Lab for helpful discussions.

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5.6 Effects of Generalization Strength of Concept Set (RQ6)

Two parameters controls the generalization strength as shown in Figure 9: 1) $k$ decides the number of concepts used to guide generation. Concept set expansion operation will fill concepts from near to far until the number of the set reaches $k$. 2) $r$ decides how close two concepts can they considered as “same”. If $r$ approaches to zero, then the concept set intersection operation will degenerate into the traditional one. It is clearly that both without and over generalizing concepts decrease the performance.

5.7 Case Study (RQ7)

Figure 1 shows three generated responses compared with our two baselines: TransferTransfo (SOTA 1) and $P^{\mathcal{S}}$ Bot (SOTA 2). Based on the analyses demonstrated in the Introduction and the section §5.3, we conclude that by improving attention to the partner, our model is able to generate less egocentric and more human-like responses.

5.8 Limitations

One major limitation of the Concept Set framework is that all concepts considered are single content words, which sometimes makes the COSPLAY separately process the phrase. For example, as shown in Figure 8, the model says “I’m watching TV” (line 1) where the word “watching” is partly copied from the phrase “bird watching” to construct the response. A potential solution is to extend the framework into its phrase version. In addition, to further take advantage of the matrix calculation feature of the Concept Set framework, making the concept set matrix trainable leaves another research direction.
