Enhancing Personality Recognition in Dialogue by Data Augmentation and Heterogeneous Conversational Graph Networks

Yahui Fu, Haiyue Song, Tianyu Zhao, Tatsuya Kawahara

Abstract Personality recognition is useful for enhancing robots' ability to tailor user-adaptive responses, thus fostering rich human-robot interactions. One of the challenges in this task is a limited number of speakers in existing dialogue corpora, which hampers the development of robust, speaker-independent personality recognition models. Additionally, accurately modeling both the interdependencies among interlocutors and the intra-dependencies within the speaker in dialogues remains a significant issue. To address the first challenge, we introduce personality trait interpolation for speaker data augmentation. For the second, we propose heterogeneous conversational graph networks to independently capture both contextual influences and inherent personality traits. Evaluations on the RealPersonaChat corpus demonstrate our method's significant improvements over existing baselines.[1]

1 Introduction

Personality recognition aims to identify an individual's characteristic patterns of feeling, thinking, and behaving, which make each different from one another [1]. Such capability is essential in the realm of human-robot interaction, where correctly

Yahui Fu, Tatsuya Kawahara
Graduate School of Informatics, Kyoto University, Japan
e-mail: `[fu][kawahara]@sap.ist.i.kyoto-u.ac.jp`

Haiyue Song
Graduate School of Informatics, Kyoto University, Japan and NICT, Japan
e-mail: `song@nlp.ist.i.kyoto-u.ac.jp`

Tianyu Zhao
rinna Co., Ltd., Japan
e-mail: `tianyuz@rinna.co.jp`

[1] Our codes are available at https://github.com/fuyahuii/Personality-Recognition-on-RealPersonaChat.
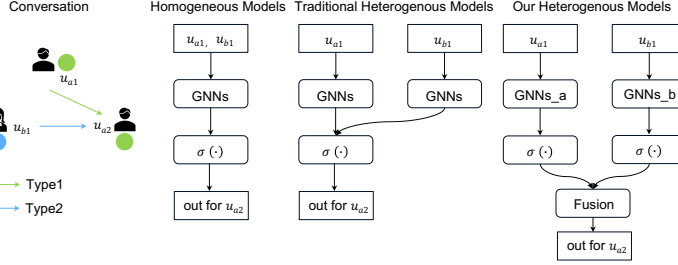
Fig. 1: Homogeneous and different heterogeneous models. u_{a1}, u_{a2}, u_{b1} represents alternant utterance of *speaker a* and *b*. $\sigma(\cdot)$ represents activation function.

detecting the user's personality can significantly enhance the robot's ability to tailor user-adaptive responses, thus fostering richer and more effective human-robot dialogues. Big-five traits [2], which encompass the dimensions of Openness, Neuroticism, Extraversion, Agreeableness, and Conscientiousness, and their respective counter-traits are commonly used in the community for personality assessment. In contrast to prior approaches that infer personality traits from self-reported essays [3, 4, 5], first impressions [6, 7], or social media activities [8], this study focuses on the extraction of personality traits from dialogue [9, 10, 11, 12, 13].

However, the lack of data is a major obstacle because annotating dialogue-level data with personality information is expensive and time-consuming. Each dialogue involves two participants and personality traits are obtained through psychology questionnaires. Thus, we investigate a data augmentation approach. While previous data augmentation studies focus on generating sentence-level data *invariants* [14, 15, 16, 17] without corresponding labels, in this study, we generate both the synthetic dialogue data and corresponding synthetic personality traits through the proposed data interpolation method, which fuses two existing data points controlled by a *continuous ratio variable*.

Additionally, accurately modeling both the inter-dependencies between context and interlocutors, as well as the intra-dependencies within speakers in dialogues, remains a significant challenge. Previous homogeneous models, such as the graph attention network [18] [19], did not consider the variations in link types. Heterogeneous models like relational graph convolution networks (RGCN) employ distinct relation types to model various dependencies. Yet, they utilize shared coefficients across all relation types, which may fail to capture the unique attributes of each relation type, as shown in Fig 1. To address this issue, we propose a method to independently model heterogeneous conversational interactions, capturing both contextual influences and inherent personality traits. Our main contributions are as follows:

- We propose a data augmentation method for personality recognition by interpolation from any two existing data points.

- We propose a heterogeneous conversational graph neural network (HC-GNN) to independently model both the interdependencies among interlocutors, as well as the intra-dependencies within the speaker in dialogues.
- Experimental results using the RealPersonaChat corpus demonstrate that increasing speaker diversity significantly improves personality recognition in both monologue and dialogue settings. The proposed HC-GNN method outperforms baseline models, showcasing its effectiveness.

2 Related Work

2.1 Personality Recognition in Dialogue

Mehl et al. [12] pioneered the automatic personality assessment of all Big Five personality traits using various psycholinguistic attributes. To this end, they analyzed a collection of daily-life conversations by 96 participants over 2 days. However, it only contains the subjects' conversation; we also want to analyze how interlocutors impact the subject's personality expression in the dialogue. Jiang et al. [10] and Chen et al. [11] collected conversation corpus with rich data based on the "Friends" and 40 Chinese television series, respectively. Nonetheless, the Big Five personality labels were assigned by external observers rather than derived from self-assessments by the speakers. Most recently, Yamashita et al. [13] presented the RealPersonaChat (RPC) corpus by documenting the authentic personality traits of the participants and allowing them to freely engage in dialogues. This corpus aligns closely with our research objectives, as it provides a foundation for evaluating the personality traits of subjects who may engage in chit-chatting dialogue with a conversational agent. However, this corpus has a relatively limited number of speakers (233). This sparsity poses a challenge in effectively detecting the personality traits of unseen speakers. We propose a data augmentation method to enrich the speaker diversity.

2.2 Data Augmentation

Data augmentation (DA) tries to fill the gap between the data distribution of the training set and the real data with no annotation cost. Previous DA studies focus on generating data *invariants*. In the computer vision field, simple geometric transformations like cropping, rotation, and noise injection can be easily applied to continuous image data [20]. Due to the discrete nature of language data, previous DA studies in NLP usually involve discrete noises including *1)* character-level modification like changing character case [14], *2)* subword-level regularization such as BPE-dropout [21], *3)* word-level replacement, insertion, or deletion [15], and *4)* sentence-level modification such as paraphrasing [22, 16] and

back-translation [17, 23, 24, 25]. Our method differs from them in two aspects. First, we generate data *variants* including both dialogue data and corresponding personality labels. Second, we generate synthetic personality traits following continuous distribution from existing discrete trait data by introducing a random fusion variable. This bridges the gap between the discrete distribution in the corpus and the continuous distribution in reality. A similar work is the example extrapolation method [26] which generates augmented embeddings of the target domain by leveraging the similarity of embedding spaces from another assisting domain. Different from it, our interpolation method requires only one dataset.

2.3 Graph Neural Networks

Graph Neural Networks (GNNs) and their variants have been widely applied in dialogue-related tasks, like conversational emotion recognition [27, 28], and dialog act classification [29]. This is primarily due to the adjacency matrix in GNNs effectively simulating interactions within conversations. Yang et al. [30] proposed a dynamic deep graph convolutional network for personality detection on social media posts. Existing methodologies, whether employing static or dynamic approaches to construct interactions within graphs, mainly focus on homogeneous or heterogeneous conversation modeling. Nevertheless, various types of nodes and links have different traits and their features may fall in different spaces. For instance, as illustrated in Fig 1, traditional heterogeneous models like RGCN [31] utilize shared coefficients across all relation types, potentially failing to capture the unique attributes of each relation type. To solve this, this paper proposes a modification to the existing heterogeneous model framework. We introduce separate GNNs to distinctly capture the diverse relation types, thereby respecting the unique properties of each node and link type.

3 Preliminary Dataset Analysis

Table 1: Pearson correlation between pairs of Big-Five personality traits in the dataset. N, E, O, A, and C represent Neuroticism, Extraversion, Openness, Agreeableness, and Conscientiousness, respectively.

Big-Five Pair	(N, E)	(N, O)	(N, A)	(N, C)	(E, O)	(E, A)	(E, C)	(O, A)	(O, C)	(A, C)
Pearson Correlation	-0.49	-0.23	-0.27	-0.15	0.47	0.46	0.26	0.40	0.15	0.36

(for all pairs $p < .05$)

We conduct experiments using the RealPersonaChat corpus [13], comprising 14,000 Japanese dialogues and a total of 421,203 utterances. In this corpus, 233 participants (141 females, 90 males) completed a questionnaire regarding their Big Five personality score (in a range from 1-7) and then engaged in unstructured conversation. We normalize the score to 0-1. We analyze the correlations between pairs of personality traits in the dataset, as shown in Table 1. The p-value of the Pearson correlation for each pair is less than 0.05, indicating statistically significant relationships between each pair of Big-Five personality traits.

4 Proposed Method

4.1 Data Interpolation

This section describes math notations, how to fuse two existing data points to generate synthetic dialogue and Big-five traits, and variants of the proposed method.

Notations. Each dialogue D contains utterances u_a from the *speaker a* or u_b from the *speaker b* in alternant turns, that is $D = \{u_{a1}, u_{b1}, u_{a2}, u_{b2}, ..., u_{an}, u_{bn}\}$, where n is the number of turns. Each dialogue is accompanied by a label $\mathbf{y}$ that is a vector containing the Big-five personality traits of the target speaker. We aim to generate synthetic dialogue D_{syn} and its label $\mathbf{y}_{syn}$ from two existing dialogues D_1 and D_2 and their labels $\mathbf{y}_1$ and $\mathbf{y}_2$.[2]

Dialogue Interpolation. First, we randomly select two dialogues D_1 and D_2 in the training set. Second, we split each dialogue into chunks (c) each containing t turns, which is a hyper-parameter controlling the context length we desire (we set t=3). This results in $D_1 = \{c_1, c_2, ..., c_l\}$ and $D_2 = \{c'_1, c'_2, ..., c'_l\}$, where $l = \frac{n}{t}$ is the number of chunk one dialogue contains. Finally, we combine chunks from D_1 and D_2 to generate D_{syn} using a fusion ratio β that is a random variable independently sampled from Uniform$(0, 1)$ for each synthetic data point. D_{syn} can be represented as:

$$
\begin{aligned}
D_{\text{syn}} &= \beta D_1 \oplus (1 - \beta) D_2, \text{resulting in} \\
D_{\text{syn}} &= \{c_i^{\text{syn}} \mid 1 \leq i \leq l\}, \text{where} \\
c_i^{\text{syn}} &= \begin{cases} c_i & \text{with probability } \beta, \\ c'_i & \text{with probability } 1 - \beta. \end{cases}
\end{aligned}
\tag{1}
$$

Specially, when generating synthetic monologue data, we split each monologue D into utterances instead of chunks.

Label Interpolation. Because each label is a vector of real numbers represented as $\mathbf{y} \in \mathbb{R}^5$, we can simply obtain the synthetic label through:

---

[2] Since we focus on the personality of the initiating *speaker a* in the experiments, $\mathbf{y}_1$ or $\mathbf{y}_2$ refers to the personality of *speaker a*.
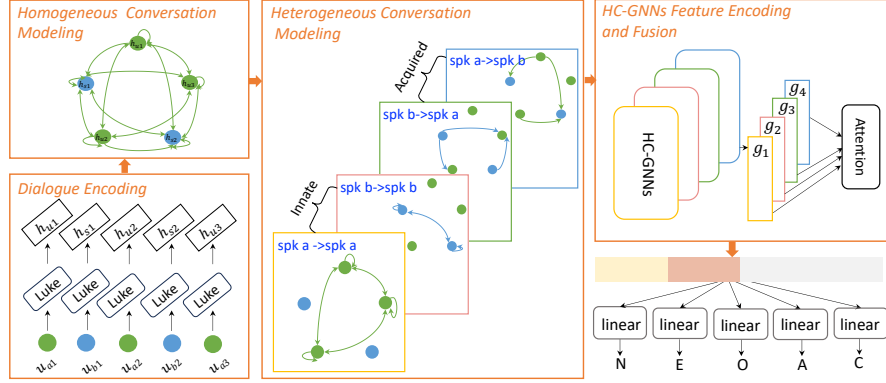
Fig. 2: **Heterogeneous conversational graph neural network (HC-GNN)**, which captures the interdependencies among interlocutors (acquired) and the intra-dependencies within *speaker a* or *b* (innate).

$$\mathbf{y}_{syn} = \beta \mathbf{y}_1 + (1 - \beta) \mathbf{y}_2. \tag{2}$$

Method Variants. There are three types of variants of the proposed method (former setting used). First, we can sample $\beta \sim \text{Uniform}(0, 1)$ or fixing β to 0.5. The former setting produces a richer variety of data. Second, we can either select two dialogues possibly from different speakers, where $\mathbf{y}_1$ and $\mathbf{y}_2$ are independently and identically distributed ($\mathbf{y}_1 \overset{\text{iid}}{\sim} \mathbf{y}_2$), or select two dialogues from the same speaker $\mathbf{y}_1 = \mathbf{y}_2$ which results in $\mathbf{y}_1 = \mathbf{y}_2 = \mathbf{y}_{syn}$. The former setting can produce new speakers with synthetic personality traits. Third, the synthetic dialogue can be truncated to length $l' \sim \text{Uniform}(t_{min}, |D_{syn}|)$ (we set $t_{min} = 2$). This enables personality recognition in early turns which is preferred in real application.

4.2 Heterogeneous Conversational Graph Neural Network

We map each utterance in the dialogue into embeddings, as presented in Section 4.2.1. Subsequently, we describe heterogeneous conversation modeling in Section 4.2.2, followed by an explanation of heterogeneous conversational graph neural network feature encoding and fusion in Section 4.2.3.

4.2.1 Dialogue Encoding

For each dialogue $D = \{u_{a1}, u_{b1}, u_{a2}, u_{b2}, u_{a3}...\}$, we employ a BERT-like model Japanese Language Understanding with Knowledge-based Embeddings (LUKE)

[32] [3] to encode each utterance in the dialogue:

$$\mathbf{h}_{u_i} = \text{LUKE}(u_i) \in \mathbb{R}^{1 \times d} \tag{3}$$

where h_{u_i} denotes the final hidden state of the "[CLS]" token to represent the meaning of the whole utterance, and d is the dimension of the output.

4.2.2 Heterogeneous Conversation Modeling

To explicitly model the interaction between speakers, we independently model the intra-dependency (innate personality) and inter-dependency (acquired personality which is influenced by the interlocutor), as shown in Fig. 2. We introduce the following notation: we denote directed and labeled multi-graphs as $\mathscr{G}_r = (\mathscr{V}_r, \mathscr{E}_r, r)$ with nodes $\vartheta_{r,i} \in \mathscr{V}_r$ and labeled edges (relations) $(\vartheta_{r,i}, r, \vartheta_{r,j}) \in \mathscr{E}_r$, where $r \in \mathscr{R}$ represents one of the conversation relation types $\{spk\ a \to spk\ a, spk\ b \to spk\ b, spk\ b \to spk\ a, spk\ a \to spk\ b\}$.

4.2.3 HC-GNNs Feature Encoding and Fusion

For each relation type in each graph $\mathscr{G}$, we then encode the features of node i with dynamic attention and graph attention networks (GATv2) [19] to aggregate the interactions between each group of speakers (self and interlocutor):

$$\mathbf{h}_i^{n(l)} = \sigma\Big(\sum_{k \in K} \sum_{j \in N_i^r} \frac{a_{i,j}^{(k)}}{N_i^r} \mathbf{W}_r^{(l)} \mathbf{h}_{u_j} + a_{i,i}^{(k)} \mathbf{W}_0^{(l)} \mathbf{h}_{u_i}\Big) \tag{4}$$

where N_i^r denotes the neighboring indices of node i under relation $r \in \mathscr{R}$. This notation encompasses both forward and backward relation directions. K represents the number of attention head. $\mathbf{W}_r^{(l)}$, $\mathbf{W}_0^{(l)}$ are the learnable weight metrics, l is the number of layer of HC-GNN, and $\sigma(.)$ is an ReLU activation function. The attention scores are normalized across all neighbors $j \in N_i^r$ using softmax, and the attention function is defined as:

$$a_{i,j} = softmax_j(e(\mathbf{h}_{u_i}, \mathbf{h}_{u_j})) = \frac{exp(e(\mathbf{h}_{u_i}, \mathbf{h}_{u_j}))}{\sum_{j' \in N_i^r} exp(e(\mathbf{h}_{u_i}, \mathbf{h}_{u_{j'}}))}$$

$$e(\mathbf{h}_{u_i}, \mathbf{h}_{u_j}) = \mathbf{a}^\top LeakyReLU(\mathbf{W} \cdot [\mathbf{h}_{u_i} || \mathbf{h}_{u_j}]) \tag{5}$$

where $\mathbf{a} \in \mathbb{R}^d$ and $\mathbf{W} \in \mathbb{R}^{d' \times d}$ are learned, $||$ denotes vector concatenation. We use graph neural network (GCN) [18] to capture the deeper interaction representations:

---

[3] https://huggingface.co/studio-ousia/luke-japanese-base

$$\mathbf{h}_i^{n(l+1)} = \sigma\left(\sum_{j \in N_i^r} \mathbf{W}^{(l+1)}\mathbf{h}_j^{n(l)} + \mathbf{W}_0^{(l+1)}\mathbf{h}_i^{n(l)}\right) \tag{6}$$

where $\mathbf{W}^{(l+1)}, \mathbf{W}_0^{(l+1)}$ are learnable metrics. Given the latent representation $\mathbf{g}_r$ [18] of each graph which corresponds to a distinct relation, we then use the self-attention mechanism to fuse the graph outputs of innate and acquired relations:

$$\begin{aligned}
\mathbf{z} &= \mathbf{g}_0||\mathbf{g}_1||...||\mathbf{g}_r \\
\mathbf{z}' &= Attn(\mathbf{z,z,z})
\end{aligned} \tag{7}$$

4.3 Personality Recognition with Multi-task Learning

Since each pair of Big-Five is statistically significantly related as shown in Table 1, we recognize Openness, Neuroticism, Extraversion, Agreeableness, and Conscientiousness in the manner of multi-task learning using five linear layers. The i_{th} layer can be represented as:

$$\mathscr{P}_i = \sigma(\mathbf{W}_p^i \mathbf{z}' + b_p^i) \tag{8}$$

where σ denotes the activation function ReLU, $\mathbf{W}_p^i$ and b_p^i are the learnable weight matrix and bias. We treat them as regression tasks and use the mean absolute error (MAE) as the loss function for model optimization. The loss item of each data sample j is denoted as $l(\mathbf{P}^j, \mathbf{y}^j)$ that is calculated by averaging the loss of five tasks, where $\mathbf{P}^j$ is the vector of 5 predictions and $\mathbf{y}^j$ is the vector of 5 ground truth personality traits. The loss item of one batch containing N data samples is denoted as L. They are calculated as follows:

$$\begin{aligned}
l(\mathbf{P}^j, \mathbf{y}^j) &= \frac{1}{5}\sum_{i=1}^{5}\left|\mathscr{P}_i^j - y_i^j\right| \\
L &= \frac{1}{N}\sum_{j=1}^{N} l(\mathbf{P}^j, \mathbf{y}^j).
\end{aligned} \tag{9}$$

5 Experimental Settings

5.1 Dataset Partitioning

We conduct two experimental settings, one based on **monologues** and the other on **dialogues**. The monologue setting focuses on a speaker's own utterances, while the dialogue setting integrates utterances from both the speaker and the interlocutor for personality recognition. In the monologue experiments, we implemented strict

speaker splitting to ensure no overlap among speakers across the training, validation, and test sets. This approach meant the model was evaluated on unseen speakers.

In the dialogue experiments, ensuring non-overlap of both speakers in all datasets proved challenging. Therefore, we ensured that only the initiating speaker was non-repeating across datasets, and the model was tasked with predicting only the initiating speaker's personality. Therefore, we only use relation *spk a→spk a* and *spk b→spk a* in the HC-GNN model. We created training, validation, and test sets by randomly dividing the speakers in an 8:1:1 ratio for 100 times and selecting the split that most closely matched 8:1:1 distribution for monologues and dialogues. We then fixed the split across all experiments.

5.2 Models

All the models are based on a BERT-like model which converts utterances into embeddings. In all experiments, we used pooled output from LUKE base model [32] because it showed the best performance in terms of average balanced accuracy among LUKE-base/large, RoBERTa-base/large, xlm-roberta base/large, mdeberta-v3-base models. We experimented with different models after the base model:

MLP: Five linear module joints with regression heads are used to predict each personality. Each regression head contains 2 linear layers where the first layer maps embedding from LUKE to embedding with a size 16 and the second layer maps embedding with a size 16 to 1.

Homogeneous Methods:

GCNs [33]: represents one of the most prevalent methods for handling graph-structured data, particularly in node classification and link prediction tasks.

GATv2 [19]: introduces a significant enhancement by transitioning from a static to a dynamic attention mechanism.

In our experiments, we utilize either two GraphConv layers or a single GATv2Conv layer to process the union of relation types within the set $\mathcal{R}$.

Heterogenous Methods:

RGCN [31]: relational graph convolutional network, which is developed to handle multi-relational data with a heterogeneous architecture, as shown in Fig. 1. Specifically, we use one RGCNConv layer connected by one GraphConv layer to handle the union of relation types in $\mathcal{R}$, setting the number of relations to 2.

HCGNN: our proposed method, the heterogeneous conversation graph neural network, independently models the interdependencies and intra-dependencies within speakers. Specifically, a GATv2Conv layer, interconnected with two GraphConv layers, is employed to extract distinct relational information corresponding to each relation type in the set $\mathcal{R}$. GraphConv, GATv2Conv and RGCNConv layers are imported from torch_geometric.nn [4]. The number of the attention head in GATv2Conv is set to 2.

---

[4] https://pytorch-geometric.readthedocs.io/en/latest/modules/nn.html

5.3 Training

We used the Adam optimizer with $\beta_1 = 0.9, \beta_2 = 0.999$ and a learning rate of 1×10^{-5}. We used a linear scheduler with warmup step $= 150$. We used Mean Absolute Error (MAE) criterion because it outperformed the Mean Squared Error (MSE) greatly in terms of balanced accuracy. We set the batch size to 128 for linear models and 32 for graph neural network models, which reach the memory limitation of eight 32G GPUs. We calculated the loss on the validation set after each epoch and applied early stopping when no improvement was observed for 3 epochs. We conducted single-round experiments for each configuration. We employed four distinct metrics to assess the model's performance across five different personality traits, which will offer insight into the model's overall capabilities.

5.4 Evaluation Metrics

We report binary classification accuracy and balanced accuracy together with Pearson correlation and Spearman correlation for regression tasks. The threshold for the binary classification task of each personality trait is set to the median score in the training set. Here are the details of each metric:

Accuracy: a metric that summarizes the performance of a classification task, which is the number of correctly predicted data points out of all the data points.

Balanced Accuracy: arithmetic mean of sensitivity and specificity to deal with imbalanced data.

Pearson Correlation: a correlation coefficient that measures the linear correlation between the predicted personality values and the ground truth.

Spearman Correlation: a nonparametric measure of rank correlation (statistical dependence between the rankings of two variables).

6 Results and Analysis

6.1 Monologue

Main Results. Table 2 presents a comparative analysis of the accuracy and balanced accuracy of the data augmentation method at various data sizes. With the addition of augmented data, both accuracy and balanced accuracy show significant improvements, increasing from 57.4% to 61.2% and from 55.6% to 60.4%, respectively. Table 3 shows the Pearson and Spearman correlation results. We observe that data augmentation generally improves correlation in most traits, and the impact of augmentation is more pronounced in N and A than in others. We fail to predict personality trait E in any setting. We believe this may be due to our dataset being based

Table 2: Accuracy results in monologue setting with original data and augmented dataset. The best result in each column is in **bold**.

Data	Accuracy						Balanced Accuracy					
	N	E	O	A	C	Avg.	N	E	O	A	C	Avg.
Original	66.2	52.6	57.6	52.7	57.9	57.4	59.7	54.3	58.8	50.3	55.0	55.6
+10k	74.3	55.5	56.6	49.9	51.2	57.5	60.4	52.5	55.4	47.8	52.8	53.8
+20k	**74.5**	54.3	55.5	**59.0**	60.1	60.7	**65.9**	53.8	56.0	58.5	48.3	56.5
+50k	60.5	53.0	60.9	58.7	59.8	58.6	60.2	55.0	61.2	**62.0**	52.4	58.2
+500k	62.7	**58.2**	**62.0**	57.9	**65.4**	**61.2**	64.6	**56.0**	**61.3**	60.3	**59.7**	**60.4**

Table 3: Correlation results in monologue setting with various data sizes.

Data	Pearson Correlation					Spearman Correlation				
	N	E	O	A	C	N	E	O	A	C
Original	*.279*	-.040	*.473*	*.105*	*.166*	*.292*	-.014	*.282*	*.104*	*.200*
+10k	*.389*	-.092	*.510*	*.100*	***.200***	*.283*	-.064	*.277*	*.091*	*.180*
+20k	***.492***	.054	***.510***	*.268*	*.113*	***.495***	.063	*.276*	*.261*	*.126*
+50k	*.224*	.067	*.486*	***.387***	*.099*	*.264*	.085	*.378*	***.375***	*.119*
+500k	*.267*	.025	*.459*	*.232*	*.164*	*.333*	.045	***.388***	*.230*	***.203***

<div align="right">(Italic means $p < .05$)</div>

on first-meeting spontaneous situations, where people tend not to exhibit extrovert traits explicitly. We also find that the optimal results for different personality traits, in terms of accuracy, balanced accuracy, Pearson correlation, and Spearman correlation, do not consistently align with the same data augmentation size. We attribute this variability primarily to the inherent randomness associated with data synthesis.

Results of Data Augmentation Variants.

1. Fusing Ratio. We compare results using $\beta \sim \text{Uniform}(0,1)$ and fixed $\beta = 0.5$. With 500k additional data, using random β achieved 61.2% averaged accuracy and 60.4% averaged balanced accuracy whereas using fixed β showed 59.3% accuracy and 58.4% balanced accuracy. This is because using random β results in more various data. Since the original label score distribution is discrete (there are only a limited number of score values), using β following a continuous distribution yields a higher variety of labels and corresponding textual data compared to using fixed β.

2. Speaker Choice. We compare generating synthetic dialogue from the same speaker or two different speakers. We observe using dialogues from different speakers not only enables continuous data distribution as shown in Fig. 3 but also showed much higher averaged accuracy (61.2% vs 57.3%) and balanced accuracy (60.4% vs 58.1%), which demonstrates that speaker variety is more crucial than the number of conversations for personality recognition within this dataset.

3. Various Context Lengths. Real-time personality recognition in dialogue is essential for human-robot interaction. To enable this, we propose to use various context lengths of dialogues for training. Table 4 presents comparative results on a range

of test context turns when training with various context lengths and full context lengths, using an augmented data set of 500k. When testing the first 2 turns using various context lengths during training results in 58.2% averaged balanced accuracy, which is comparable to the result of 60.4% using the full contexts during inference. On the other hand, we got only 55.5% when training with full contexts (approximately 15 turns). In addition to context turns being 2 during inference, similar trends can also be observed in other numbers.

(a) Generate synthetic data by combining two dialogues from two different speakers.

(b) Generate synthetic data by combining two dialogues from the same speaker.
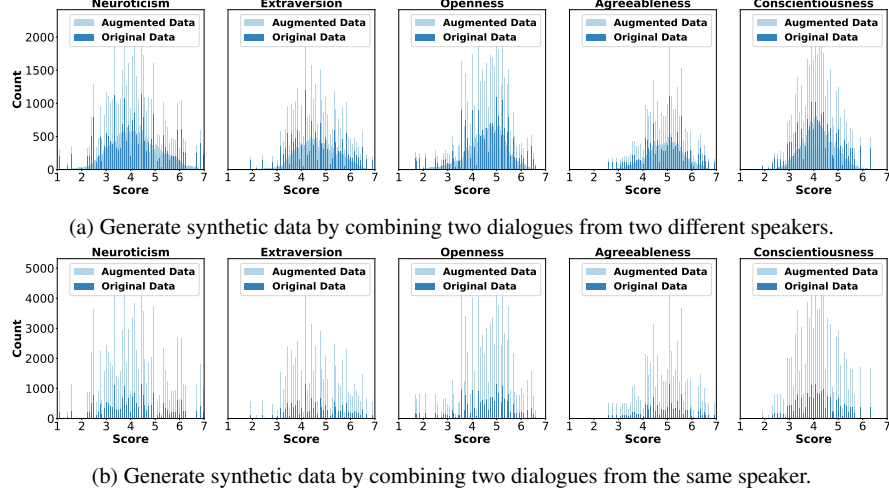
Fig. 3: Data distribution of augmented data and original data.

Table 4: Comparative results of accuracy and balanced accuracy for a range of test context turns: training with various context turns (≥ 2) vs. full context turns, using an augmented data set of 500k.

test	train	Accuracy		Balanced Accuracy	
		various context	full context	various context	full context
2		59.7	57.8	58.2	55.5
3		59.6	57.6	57.8	55.8
4		59.9	58.1	58.4	56.6
5		60.3	58.0	58.6	56.3
10		60.7	57.6	59.6	56.6
full		61.2	57.1	60.4	57.0

6.2 Dialogue

Comparisons between Monologue and Dialogue. To explore the impact of context on personality recognition, we first prepend the [SPK1] or [SPK2] token to the

Table 5: Accuracy results in the comparisons among monologue and dialogue.

	Model	Accuracy						Balanced Accuracy					
		N	E	O	A	C	Avg.	N	E	O	A	C	Avg.
Monologue	MLP	66.2	52.6	57.6	52.7	57.9	57.4	59.7	54.3	**58.8**	50.3	**55.0**	55.6
Dialogue	MLP	66.8	53.2	**57.9**	49.0	58.4	57.1	59.5	**56.9**	57.9	49.8	47.5	54.3
	GCN [33]	**69.5**	40.3	52.9	33.3	**72.1**	53.6	50.0	50.4	53.7	34.4	50.1	47.7
	GAT [19]	66.4	54.5	52.7	59.9	54.6	57.6	60.4	51.3	50.1	52.2	52.1	53.2
	RGCN [31]	68.5	**57.2**	55.4	41.9	56.7	55.9	**63.0**	54.5	55.9	47.2	51.9	54.5
	HC-GNN (ours)	69.0	53.5	55.6	**65.9**	52.2	**59.2**	60.9	54.3	52.6	**59.6**	54.6	**56.4**

Table 6: Correlation results in the comparisons among monologue and dialogue.

	Model	Pearson Correlation					Spearman Correlation				
		N	E	O	A	C	N	E	O	A	C
Monologue	MLP	.279	-.040	.473	.105	.166	.292	-.014	.282	.104	**.200**
Dialogue	MLP	.288	.048	**.492**	.174	.077	.214	.088	.262	.123	.072
	GCN [33]	.170	-.015	.298	-.203	.079	.173	.017	.164	-.227	.105
	GAT [19]	.307	-.067	.420	.079	.134	.284	-.030	.226	.082	.135
	RGCN [31]	**.377**	.048	.490	.152	.148	**.375**	.078	**.311**	.146	.160
	HC-GNN (ours)	.285	.040	.347	**.216**	**.169**	.304	.066	.243	**.191**	.193

(*Italic* means $p < .05$)

respective utterances and then concatenate all utterances using the [SEP] token. We employ the same model as in the monologue experiment. As indicated in Table 5 and 6, the results with conventional methods using the context (dialogue) show a decrease in performance compared to the monologue setting across most evaluation metrics. We hypothesize that merely concatenating utterances between two speakers is not an effective method for modeling the interactions between interlocutors. Therefore, we propose independently modeling both the interdependency among speakers and the intra-dependency within the speaker. The results, as shown in Tables 5 and 6, indicate that our proposed method surpasses all baseline methods in the dialogue setting and marginally improves upon the results in the monologue setting.
Data Augmentation in Dialogue. We test the effectiveness of data augmentation in the dialogue setting. The results, as shown in Table 7 and 8, indicate that increasing speaker variety can enhance personality recognition in dialogue. Although the highest balanced accuracy achieved in the dialogue setting is 58.6, falling short of the monologue setting's best result of 60.4. Due to our focus on predicting only *speaker a*'s personality in the dialogue setting, the original dataset lost half of its conversational data for augmentation purposes. This loss is an inevitable trade-off in the pursuit of speaker-independent personality recognition within dialogue settings.

Table 7: Accuracy results of HC-GNN in dialogue setting with various data sizes.

Data		Accuracy						Balanced Accuracy					
		N	E	O	A	C	Avg.	N	E	O	A	C	Avg.
Monologue +500k		62.7	58.2	**62.0**	57.9	**65.4**	61.2	**64.6**	**56.0**	**61.3**	60.3	**59.7**	**60.4**
Dialogue (HC-GNN)	Original	69.0	53.5	55.6	65.9	52.2	59.2	60.9	54.3	52.6	59.6	54.6	56.4
	+10k	73.9	59.7	54.0	63.9	54.6	61.2	59.5	52.8	50.7	55.6	59.0	55.5
	+20k	**74.3**	**60.1**	58.4	**67.5**	40.8	60.2	60.8	54.4	55.8	61.6	55.5	57.6
	+50k	69.6	54.7	58.7	62.2	63.8	**61.8**	61.9	55.5	58.4	**62.3**	55.1	58.6
	+500k	66.3	56.6	58.8	60.1	59.0	60.2	63.7	53.8	57.0	57.7	59.2	58.3

Table 8: Correlation results of HC-GNN in dialogue setting with various data sizes.

Data		Pearson Correlation					Spearman Correlation				
		N	E	O	A	C	N	E	O	A	C
Monologue +500k		.267	.025	***.459***	*.232*	*.164*	*.333*	.045	***.388***	*.230*	*.203*
Dialogue (HC-GNN)	Original	*.285*	.040	*.347*	*.216*	*.169*	*.304*	.066	*.243*	*.191*	*.193*
	+10k	*.369*	.019	*.329*	*.235*	***.234***	*.343*	.058	*.226*	*.234*	***.263***
	+20k	*.327*	-.052	*.441*	***.314***	*.110*	*.301*	.003	*.245*	*.278*	*.142*
	+50k	*.345*	.030	*.312*	*.300*	*.162*	*.374*	.050	*.250*	***.281***	*.183*
	+500k	***.426***	.046	*.411*	*.209*	*.223*	***.439***	.062	*.315*	*.194*	*.242*

(*Italic* means $p < .05$)

7 Conclusion

We have proposed a data augmentation method for personality recognition, which involves interpolating between two existing data points to enhance speaker diversity. Additionally, we have introduced the HC-GNN method to independently model the interdependencies among interlocutors, as well as the intra-dependencies within the speaker in dialogues. Experimental results from the RealPersonaChat corpus demonstrate that increasing speaker diversity significantly improves personality recognition in both monologue and dialogue settings. Our HC-GNN method outperforms baseline models, showcasing its effectiveness. However, our experiments suggest that context did not make a large improvement in personality recognition. Further exploration of the dialogue setting will be the focus of our future work.

References

[1] François Mairesse, Marilyn A. Walker, Matthias R. Mehl, and Roger K. Moore. Using linguistic cues for the automatic recognition of personality in conversation and text. *J. Artif. Int. Res.*, 30(1):457–500, nov 2007. ISSN 1076-9757.

[2] Robert R McCrae and Oliver P John. An introduction to the five-factor model and its applications. *Journal of personality*, 60(2):175–215, 1992.

[3] James W Pennebaker and Laura A King. Linguistic styles: language use as an individual difference. *Journal of personality and social psychology*, 77(6): 1296, 1999.

[4] Majid Ramezani, Mohammad-Reza Feizi-Derakhshi, and Mohammad-Ali Balafar. Text-based automatic personality prediction using kgrat-net: a knowledge graph attention network classifier. *Scientific Reports*, 12(1):21453, 2022.

[5] Zhiyuan Wen, Jiannong Cao, Yu Yang, Haoli Wang, Ruosong Yang, and Shuaiqi Liu. Desprompt: Personality-descriptive prompt tuning for few-shot personality recognition. *Information Processing & Management*, 60(5): 103422, 2023.

[6] Víctor Ponce-López, Baiyu Chen, Marc Oliu, Ciprian Corneanu, Albert Clapés, Isabelle Guyon, Xavier Baró, Hugo Jair Escalante, and Sergio Escalera. Chalearn lap 2016: First round challenge on first impressions-dataset and results. In *Computer Vision–ECCV 2016 Workshops: Amsterdam, The Netherlands, October 8-10 and 15-16, 2016, Proceedings, Part III 14*, pages 400–418. Springer, 2016.

[7] M. M. Amin, E. Cambria, and B. W. Schuller. Can chatgpt's responses boost traditional natural language processing? *IEEE Intelligent Systems*, 38(05):5–11, sep 2023. ISSN 1941-1294. doi: 10.1109/MIS.2023.3305861.

[8] Matej Gjurković, Mladen Karan, Iva Vukojević, Mihaela Bošnjak, and Jan Snajder. PANDORA talks: Personality and demographics on Reddit. In *Proceedings of the Ninth International Workshop on Natural Language Processing for Social Media*, pages 138–152, June 2021.

[9] Esteban Andres Rissola, Seyed Ali Bahrainian, and Fabio Crestani. Personality recognition in conversations using capsule neural networks. In *IEEE/WIC/ACM International Conference on Web Intelligence*, pages 180–187, 2019.

[10] Hang Jiang, Xianzhe Zhang, and Jinho D Choi. Automatic text-based personality recognition on monologues and multiparty dialogues using attentive networks and contextual embeddings (student abstract). In *Proceedings of the AAAI conference on artificial intelligence*, volume 34, pages 13821–13822, 2020.

[11] Yirong Chen, Weiquan Fan, Xiaofen Xing, Jianxin Pang, Minlie Huang, Wenjing Han, Qianfeng Tie, and Xiangmin Xu. CPED: A large-scale chinese personalized and emotional dialogue dataset for conversational ai. *arXiv preprint arXiv:2205.14727*, 2022. URL https://arxiv.org/abs/2205.14727.

[12] Matthias R Mehl, Samuel D Gosling, and James W Pennebaker. Personality in its natural habitat: manifestations and implicit folk theories of personality in daily life. *Journal of personality and social psychology*, 90(5):862, 2006.

[13] Sanae Yamashita, Koji Inoue, Ao Guo, Shota Mochizuki, Tatsuya Kawahara, and Ryuichiro Higashinaka. RealPersonaChat: A realistic persona chat corpus with interlocutors' own personalities. In *Proceedings of the 37th Pacific Asia Conference on Language, Information and Computation*, 2023.

[14] Kaustubh D Dhole, Varun Gangal, Sebastian Gehrmann, Aadesh Gupta, Zhenhao Li, Saad Mahamood, Abinaya Mahendiran, Simon Mille, Ashish Shrivastava, Samson Tan, et al. Nl-augmenter: A framework for task-sensitive natural language augmentation. *arXiv preprint arXiv:2112.02721*, 2021.

[15] Jason Wei and Kai Zou. EDA: Easy data augmentation techniques for boosting performance on text classification tasks. In *EMNLP-IJCNLP*, pages 6382–6388, November 2019.

[16] Silin Gao, Yichi Zhang, Zhijian Ou, and Zhou Yu. Paraphrase augmented task-oriented dialog generation. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 639–649, July 2020.

[17] Rico Sennrich, Barry Haddow, and Alexandra Birch. Improving neural machine translation models with monolingual data. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 86–96, August 2016.

[18] Petar Veličković, Guillem Cucurull, Arantxa Casanova, Adriana Romero, Pietro Lio, and Yoshua Bengio. Graph attention networks. *arXiv preprint arXiv:1710.10903*, 2017.

[19] Shaked Brody, Uri Alon, and Eran Yahav. How attentive are graph attention networks? *arXiv preprint arXiv:2105.14491*, 2021.

[20] Connor Shorten and Taghi M Khoshgoftaar. A survey on image data augmentation for deep learning. *Journal of big data*, 6(1):1–48, 2019.

[21] Ivan Provilkov, Dmitrii Emelianenko, and Elena Voita. BPE-dropout: Simple and effective subword regularization. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 1882–1892, July 2020.

[22] Su Wang, Rahul Gupta, Nancy Chang, and Jason Baldridge. A task in a suit and a tie: paraphrase generation with semantic augmentation. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 33, pages 7176–7183, 2019.

[23] Ziang Xie, Guillaume Genthial, Stanley Xie, Andrew Ng, and Dan Jurafsky. Noising and denoising natural language: Diverse backtranslation for grammar correction. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pages 619–628, June 2018.

[24] Miguel Graça, Yunsu Kim, Julian Schamper, Shahram Khadivi, and Hermann Ney. Generalizing back-translation in neural machine translation. In *Proceedings of the Fourth Conference on Machine Translation (Volume 1: Research Papers)*, pages 45–52, August 2019.

[25] Maxwell Mojapelo and Jan Buys. Data augmentation for low resource neural machine translation for sotho-tswana languages. In *Proceedings of Southern African Conference for AI Research (SACAIR 2023)*, Johannesburg, South Africa, 2023.

[26] Jason Wei. Good-enough example extrapolation. In Marie-Francine Moens, Xuanjing Huang, Lucia Specia, and Scott Wen-tau Yih, editors, *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 5923–5929, November 2021.

[27] Yahui Fu, Shogo Okada, Longbiao Wang, Lili Guo, Yaodong Song, Jiaxing Liu, and Jianwu Dang. CONSK-GCN: conversational semantic-and knowledge-oriented graph convolutional network for multimodal emotion recognition. In *2021 IEEE International Conference on Multimedia and Expo (ICME)*, pages 1–6. IEEE, 2021.

[28] Yahui Fu, Okada Shogo, Longbiao Wang, Guo Lili, Song Yaodong, Liu Jiaxing, and Dang Jianwu. Context-and knowledge-aware graph convolutional network for multimodal emotion recognition. *IEEE MultiMedia*, 29(3):91–100, 2022.

[29] Fu Changzeng, Chen Zhenghan, Shi Jiaqi, Wu Bowen, Liu Chaoran, Ishi Carlos Toshinori, and Ishiguro Hiroshi. Hag: Hierarchical attention with graph network for dialogue act classification in conversation. In *ICASSP*, pages 1–5. IEEE, 2023.

[30] Yang Tao, Deng Jinghao, Quan Xiaojun, and Wang Qifan. Orders are unwanted: dynamic deep graph convolutional network for personality detection. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 37, pages 13896–13904, 2023.

[31] Michael Schlichtkrull, Thomas N Kipf, Peter Bloem, Rianne Van Den Berg, Ivan Titov, and Max Welling. Modeling relational data with graph convolutional networks. In *The Semantic Web: 15th International Conference, ESWC 2018, Heraklion, Crete, Greece, June 3–7, 2018, Proceedings 15*, pages 593–607. Springer, 2018.

[32] Yamada Ikuya, Asai Akari, Shindo Hiroyuki, Takeda Hideaki, and Matsumoto Yuji. Luke: deep contextualized entity representations with entity-aware self-attention. *arXiv preprint arXiv:2010.01057*, 2020.

[33] Thomas N Kipf and Max Welling. Semi-supervised classification with graph convolutional networks. *arXiv preprint arXiv:1609.02907*, 2016.