PERSONAChatGen: Generating Personalized Dialogues using GPT-3

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Abstract

Recently, many prior works have made their own agents generate more personalized and engaging responses using PERSONAChat (Zhang et al., 2018). However, since this dataset is frozen in 2018, the dialogue agents trained on this dataset would not know how to interact with a human who loves “WandaVision.” One way to alleviate this problem is to create a large-scale dataset. In this work, we introduce the pipeline\textsuperscript{1} of creating PERSONAChatGen, which is comprised of three main components: Creating (1) PROFILEGen, (2) Persona Set, and (3) PERSONAChatGen. To encourage GPT-3’s generation ability, we also defined a taxonomy of hierarchical persona category derived from social profiling taxonomy (Bilal et al., 2019). To create the speaker consistent persona set, we propose a simple contradiction-based iterative sentence replacement algorithm, named CONL. Moreover, to prevent GPT-3 generating harmful content, we presented two filtering pipelines, one each for PROFILEGen and PERSONAChatGen. Through analyzing of PERSONAChatGen, we showed that GPT-3 can generate personalized dialogue containing diverse persona. Furthermore, we revealed a state-of-the-art Blender 90M trained on our dataset that leads to higher performance.

1 Introduction

Considering users’ personal information (e.g., preferences, gender, age, and profession) is an essential capability for chit-chat dialogue agents. Since PERSONAChat was released in 2018, many studies have attempted to build their own dialogue agents to generate personalized and engaging responses in dialogue. These studies published in ACL Venues usually utilized the PERSONAChat dataset. However, this dataset was constructed in 2018, so dialogue agents trained on it cannot understand how to interact with users who loved the “Avengers: Endgame” movie, which can be regarded as unseen information. One way to solve this problem is to construct a large-scale dataset that includes more diverse personal information and how to interact with a conversation partner based on them. However, the process of manually creating dataset is time-consuming and costly.

Recently, as an alternate way, many studies have created datasets by leveraging pre-trained language models with designed prompt instructions (Yoo et al., 2021; Baheti et al., 2021; Hartvigsen et al., 2022) due to their enormous ability to produce more human-like text (Clark et al., 2021; Dou et al., 2021). They mainly focused on creating datasets related to NLU tasks, such as text classification, textual similarity, and natural language inference. However, no approach has generated a personalized dialogue dataset using a pre-trained language model, especially GPT-3. Note that our goal is to provide insights that prompting language models can create such datasets, not to release a new dataset generated by a language model.

In this work, we introduce the pipeline of creating PERSONAChatGen, a small-scale machine-generated dataset of 1,649 dialogues. Motivated by (Mishra et al., 2021) and the collection process of PERSONAChat, our pipeline consists of three main parts: (1) PROFILEGen Creation, (2) Persona Set Creation, and (3) PERSONAChatGen Creation. To obtain high-quality generated results from (1) and (2), we first defined a taxonomy of hierarchical persona category based on the social profiling taxonomy (Bilal et al., 2019). Then, we carefully designed prompts. Since GPT-3 can generate offensive and socially biased text (Baheti et al., 2021; Hartvigsen et al., 2022), we also present filtering steps in our pipeline.

- We introduced a novel pipeline for automatically generating PERSONAChatGen, that consists of three parts: (1) PROFILEGen Cre-
This task aims to generate more consistent responses \( y \) conditioned on given dialogue context \( x \) and persona set \( P \) by maximizing \( p(y|x, P) = \prod_i p(y_i|y_1, ..., y_{i-1}, x, P), \) where \( P = \{p_i\}_{i=1}^N \) and \( N \) denotes the number of sentences that the persona set \( P \) contains. Since PERSONACHAT (Zhang et al., 2018) is created by two humans who are assigned to each persona set, it contains two persona sets for each dialogue.

3.2 Persona Definition

First, we define a persona in this work based on the literature survey. Following the Wikipedia definition, a persona is simply a fictional character. Li et al. (2016) regarded personas as compositions of identities (background facts or user profile), language behavior, and interaction style. Zhang et al. (2018) defined a persona as a character created by multiple profile sentences. In this work, we define a personas as user profiles. Several works considered each profile sentence (e.g., I like to play a soccer) as personal attribute, which explicitly represents an identity and characteristics (Welleck et al., 2018; Wu et al., 2019; Wang, 2021). This personal attribute is mainly represented in the triple format of \( (e_1, r, e_2) \), where \( e_1, r, \) and \( e_2 \) denote entity 1, relation type, and entity 2, respectively. Herein, we define this relation type as persona category and entity 2 as persona entity. The persona entity is a key-value format. For example, in the personal attribute of “I’m from Boston, MA”, the persona category is “location” and the persona entity is “(city-state, Boston, MA)”.

4 A Taxonomy of Hierarchical Persona Categories

Most previous studies have not explicitly established a taxonomy for the persona category. Welleck et al. (2018) defined various relation types and entity categories (See Appendix F). Furthermore, they presented the hierarchical category for relation types. However, there is significant room to establish more sophisticated categories. We have several reasons for introducing the hierarchical persona category. In the real world, the persona comprises a hierarchical structure. For example, within the “preference” category, there is a preference about “movie” and a further preference about “movie title” or “movie genre.” In the practical perspective, we should provide well-designed prompts into GPT-3 to enhance the quality of generated dialogues (Mishra et al., 2021). As we mentioned in

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3 In this work, we use GPT-3 (Brown et al., 2020), but our pipeline could work with any prompting language model, such as OPT (Zhang et al., 2022)

3 https://en.wikipedia.org/wiki/Pronoun
the definition of persona (§3.2), we can regard a persona as a user profile, which can be also viewed as an individual profile. Following (Bilal et al., 2019), we introduce a taxonomy of three main hierarchical persona categories: DEMOGRAPHICS, PSYCHOGRAPHICS, and WELLNESS.

Note that we provide a basic taxonomy of hierarchical persona categories. Appendix E describes these taxonomies in more detail.

5 A Pipeline of Creating PERSONACHATGEN

This section introduces the pipeline of creating PERSONACHATGEN, which consists of three main parts: (i) PROFILEGEN Creation, (ii) Persona Set Creation and (iii) PERSONACHATGEN Creation. To create a consistent persona set, we also propose a simple contradiction-based iterative replacement algorithm, named CoNL.

5.1 DECOMPOSITION REFRAMING-based Prompt Engineering

Generating a personalized dialogue dataset from scratch using GPT-3 is challenging for two likely reasons: if a target task itself is inherently difficult or if the task instruction itself is complicated, thus a prompting language model (e.g., GPT-3) cannot achieve higher performance, as reported in Mishra et al. (2021). Furthermore, since the datasets used in GPT-3 pre-training are mainly formal languages (e.g., books and Wikipedia), the generative probability distribution itself learned in GPT-3 will be biased toward formal language. Therefore, we should design prompts to be intuitive and understandable from the GPT-3’s perspective.

To make a prompt suitable for creating PERSONACHATGEN, we ponder: "how was PERSONACHAT collected?" First, they collected 1,155 persona sets. Each persona set $P$ consists of multiple profile sentences (i.e., four or five sentences) and each sentence is written by Turkers. Then, two Turkers chat to get to know one another, where the persona set $P$ is randomly assigned to each Turker. Inspired by this collecting process, we decompose our task into two different sub-tasks, which is similar to the DECOMPOSITION REFRAMING techniques in Mishra et al. (2021). Both creating PROFILEGEN and PERSONACHATGEN parts equally include (1) generation describes how GPT-3 generates contents with our designed prompt and (2) filtering describes how we remove unreasonable content to enhance the quality of PERSONACHATGEN.

5.2 PROFILEGEN Creation

Here, we describe how we create PROFILEGEN; Figure 1 illustrates the overall process.

5.2.1 Generation

We utilized GPT-3 to create the persona set consisting of multiple profile sentences. In PERSONACHAT, when collecting several profile sentences, the researchers did not explicitly instruct the Turkers to generate sentences corresponding to given persona categories. However, in this study, the persona category should be explicitly indicated so that GPT-3 understands the given task well. Therefore, we carefully designed the tax-
onomy in Section 4. Table 12 and 13 show the prompt template for PROFILEGEN and an example of the constructed prompt with generated profile sentences, respectively.

5.2.2 Filtering
To obtain high quality results, we present a filtering pipeline for PROFILEGEN. Table 1 shows final statistics of filtered results of PROFILEGEN.

**Regex-based Filtering.** The prompt are providing to GPT-3 has a structured format, which requires generating the persona category and persona entity in key-value format (shown in Table 12). Thus, we apply the regex pattern to confirm whether it is extracted in the form of a key-value. Otherwise, we can consider that GPT-3 doesn’t appropriately understand the given prompt. Appendix J shows our regex pattern.

**Exact Matching Persona Entity.** We observe that some sentences do not explicitly contain corresponding persona entity keys and values. For example, given the persona category "Preference | Music | Artist", GPT-3 generates the sentence "I love listening to music by Taylor Swift." with both a persona entity key of "artist" and a persona entity value of "pop". Since this was not an accurate or direct result that we intended, we removed it.

**Preserving Persona Category.** To verify that GPT-3 generates a profile sentences that are relevant to the given persona category, we leveraged an NLI-based zero-shot classification task (Yin et al., 2019), that classifies a sentence through the "entailment" label predicted by NLI model. We used a BART-large (Lewis et al., 2019) model trained on the MNLI dataset (Williams et al., 2017). We removed sentences whose probability values were <90% as predicted by the model. For example, the sentence "I often listen to Billie Eilish." is classified as the "music artist" label with 99.7%.

**Duplication Filtering.** We observe GPT-3 tends to generate repetitive sentences. Thus, we removed duplicated results.

5.3 **ConL:** Contradiction-based Iterative Sentence Replacement

To create PERSONAChatGEN, we should prepare the persona set, which consists of multiple profile sentences. Unlike PERSONAChat where each

| Cumulative Survival Rate (%) | Regex | Exact | Preserving | Dup. |
|------------------------------|-------|-------|------------|------|
| # of Sentences               | 69,290| 43,753| 35,423     | 16,099|

Table 1: The cumulative survival rate of PROFILEGEN for all persona categories after each filtering part. We also describe the number of sentences after each filtering.

Turker creates a persona set, we should create persona sets automatically by combining the generated profile sentences from above two phases. Hence, we can maintain speaker consistency as if an automatically constructed persona set was written by one speaker. The easiest way is to sample generated sentences randomly. However, this creates inconsistencies between sentences (See Table 11a). To alleviate these inconsistencies, we propose a simple contradiction-based iterative sentence replacement algorithm named CoNL; the key idea is that we compare all pairs of sentences within the persona set $P$.

Specifically, we first prepared sentence pool $M$ by grouping all profile sentences by persona category. Then, we randomly selected one profile sentence $p_i$ for each persona category and prepared a candidate pool $M_{cand}$. To calculate the contradiction score between all pairs $\{p_i, p_j\}_{i=50, j=51}^{-}$, we leveraged the dialogue contradiction detection (DECODE) task (Nie et al., 2020), which determines whether the previous utterance is inconsistent with any previous utterances. We used a fine-tuned RoBERTa model (Liu et al., 2019) on the DECODE dataset. Repeatedly getting contradiction scores between $p_i$ and $p_j$, if a score is higher than the predefined threshold (in this work, we set 0.9), we replaced the $p_j$ sentence with another sentence by random sampling again from $M$ corresponding to the persona category. Again, we calculated the contradiction score with all sentences $\{s_i\}$ again. If there were no more $s_j$ sentences to replace, we exclude the entire category from $M_{cand}$. As such, we create a consistent persona set where all sentences are consistent. In turn, we randomly selected 4-5

\[https://huggingface.co/ynie/roberta-large_conly_convy_contradiction_detector_v0\]

There are two reasons why we set this to 0.9. First, if the threshold is high, we can create a more consistent persona set. Second, our proposed algorithm actually takes a long time. The lower the threshold, the higher the likelihood more sentences will be replaced, which can take a long time. Thus, we judge that it is appropriate to set it to 0.9.
sentences from the persona set candidate categories pool. However, if five are randomly selected, all sentences might correspond to the DEMOGRAPHICS category. Thus, we simply pull out two sentences that belong to DEMOGRAPHICS, two sentences that belong to PSYCHOGRAPHICS, and one sentence that belongs to WELLNESS. Table 11b shows how CONL can make a consistent persona set, such as "I am a very creative and imaginative person." and "I love to read books that are science fiction." In a further work, we will apply the speaker detection model (Gu et al., 2021) to create more consistent persona sets.

5.4 PERSONAChatGen Creation

We describe the overall process of creating PERSONAChatGen, which is shown in Figure 3.

5.4.1 Generation

If we ask one GPT-3 to create a dialogue while being given two different personas, it can be considered cheating because the model already knows two personas. Therefore, motivated by PERSONAChat, we use two GPT-3 with two different persona sets created from CONL (in 5.3). First, we designed our prompt template for generating PERSONAChatGen based on the prompt provided by OpenAI, which we call RAW. However, we observe GPT-3 sometimes simply copies given profile sentences when generating personalized dialogue. We measured how many profile sentences are copied into dialogues by using the F1 scores, which are shown in Figure 2. The average F1 score of RAW is much higher than that of PERSONAChat because PERSONAChat asked Turkers not to copy profile sentences into dialogues in explicit instructions. As such, we re-designed RAW prompts by adding the keyword "implicit" (we call it RAW+), which induces it to not produce copies. We show our prompt template for the PERSONAChatGen and an example of the constructed prompt in Appendix A.1.2.

The advantages of this generation are: (1) GPT-3 doesn’t get confused between two different personas, so we expect better-quality dialogues (2) GPT-3 can create by adjusting the number of dialogue turns, which is an impactful advantage due to a recent trend when dealing with long-term memory in dialogues (Xu et al., 2021, 2022).

5.4.2 Filtering

We present a filtering pipeline for PERSONAChatGen. Table 2 shows final statistics of filtered results for PERSONAChatGen.

**Copy–Paste.** Even if we modified RAW, GPT-3 still tends to simply copy the given profile sentences. Since the dialogue generative model trained on this copied dialogues generate dull responses (i.e., simply copying the given persona), we removed dialogues where the number of profile sentences copied is more than one in either persona 1 or 2. We consider it a copied sentence when the F1 score with respect to the utterance is > 0.8.

**Persona Consistency.** Persona consistency has been a long-standing issue in the dialogue domain. It means that dialogue agents generate utterances that are contradicted in given a subset of its persona. As described in (Brown et al., 2020), GPT-3 can generate repetitive and contradictory sentences. We thought this problem also occurs. To prevent this problem, we leveraged the fine-tuned RoBERTa model on the DECODE dataset which is same model as in §5.3. Specifically, given two persona set

| Copy-Paste | Consistency | Toxicity |
|------------|-------------|----------|
| Cumulative Survival Rate (%) | 73.1 | 46.0 | 45.3 |
| # of Dialog | 2,663 | 1,675 | 1,649 |

Table 2: The cumulative survival rate of PERSONAChatGen after each filtering part. We also describe the number of dialogues after each filtering.

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8In a toy experiment, we found contradictions and misunderstandings between two given personas as if GPT-3 was confused about the two personas.

9Recently, two GPT-3 bots have attempted to discuss human subjects. https://www.youtube.com/watch?v=jZ78fSnBqEs&t=3s

10https://beta.openai.com/examples/default-chat
Figure 3: The overall pipeline of PERSONAChatGen.

Table 3: Statistics of our PERSONAChatGen compared to PERSONAChat which is collected through crowdsourcing (CS). Utt. indicates utterances.

| Datasets   | Source   | #Dialog | #Utterances | Avg. Turns | Avg. Length of Utt. |
|------------|----------|---------|-------------|------------|---------------------|
| PERSONAChat | CS       | 11k     | 164k        | 14.8       | 14.2                |
| PERSONAChatGen | GPT-3  | 1.6k    | 26k         | 16.0       | 9.5                 |

Table 4: Results of the overlapped ratio (%) between entity values of PERSONAChatGen and PERSONAChat (Zhang et al., 2018) by measuring the Jaccard similarity. In PERSONAChatGen, Count denotes the number of entity values corresponding to the entity key.

| Persona Entity Key | PERSONAChat | PERSONAChatGen | Overlap Ratio(%) |
|--------------------|-------------|----------------|-----------------|
| season             | 4           | 13             | 30.77           |
| music instrument   | 19          | 21             | 25.0            |
| profession         | 124         | 116            | 21.21           |
| animal             | 54          | 84             | 20.0            |
| vehicle            | 70          | 82             | 18.75           |
| food               | 261         | 107            | 13.93           |
| music artist       | 105         | 99             | 8.51            |
| school status      | 4           | 97             | 3.06            |
| book author        | 7           | 63             | 2.94            |
| movie title        | 1           | 75             | 0.0             |
| book title         | 1           | 44             | 0.0             |

6.1 Statistics

Table 3 shows the statistics of PERSONAChatGen. Our PERSONAChatGen comprises 1,649 dialogues and 26,384 utterances (with roughly 14% the size of PERSONAChat). Compared to PERSONAChat, our dataset created by GPT-3 (not a human) had longer utterance lengths and larger utterances included in dialogues. Since our method is based on two GPT-3, we adjusted the number of turns, but this cost too much. In further work, we will reduce the costs by leveraging other available language models at no cost (e.g., OPT (Zhang et al., 2022)).

6.2 Quantitative Analysis

For PROFILEGen, we measure how much different entity values are generated by GPT-3 by using Jaccard similarity. The lower value indicates more different entities are generated by GPT-3. In Table 4, PROFILEGen contain more diverse entity values corresponding to book author, movie title, and book title.
7 Experiments

To understand how PERSONAChatGen affects existing the state-of-the-art model, we trained Blender 90M (Roller et al., 2020) using our dataset.

7.1 Experimental Setting

7.1.1 Datasets

**DialogueNLI** (Welleck et al., 2018) This dataset annotates NLI labels (i.e., entailment, contradiction, and neutral) on PERSONAChat. For this, they require human annotation of profile sentences and utterances by defining a schema related to relation types (persona category) and entity categories (entity key). In addition, they present the hierarchy relation types. We lists all information in Appendix F.

**PERSONAChat** (Zhang et al., 2018) This dataset was collected through crowdsourcing platform (i.e., Amazon Mechanical Turk) as two Turkers tried to get to know each other based on the personas they were each given. This is a subject of ConvAI2 competition (Dinan et al., 2020) at NeurIPS 2018. In fact, this version was used to fine-tune Blender (Roller et al., 2020).

7.1.2 Persona-based Dialogue Generator

We used Blender (Roller et al., 2020)—a state-of-the-art dialogue generative model—as our generator. We fine-tuned Blender 90M on PERSONAChat in the same manner as the original paper. For the implementation details, please refer to C.

7.1.3 Evaluation Metrics

To measure the performance of dialogue generative model, we adopted the perplexity (PPL), F1 score, and C score, which are widely used in prior works (Madotto et al., 2019; Kim et al., 2020; Wu et al., 2021). For PPL and F1, we measured the quality of generated responses by comparing them with the golden response. For C score, we measured whether the generated responses are consistent with their given persona by using the fine-tuned BERT-based NLI model from (Kim et al., 2020; Wu et al., 2021). For PPL and F1, we measured the quality of generated responses by comparing them with the golden response. For C score, we measured whether the generated responses are consistent with their given persona by using the fine-tuned BERT-based NLI model from (Kim et al., 2020; Wu et al., 2021).

7.2 Experimental Results

7.2.1 Quantitative Results

Table 7 reports that Blender trained COMB dataset achieves higher performance across all evaluation
Figure 4: Example of generated dialogue based on two personas. The teal utterances means directly related to the given P1 and the magenta ones are related to P2.

| P1’s Persona                                                                 | P2’s Persona                                                                 |
|-------------------------------------------------------------------------------|-------------------------------------------------------------------------------|
| I have three brothers and sisters.                                           | I love food and I love to eat.                                                |
| I am the middle child.                                                        | I am a woman who loves fashion.                                               |
| I’m a big fan of Beyoncé.                                                     | I love reality TV.                                                           |
| I like reading books about romance.                                           | I prefer to watch comedies.                                                  |
| I have been diagnosed with post-traumatic stress disorder.                   | I have hay fever.                                                           |

Generated Dialogue

P1: Hi, how are you?
P2: I’m good! I love food and I love to eat.
P1: Oh, what’s your favorite food?
P2: I love all kinds of food, but my favorite food is probably sushi.
P1: Sushi is really good! I love it too.
P2: Yeah, it’s one of my favorite things to eat. I also love fashion.
P1: Beyoncé is a really good fashion icon.
P2: Yeah, she is! I love her style, I also love reality TV.
P1: Oh, what’s your favorite reality TV show?
P2: I love a lot of reality TV shows, but my favorite is probably The Bachelor.
P1: The Bachelor is a really good show! I love it too.
P2: Yeah, it’s one of my favorite shows. I also love comedies.
P1: What’s your favorite comedy?
P2: I love all kinds of comedies, but my favorite is probably The Office.
P1: The Office is a really good comedy! I love it too.
P2: Yeah, it’s one of my favorite shows. I also have hay fever.

Table 7: Results of model performance on the test set of PERSONAChat and COMB. [M1] and [M2] refer to Blender 90M finetuned on PERSONAChat and COMB, respectively. COMB refers to the combination of PERSONAChat and PERSONAChatGen.

| Model                                                                 | F1  | PPL   | C  |
|-----------------------------------------------------------------------|-----|-------|----|
| [M1] Blender + PERSONAChat                                            |     |       |    |
| PERSONAChat                                                           | 18.7| 11.30 | 0.54|
| COMB                                                                  | 20.3| 8.22  | 0.51|
| [M2] Blender + COMB                                                  |     |       |    |
| PERSONAChat                                                           | 19.4| 11.83 | 0.63|
| COMB                                                                  | 24.5| 7.79  | 0.55|

| Fluency† | Engagingness† | Consistency† |
|----------|--------------|--------------|
| [M1]     | 3.17         | 2.53         | 2.47         |
| [M2]     | 3.47         | 2.66         | 2.69         |

(a) Results of Human Ratings.

Table 8: Human evaluation results comparison for Human Ratings and Human A/B test on 50 samples randomly chosen from the test set of PERSONAChatGen.

| Win (%) | Lose (%) | Tie (%) |
|---------|----------|---------|
| [M2] vs. [M1] | 47.3     | 28.7    | 24.0    |

(b) Results of Human A/B Test.

7.2.2 Human Evaluation Results

Following the prior works (Zhang et al., 2018; Kim et al., 2020), we evaluated (i) Human A/B Test and (ii) Human Ratings with three annotators. For Human A/B Test, we asked annotators to choose better responses; they could choose “Tie” if the two given responses are either both good or both bad. For Human Ratings, we asked annotators to rate generated responses on three metrics (using a 4-point Likert scale): Fluency, Engagingness, and Consistency. Appendix H.3 describes the questionnaires and Appendix I system used for the human metrics. This implies that PERSONAChatGen contribute to improve the model performance. Furthermore, we find that Blender trained on PERSONAChat has relatively lower C score on PERSONAChatGen compared to one trained on PERSONAChatGen.
Table 8 shows that annotators prefer responses generated by Blender trained on PERSONACHATGEN for both Human A/B and Human Ratings. In addition, we measured the inter-rater agreement using Krippendorff’s α and obtained 0.12, which implies slight agreement.

7.2.3 Case Studies

As shown in Figure 5, the [M2] model generates more relevant responses to the given persona, which corresponds to the consistency results in Table 8a. In addition, as our PERSONACHATGEN covers diverse persona entities (see in Table 4) compared to PERSONACHAT, the [M2] model generates "The catcher in the eye", which is a novel by J.D.Salinger, not "The power of friendship", which is a TV series.

8 Conclusion

This paper introduces the pipeline for creating PERSONACHATGEN, a machined-generated dataset of 1,649 dialogues. Our pipeline consists of three main parts: (1) PROFILEGEN creation, (2) Persona Set Creation, and (3) PERSONACHATGEN Creation. Moreover, we present two filtering steps, one for PROFILEGEN and one for PERSONACHATGEN. We reveal that GPT-3 has the ability to generate personalized dialogue datasets on both manual and automatic evaluation. In future work, we intend to leverage OPT (Zhang et al., 2022), which is publicly available and free, with our proposed prompt and pipeline.

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A Appendices

A.1 Prompts

In this section, we show our designed prompt template for generating profile sentences and personalized dialogue dataset. All generation processes are based on the one-shot setting. In toy experiment, if we don’t provide any in-context examples to GPT-3 (i.e., zero-shot setting), the quality of generated results is not high. Actually, we don’t posit an exact reason why zero-shot setting induces degenerated results. The possible reason is that PERSONA task itself is inherently difficult for GPT-3 to understand and follow how to generate corresponded results without in-context examples.

A.1.1 Prompts for Creating PROFILEGEN

In Table 12, we show the prompt template (used in §5.2.1) to generate profile sentences. First, we fill out <Category>, <Sub Category>, and <Sub Sub Category> based on the hierarchical persona category (defined in Section 4). Next, we randomly choose five profile sentences with corresponding entity key and value from PERSONA. For example, given in-context examples belonging to "Want | Activity" and target persona category "Preference | Movie | Title", the constructed prompt is presented in Table 13. The profile sentences generated by GPT-3 is marked in blue. We confirm GPT-3 can generate profile sentences with persona entities, which are relevant to the given persona category. It implies that our designed prompt is proper to create profile sentences with various persona entities.

A.1.2 Prompts for Creating PERSONACHATGEN

Table 14 presents the prompt template (used in §5.4.1) to generate PERSONACHATGEN. As we mentioned in §5.4.1, we leverage two GPT-3 as if two humans converse with each other. We construct two prompts including two different personas. Moreover, since we want to encourage GPT-3 to recognize their own persona well, the positions of You: and Friend: are opposite in two prompts.

B Analysis of PERSONACHATGEN

Table 9 shows full results of the overlapped ratio (%) between entity values of PERSONACHAT and PERSONACHATGEN. Table 10 shows full results of inter-rater agreement for each persona entity.

### Table 9: Full results of the overlapped ratio (%) between entity values of PERSONACHAT and PERSONACHATGEN (Zhang et al., 2018) by measuring the Jaccard similarity.

| Persona Entity Key | Count PERSONACHAT | Count PERSONACHATGEN | Overlap Ratio(%) |
|--------------------|-------------------|----------------------|------------------|
| season             | 4                 | 13                   | 30.77            |
| music instrument   | 19                | 21                   | 25.0             |
| music genre        | 52                | 39                   | 24.66            |
| book genre         | 28                | 53                   | 24.62            |
| movie genre        | 25                | 42                   | 21.82            |
| profession         | 124               | 116                  | 21.21            |
| degree subject     | 41                | 81                   | 19.61            |
| hobby              | 122               | 74                   | 19.51            |
| sport              | 58                | 42                   | 19.03            |
| color              | 43                | 39                   | 18.84            |
| vehicle            | 70                | 82                   | 18.75            |
| age                | 104               | 75                   | 17.76            |
| country            | 25                | 79                   | 16.85            |
| activity           | 90                | 39                   | 16.22            |
| media genre        | 25                | 101                  | 15.6             |
| personality trait  | 196               | 103                  | 15.0             |
| children           | 27                | 61                   | 14.29            |
| food               | 261               | 107                  | 13.93            |
| drink              | 16                | 67                   | 12.16            |
| workplace          | 73                | 81                   | 11.59            |
| gender             | 3                 | 21                   | 9.09             |
| physical attribute  | 27                | 98                   | 8.7              |
| music artist       | 105               | 99                   | 8.51             |
| sibling             | 27                | 55                   | 7.89             |
| job status         | 4                 | 37                   | 7.89             |
| city-state         | 70                | 56                   | 6.78             |
| family status      | 27                | 88                   | 6.48             |
| school type        | 5                 | 92                   | 5.43             |
| company name       | 18                | 22                   | 5.26             |
| subject            | 41                | 26                   | 4.69             |
| location           | 73                | 141                  | 4.39             |
| eating habit       | 4                 | 93                   | 4.3              |
| show               | 25                | 145                  | 4.29             |
| place              | 94                | 99                   | 3.76             |
| school status      | 4                 | 97                   | 3.06             |
| book author        | 7                 | 63                   | 2.94             |
| degree             | 11                | 97                   | 2.86             |
| school name        | 20                | 139                  | 0.63             |
| nationality        | 25                | 63                   | 0.0              |
| movie title        | 1                 | 75                   | 0.0              |
| book title         | 1                 | 44                   | 0.0              |

C Implementation Details.

To generate PERSONAChat and PERSONAChatGen, we leverage an instruct version of GPT-3 (text-davinci-002) provided by OpenAI. All experiments are conducted on a single A100 (40GB) GPU. For each stage, the hyperparameter setting used in GPT-3 is as follows:

- For PROFILEGEN Creation (§5.2), we set maximum tokens to 128, temperature to 0.7, frequency penalty to 0.4, and presence penalty 0.4. For the stop tokens, we use ###.
- For PERSONAChatGen Creation (§5.4), we set maximum tokens to 128, temperature to 0.8, frequency penalty to 0.4, and presence penalty 0.4. For the stop tokens, we use You:, Friend:, and \n.
Table 10: Full results of inter-rater agreement (Krippendorff’s alpha) for each persona entity. We present the degree of agreement as either ‘moderate’ or ‘fair’.

We fine-tuned Blender 90M (Roller et al., 2020) on PERSONACHAT dataset by using default hyperparameter settings provided by a ParlAI framework. Also, we used same hyperparameter settings to fine-tune Blender 90M on COMB for fair comparisons. To compute the persona consistency score (in §5.3 and §5.4.2), we used the finetuned RoBERTa model on the DECODE dataset which achieved 93.71% (reported in (Nie et al., 2020)).

D Persona Set Results

Table 11 shows examples of persona set created by random sampling and CoNL.

(a) An example of persona set containing contradiction between profile sentences

I am studying at a community college.
I am a teacher at the high school.
"The Great Gatsby" is another book I enjoy.
I’m a big fan of the violin.
I love reading books that are full of adventure.

(b) An example of persona set containing no contradiction between profile sentences

I am a very creative and imaginative person.
My older sister is a doctor.
I love to read books that are science fiction.
I enjoy watching suspenseful movies.
I have to be very careful in the springtime because of my allergies.

Table 11: Examples of persona set created by (a) random sampling and (b) CoNL. Red sentences are a case of contradiction.

\[\text{https://github.com/facebookresearch/ParlAI}\]
### User's persona: Category | Sub Category | Sub Sub Category

Generate five profile sentences related to the given user's persona and the "<Entity Key>" in each sentence:

1. Profile Sentence (<Entity Key>: Entity Value)
2. Profile Sentence (<Entity Key>: Entity Value)
3. Profile Sentence (<Entity Key>: Entity Value)
4. Profile Sentence (<Entity Key>: Entity Value)
5. Profile Sentence (<Entity Key>: Entity Value)

### User's persona: Want | Activity

Generate five profile sentences related to the given user's persona and the "activity" in each sentence:

1. I have always wanted to travel to ireland or puerto rico. (activity: travel)
2. I hope to visit quebec, canada someday. (activity: travel)
3. One day I would really like to skydive. (activity: skydiving)
4. Before I die, I want to skydive. (activity: skydiving)
5. I hope to see the world with my husband. (activity: travel)

### User's persona: Preference | Movie | Title

Generate five profile sentences related to the given user's persona and the "movie title" in each sentence:

1. I am a big fan of the Lord of the Rings movies. (movie title: Lord of the Rings)
2. I love all of the Harry Potter movies. (movie title: Harry Potter)
3. The Hobbit is one of my favorite movies. (movie title: The Hobbit)
4. I have seen all of the Star Wars movies. (movie title: Star Wars)
5. I enjoy watching Marvel movies. (movie title: Marvel)

Table 12: The prompt template which is used for generating PROFILEGEN given the persona category.

Table 13: Example of the constructed prompt and generated profile sentences which are marked in blue.

### Persona:

<FEWSHOT PERSONA>

The following is a daily conversation with your friend implicitly containing the given persona.

<FEWSHOT CONV>

### Persona:

<TARGET PERSONA>

The following is a daily conversation with your friend implicitly containing the given persona.

You:

Table 14: The prompt template which is used for generating PERSONACHATGEN.
### E Detailed Information of Taxonomy

#### E.1 DEMOGRAPHICS

Table 15 shows a taxonomy of DEMOGRAPHICS category with few examples.

| Category | Sub Category | Entity Value | Examples | Count |
|----------|--------------|--------------|----------|-------|
| Location | Birthplace | city-state | I was born and raised in the city-state of Detroit, Michigan. | 44 |
|          |             | country     | I am from Canada. | 349 |
|          | Residence  | city-state | I currently reside in San Francisco, CA. | 86 |
|          |             | country     | I’ve also lived in Spain. | 439 |
|          | Nationality| nationality | I’m Italian. | 228 |
|          |             |             | I want to be a French citizen. | |
| Employment| Company | company name | I would love to work for Google. | 83 |
|          | Workplace  | workplace   | I am a doctor and I work in a hospital. | 236 |
|          | Profession | profession | I am a salesperson. | 194 |
|          | Previous Profession | profession | I was a lawyer, but now I’m retired. | 274 |
|          | Job Status  | job status  | I have been employed for 5 years. | 177 |
|          | Teaching Experience | subject | I have a passion for teaching history. | 86 |
|          |             | activity    | I enjoy teaching people how to cook. | 68 |
| School   | Status      | school status | I am an alumni of the University of Michigan. | 335 |
|          | Degree      | degree      | I graduated from college in May of 2020. | 467 |
|          | Degree Subject | degree subject | I have a master’s degree in accounting from harvard. | 489 |
|          | Name        | school name | I’m in eighth grade at Roosevelt Middle School. | 443 |
|          | Type        | school type | I studied at a public university in the UK. | 434 |
| Family Status | Sibling | sibling | My twin sister and I are very close. | 187 |
|            | Children   | children    | I own a panda. | 465 |
|            |            |             | I have a dog and I love him. | |
|            |            |             | I have two teenage daughters. | 119 |
|            |            |             | I am a grandparent with six grandchildren. | |
|            |            |            | I am the youngest child in my family. | |
|            |            |            | I am a single mother of two teenage daughters. | |
|            |            |            | My sibling is my best friend. | |
| Possession | Animal     | animal      | I am selling my old car, a bmw. | 533 |
|            | Vehicle    | vehicle     | I am the proud owner of a new Tesla. | |
| Marital Status | - | marital status | I’ve been married for 5 years. | 203 |
|            |            |            | I am divorced and have been for a few years now. | |
|            | Age        | age         | I just turned 20 last month. | 248 |
|            | Gender     | gender      | I identify as a man. | 102 |
|            |            |            | I’m female. | |

Table 15: A taxonomy of DEMOGRAPHICS category. We show few examples per category and blue is the entity value corresponds to given entity key, which is generated by GPT-3. Count indicates the final number of profile sentences after our filtering pipelines.
### E.2 PSYCHOGRAPHICS

Table 16 shows a taxonomy of PSYCHOGRAPHICS category with few examples.

| Category      | Sub Category | Sub-Sub Category | Entity Key | Examples                                                                 | Count |
|---------------|--------------|------------------|------------|--------------------------------------------------------------------------|-------|
| Preference    | Genre        | movie genre      | I'm a big fan of sci-fi movies. | I love watching action movies.                                        | 272   |
|               | Title        | movie title      | I have seen all the Harry Potter movies. | I'm not a big fan of horror movies, but "A Quiet Place" was really good. | 337   |
| Music         | Genre        | music genre      | I enjoy listening to pop music. | I grew up listening to country music and it is still my favorite.     | 400   |
|               | Artist       | music artist     | I like to play acoustic guitar. | I am interested in learning how to play the cello.                   | 285   |
|               | Instrument   | music instrument | I love to read books by JRR Tolkien. | I also love To Kill A Mockingbird by Harper Lee.                    | 400   |
|               | Author       | book author      | I tend to read books from the science fiction genre. | I love reading books, but my favorite genre is Romance.          | 273   |
|               | Title        | book title       | My all-time favorite book is "The Great Gatsby." | I prefer The Catcher in the Rye.                                | 352   |
| Sport         | -            | sport            | I enjoy playing volleyball. | I enjoy playing tennis, even though I’m not very good at it.          | 444   |
| Location      | -            | location         | My favorite place to go is the park. | I love the city.                                                   | 518   |
| Media Genre   | -            | media genre      | I prefer TV shows that are reality based. | I enjoy the color pink.                                           | 526   |
| Color         | -            | color            | I love the color white. | I enjoy the color pink.                                            | 399   |
| Show          | -            | show             | I used to watch game of thrones, but I got too into it. | I also like to watch The Big Bang Theory.                          | 518   |
| Place         | -            | place            | My favorite place to be is in my garden. | I love going to the zoo.                                         | 272   |
| Hobby         | -            | hobby            | I love to play tennis, and I’m pretty good at it. | I like to play video games.                                    | 262   |
| Season        | -            | season           | I love winter because of the Christmas holidays. | I love the summer because I can go to the beach.                | 406   |
| Hobby         | Activity     | activity         | -                                                    | -                                                           |       |
|               | Sport        | sport            | -                                                    | -                                                           |       |
|               | Ability      | ability          | -                                                    | -                                                           |       |
|               | Organization | organization    | -                                                    | -                                                           |       |
| Personal Characteristics | Physical Attribute | physical attribute | I prefer men with dark hair. | I have brown eyes and dark hair.                                    | 239   |
|               | Personality  | personality trait | I am a shy woman. | I am a very honest person who always tells the truth.            | 351   |
| Eating Habit  | -            | eating habit     | I try to eat healthy. | I love to eat vegan food.                                        | 224   |

Table 16: A taxonomy of PSYCHOGRAPHICS category. We show few examples per category and blue is the entity value corresponds to given entity key, which is generated by GPT-3. Count indicates the final number of profile sentences after our filtering pipelines.
| Category  | Sub Category | Entity Key  | Examples                                                                 | Count |
|-----------|--------------|-------------|---------------------------------------------------------------------------|-------|
| Disease   | Respiratory  | respiratory disease | I have emphysema and get out of breath easily. I was diagnosed with bronchitis a few weeks ago and I'm still recovering. | 318   |
|           | Digestive    | digestive disease  | I was diagnosed with Crohn's disease when I was eighteen. I have celiac disease. | 232   |
| Symptom   | Physical     | physical symptom | I start sneezing when I eat peanuts. I have a lot of stomach problems because I eat junk food all the time. | 267   |
|           | Psychiatric  | psychiatric symptom | I have OCD and panic attacks. I have PTSD. | 267   |

Table 17: A taxonomy of WELLNESS category. We show few examples per category and blue is the entity value corresponds to given entity key, which is generated by GPT-3. Count indicates the final number of profile sentences after our filtering pipelines.

E.3 WELLNESS
Table 17 shows a taxonomy of WELLNESS category with few examples.

F Schema in DIALOGUENLI

F.1 Hierarchy Relation Types
Location, Employment, School, Likes, Hobbies, Wants, Favorites, Possessions, Personal

F.2 Relation Types
place_origin, live_in_citystatecountry, live_in_general, nationality, employed_by_company, employed_by_general, has_profession, previous_profession, job_status, teach, school_status, has_degree, attend_school, like_general, like_food, like_drink, like_animal, like_movie, like_music, like_read, like_sports, like_watching, like_activity, like_goto, dislike, has_hobby, has_ability, member_of, want_do, want_job, want, favorite_food, favorite_color, favorite_book, favorite_movie, favorite_music, favorite_music_artist, favorite_activity, favorite_drink, favorite_show, favorite_place, favorite_hobby, favorite_season, favorite_animal, favorite_sport, favorite, own, have, have_pet, have_sibling, have_children, have_family, have_vehicle, physical_attribute, misc_attribute, has_age, marital_status, gender, other

F.3 Entity Categories
ability, activity, animal, color, citystate, country, company, cuisine, degree_type, drink, family, food, gender, general_location, job_status, language, marital, media_genres, media_other, movie_title, music_artist, music_genre, music_instrument, noun, number, organization, person, person_attribute, person_label, personality_trait, profession, read_author, read_genre, read_title, read_other, school_name, school_status, school_type, season, sport_type, subject, time, vehicle, location, other

G More Examples of PERSONACHATGEN
Figure 6 shows more examples of PERSONACHATGEN. Overall, generated dialogues are natural and consistent with the given personas.
| **P1’s Persona** | **P2’s Persona** |
|-----------------|-----------------|
| I love food and I love to eat. | I’ve been to Italy three times. |
| I am a woman who loves fashion. | I graduated from Yale. |
| I love reality TV. | I’ve read all of the books by Jodi Picoult. |
| I prefer to watch comedies. | I’m a big fan of books, and my favorite genre is fantasy. |
| I have hay fever. | I have asthma and it makes it hard to breathe sometimes. |

### Generated Dialogue

**P1:** Hey, how are you?
**P2:** I'm good, just got back from Italy.
**P1:** Oh, how was it?
**P2:** It was great, I love it there.
**P1:** What did you eat?
**P2:** Everything, I love Italian food.
**P1:** That sounds amazing, I need to go there sometime.
**P2:** Yeah, you should definitely go. It’s a great place.
**P1:** I also love fashion, do you follow any trend?
**P2:** No, not really. I prefer classic styles.
**P1:** That's cool, I like to watch reality TV.
**P2:** Yeah, I don't really watch much TV. I prefer to read.
**P1:** That's great, what do you like to read?
**P2:** I like to read books, my favorite genre is fantasy.
**P1:** That's great, I have hay fever so I can't really read outside.
**P2:** Yeah, I have asthma so it's hard for me to breathe sometimes.

| **P1’s Persona** | **P2’s Persona** |
|-----------------|-----------------|
| I am retired from my previous job as a software engineer. | He is a transgender man. |
| I do not travel. | I am very responsible. |
| I like to learn from the books I read, so I tend to gravitate towards non-fiction. | I like to watch action movies because they're exciting and fun. |
| I also enjoy watching movies. | When I'm feeling down, I always listen to Sam Smith to cheer me up. |

### Generated Dialogue

**P1:** Hi, how are you today?
**P2:** I'm good, how are you?
**P1:** I'm good, thanks for asking. What have you been up to lately?
**P2:** Just hanging out with friends and family. What about you?
**P1:** I've been reading a lot of books lately.
**P2:** That sounds really great. What kind of books?
**P1:** Mostly non-fiction. I like to learn from the books I read.
**P2:** That's really admirable. I need to start reading more books.
**P1:** Yes, I think it's really beneficial. Do you like watching movies?
**P2:** Yeah, I love watching movies. Action movies are my favorite.
**P1:** That sounds great. I enjoy watching movies too.
**P2:** What's your favorite movie?
**P1:** I don't really have a favorite movie. I just enjoy watching movies in general.
**P2:** That's a great attitude to have.
**P1:** Thanks. I think it's important to just enjoy the experience and not worry about picking a favorite.
**P2:** That's definitely a good way to look at it.

Figure 6: Examples of generated dialogue based on two personas. The *teal* utterances means directly related to the given P1 and the *magenta* ones are related to P2.
H Human Evaluation Questionnaire

We present a list of questions and multiple-choice options used for human evaluation for PROFILEGEN and PERSONAChatGEN.

H.1 PROFILEGEN

• HUMANNESS: Do you think this conversation is from a model or a human?
  \hspace{1cm} \textbf{Options:} 1: Definitely a model / 2: Probably a model / 3: Probably a human / 4: Definitely a human

• FLUENCY: Does this conversation seem contextually natural? Could you understand this conversation?
  \hspace{1cm} \textbf{Options:} 1: Very unnatural / 2: Mostly unnatural / 3: Mostly natural / 4: Very natural

• PERSONA CATEGORY RELEVANCE: How consistent this sentence is with respect to the given persona category
  \hspace{1cm} \textbf{Options:} 1: Not at all / 2: A little / 3: Somewhat / 4: A lot

• ENTITY FACTUALITY: Does this entity is accompanied by the given persona category?
  \hspace{1cm} \textbf{Options:} 0: No / 1: Don’t know / 2: Yes

H.2 PERSONAChatGEN

• HUMANNESS: Do you think this conversation is from a model or a human?
  \hspace{1cm} \textbf{Options:} 1: Definitely a model / 2: Probably a model / 3: Probably a human / 4: Definitely a human

• FLUENCY: Does this conversation seem contextually natural? Could you understand this conversation?
  \hspace{1cm} \textbf{Options:} 1: Very unnatural / 2: Mostly unnatural / 3: Mostly natural / 4: Very natural

• PERSONA RELEVANCE: How consistent this conversation is with respect to the given persona (i.e., given profile sentences)
  \hspace{1cm} \textbf{Options:} 1: Not at all / 2: A little / 3: Somewhat / 4: A lot

H.3 For Human Ratings

• CONSISTENCY: How much consistent did this user speak with respect to the given persona?
  \hspace{1cm} \textbf{Options:} 1: Not at all / 2: A little / 3: Somewhat / 4: A lot

• ENGAGINGNESS: How much did you enjoy talking to this user?
  \hspace{1cm} \textbf{Options:} 1: Not at all / 2: A little / 3: Somewhat / 4: A lot

• FLUENCY: How naturally did this user speak English?
  \hspace{1cm} \textbf{Options:} 1: Very unnatural / 2: Mostly unnatural / 3: Mostly natural / 4: Very natural
I Human Evaluation System

Here is a screenshot of human evaluation system. Based on Python Flask APIs and a Web user interface with Javascript, we implemented an annotation tool for scoring the generated results from our conversational model. Each annotator can read each conversation’s persona descriptions and dialog sentences and choose their scores according to human evaluation metrics such as fluency. All changes are immediately stored on the server-side database by accessing the Flask APIs.

![Screenshot of human evaluation system](image.png)

Figure 7: Screenshot of the human evaluation system for manually checking overall quality of generated personalized dialogues.

J Regex Pattern

Since GPT-3 sometimes generates the key-value information with the square brackets `[]` not the parenthesis `()`, we consider the square brackets in the regex pattern. Finally, for the regex-based filtering (in §5.2.2), we use the following pattern:

```
(?P<utter>.*)(\(|\[)(?P<attr>.*): (?P<value>.*)(\)|\])
```