Effects of Personality Traits on Listening-oriented Dialogue

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Abstract. This paper investigates the effects of personality traits on listening-oriented dialogue to gain insight into building automated listening agents. The analysis of the frequency of dialogue act and the dialogue flow using Hidden Markov Models (HMMs) revealed that a dialogue becomes characteristically different depending on the personality traits of the listeners and the speakers, suggesting that automated listening agents must consider the personality traits of users to become good listeners.

1 Introduction

We have been investigating the characteristics of listening-oriented dialogues to build automated listening agents [Meguro et al., 2009]. A listening-oriented dialogue is one in which one conversational participant attentively listens to the other and satisfies his/her desire to speak and have himself/herself heard. We believe that automated listening agents will lead to improvements of user minds, for example, in therapy sessions and senior peer counseling.

This paper investigates the effects of the personality traits of conversational participants on listening-oriented dialogues. We examine how the frequency of dialogue acts and the dialogue flow change depending on the personality of listeners and speakers in order to gain insight into how automated listening agents should modify their behavior when users show particular personality traits.

The importance of personality is increasing in dialogue systems. For example, Mairesse et al. proposed utterance generation that reflects the big five personality traits so that systems can have personalities similar to users [Mairesse and Walker, 2007]. Note that users tend to appreciate interfaces that match their own personalities [Reeves and Nass, 1998]. [Bickmore and Cassell, 2005] also investigated the effects of a system's personality on building trust in social dialogues. This paper aims to reveal the effects of personality traits in listening-oriented dialogues.

2 Correlation with the frequency of dialogue acts

We first examined the correlation between the frequency of dialogue acts and personality traits. The dialogue data used for analysis were those collected in [Meguro et al., 2009]. The data contain 16 listening-oriented 30-minute text-based dialogues from 16 participants (eight listeners and eight speakers). Each

Table 1. Correlation coefficients between the occurrence rates of dialogue acts per dialogue and the scores of the five personality traits of the listeners and speakers. **Bold font** means coefficients over 0.5.

	listeners							speakers						
	DISC	INFO	ACK	QUES	SYM	GR	OTH	DISC	INFO	ACK	QUES	SYM	GR	OTH
At	0.03	0.41	0.11	-0.04	-0.31	-0.24	0.26	0.36	**-0.53**	**0.51**	-0.16	**-0.57**	-0.06	0.43
Co	**-0.57**	-0.36	0.36	**0.72**	-0.48	0.20	**-0.63**	-0.22	0.41	0.23	-0.34	0.18	0.27	0.44
Em	-0.33	-0.34	0.31	0.33	-0.20	-0.04	-0.19	0.01	0.20	0.04	-0.02	0.12	0.08	**-0.73**
Ex	0.16	**0.62**	0.10	-0.17	-0.26	-0.48	0.36	**0.53**	**-0.64**	0.05	0.01	0.18	0.07	-0.16
Pl	**0.79**	0.48	**-0.55**	**-0.67**	0.42	-0.36	0.40	0.47	-0.03	0.23	**-0.52**	**-0.54**	**-0.71**	0.37

listener listened to two of the speakers about various topics, such as travel, sports, and movies.

Before engaging in the dialogues, the participants filled out Five-Factor Personality Questionnaires (FFPQs) [Fujishima et al., 2005] that measure the following five personality traits: namely, Attachment (At: whether to synchronize with others), Conscientiousness (Co: whether to adhere to one's conviction), Emotionality (Em: whether to respond strongly to emotions), Extroversion (Ex: whether to be actively concerned with external things), and Playfulness (Pl: whether to offer creative thoughts). Note that these five personality traits do not strictly correspond to the standard big five personality traits in English [Barrick and Mount, 1991] because the FFPQ was customized for Japanese participants. After the data collection, all utterances were annotated with seven dialogue acts (SELF-DISCLOSURE, INFORMATION DELIVERY, ACKNOWLEDGMENT, QUESTION, SYMPATHY, GREETING, and OTHER) by an annotator.

Table 1 shows the correlation coefficients between the occurrence rates of dialogue acts per dialogue and the scores of the five personality traits of the listeners and speakers. Since the table contains a good number of relatively large correlation coefficients, the personality traits clearly affect the frequency of dialogue acts. When we focus on the speakers, we find that (1) high attachment leads to more acknowledgment for synchronization, (2) high extroversion leads to more self-disclosure and less information delivery, and (3) high playfulness leads to the increase in self-disclosure and decrease in the dialogue acts relating to the interaction (i.e., QUESTION, SYMPATHY, and GREETING) with the conversational partner. We need to take such findings as (1)–(3) into account when we build our listening agents, for example, by making the agents actively encourage self-disclosure for extrovert and playful users.

3 Effects of personality traits on dialogue flows

In addition to the frequency of dialogue acts, we investigated how dialogue flows differ depending on the personality traits of the conversational participants. For each personality trait, we divided the data into two sets: one containing eight dialogues from the top-4 listeners in the personality trait score (positive set), and the other containing those from the other four listeners (negative set). The same sets were also made for the speakers. For each set, we modeled the dialogue flow

Table 2. Accuracies of distinguishing positive and negative sets for each personality trait and for each conversational role (listener or speaker).

	At	Co	Em	Ex	Pl
Listener	56.25%	43.75%	56.25%	56.25%	56.25%
Speaker	62.50%	25.00%	43.75%	37.50%	**93.75%**

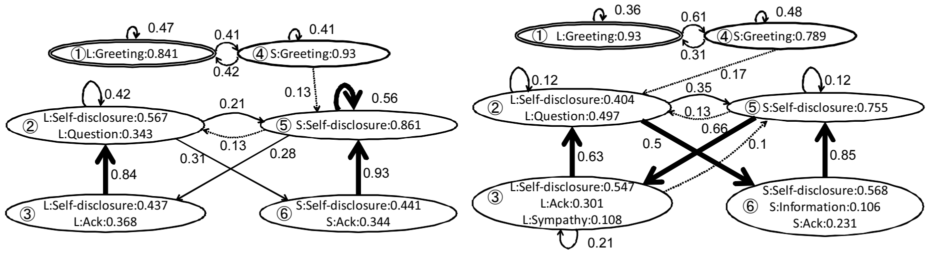

Fig. 1. Speaker HMMs for playful (left) and non-playful (right) speakers. Transitions and emissions over probability of 0.1 are shown.

by Hidden Markov Models (HMMs), which have been used for modeling dialogue act sequences [Shirai, 1996, Isomura et al., 2006].

In training the HMMs, we defined 14 observation symbols that correspond to seven tags (six dialogue act tags plus OTHER) for a listener and the same number of tags for a speaker and trained them so that half of the states only emit the listener's dialogue acts and the other half emit the speaker's dialogue acts. All states were connected to each other. We call such HMMs *speaker HMMs*. The EM algorithm was used for training, and the most fitting model was created using the Minimum Description Length (MDL) criterion.

We experimentally examined whether the trained HMMs can distinguish the positive and negative sets using half of the dialogues in each set to train the HMMs and classifying the remaining dialogues. This process was repeated for the other half to derive classification accuracy. Table 2 shows the accuracy of distinguishing the positive and negative sets for each personality trait and for each conversational role (listener or speaker). When the dialogues are divided by speaker playfulness, the accuracy is very high with 93.75%. Note that no significant differences are found in the personality traits between listeners who talked to playful speakers and those who did not. This indicates that the dialogue flow became characteristically different when the speakers had high/low playfulness in the listening-oriented dialogues.

Figure 1 shows the Speaker HMMs trained using the positive and negative sets when the dialogues were divided by the playfulness of the speakers. In both HMMs, states ①–③ correspond to those of a listener (L) and ④–⑥ of a speaker (S). The two HMMs have very similar structures, and their state IDs seem to have one-to-one correspondence from their emission probabilities. However, they have very different transition probabilities, especially in the negative set, where there are more transitions from speaker to listener. This indicates that turns are frequently switched with a non-playful speaker. In addition, when less playful speakers are involved, the speakers increase information delivery, and the listeners increase sympathy, probably because less playful speakers remain more objective during the dialogues and listeners need to show sympathy so that such speakers are more subjectively involved in the conversation. When we compare the state transitions in more detail by following the most probable state sequences, we found that the Speaker HMM for playful speakers tends to stay in ② whereas the Speaker HMM for non-playful speakers tends to stay in ③. Since ② is the sole state that emits questions in these HMMs, the listeners seem to increase questions for playful speakers, who are willing to self-disclose by nature.

From the above analysis, we can say that automated listening agents should take fewer turns for playful speakers and more for less playful ones. They should also be more sympathetic to less playful speakers. They also need to actively question playful speakers to satisfy their willingness to self-disclose.

4 Summary and Future Work

This paper investigated the effects of personality traits on listening-oriented dialogue. The analysis revealed that the frequency of dialogue acts and the dialogue flow are affected by the personality traits of listeners and speakers, suggesting that automated listening agents should consider the personality traits of users to become good listeners. Future work includes using a more elaborate tag set to further analyze the dialogue flows. We also need to analyze the listening process in spoken dialogues in addition to text-based dialogues. We also want to incorporate non-verbal features, such as nodding and shaking of the head, as studied in [Maatman et al., 2005]. We also want to implement prototypes of our listening agents based on our analysis.

References

[Barrick and Mount, 1991] Barrick, M. and Mount, M. (1991). The Big Five personality dimensions and job performance: A meta-analysis. *Personnel psychology*, 44(1):1–26.

[Bickmore and Cassell, 2005] Bickmore, T. and Cassell, J. (2005). Social dialogue with embodied conversational agents. *Natural, intelligent and effective interaction with multimodal dialogue systems. New York: Kluwer Academic*, pages 23–54.

[Fujishima et al., 2005] Fujishima, Y., Yamada, N., and Tsuji, H. (2005). Construction of short form of five factor personality questionnaire. *The Japanese Journal of Personality*, 13(2):231–241. (in Japanese).

[Isomura et al., 2006] Isomura, N., Toriumi, F., and Ishii, K. (2006). Evaluation method of non-task-oriented dialogue system by HMM. In *Proc. the 4th Symposium on Intelligent Media Integration for Social Information Infrastructure*, pages 149–152.

[Maatman et al., 2005] Maatman, R. M., Gratch, J., and Marsella, S. (2005). Natural behavior of a listening agent. *Lecture Notes in Computer Science*, 3661:25–36.

[Mairesse and Walker, 2007] Mairesse, F. and Walker, M. (2007). PERSONAGE: Personality Generation for Dialogue. In *Proc. ACL*, pages 496–503.

[Meguro et al., 2009] Meguro, T., Higashinaka, R., Dohsaka, K., Minami, Y., and Isozaki, H. (2009). Analysis of listening-oriented dialogue for building listening agents. In *Proc. SIGDial*, pages 124–127.

[Reeves and Nass, 1998] Reeves, B. and Nass, C. (1998). *The media equation.* CSLI publications.

[Shirai, 1996] Shirai, K. (1996). Modeling of spoken dialogue with and without visual information. In *Proc. ICSLP*, volume 1, pages 188–191.