Sentiment-aware Interview Chatbot Based on Deep Learning Approach for Personality Detection from Text

HAOYUE TAN [1,a)] TAKEFUMI OGAWA [2]

Abstract: Chatbots have become a new focus on human-computer interaction (HCI) and are already widely used in some services like booking assistants and customer services. The development of natural language processing (NLP) techniques enables chatbots to understand users' intent correctly and respond human-likely, leading to their fulfillment to more complicated tasks like interviews. This research built a sentiment-aware chatbot providing users a more engaging conversational experience while detecting users' MBTI personality type from input text. This research use language model BERT to extract features and generate sentence-level embeddings of raw text. Compared to traditional methods of training machine learning algorithms with psychological lexicons, this method significantly improved overall accuracy.

Keywords: Chatbot, Personality detection, Language models, Deep learning

1. Introduction

Chatbots have become a new focus in HCI due to their ability to handle more flexible and complicated situations with natural language. Many previous studies have shown that chatbot is an efficient tool to collect high-quality, distinct, self-disclosure user responses. A wide range of applications, including e-commerce, clinic, tourism, is applying chatbots to collect data and release humans from tedious work. However, traditional chatbots only focus on fulfilling tasks like setting reminders or asking specific questions. Modern chatbots aim to realize human-like conversations by giving them human characteristics, creating static profile images, and enhancing conversational skills. Researchers have made a great effort to keep users in a conversation with chatbots. Specifically, Xiao [1] enables chatbots with a subset of active listening skills – the ability to comprehend users' input and respond appropriately. Lee [2] implements and evaluates a chatbot having self-disclosure features when it performs small talk with people. Li [3] investigates how the personality of chatbots influences users' behaviors during an interview. With those techniques, modern AI chatbots can attract users' interests and keep them in the conversation. Because the more users talk, the more information chatbots can obtain. That is why using modern AI chatbots for more complicated tasks, such as interviewing and further computing users' personalities with deep learning-based personality detection models, is worth studying.

Ability to identify people's personalities has always been of great interest to researchers due to its importance. Psychology regards personality as one of the most persuasive research topics because it refers to individual differences in characteristic patterns of thinking, feeling, and behaving. It is significant to predict and describe an individual's behaviors and daily life activities [4]. The sources and methods of predicting personality models have changed considerably over time.

The most widely-used models to describe people's personalities are the Big 5 [5] and MBTI [6] the Big 5 describes personality in five traits: Openness, Conscientiousness, Extraversion, Agreeableness, Neuroticism, and will give a tendency of each trait. Compared to the Big 5, MBTI is a type model with broader applications in business [7]. MBTI is composed of a binary combination of four emotion dimensions: Extraversion (E) or Introversion (I), Sensing (S) or Intuition (N), Thinking (T) or Feeling (F), Judging (J) or Perceiving (P), leading to sixteen distinct personality types (fig1).

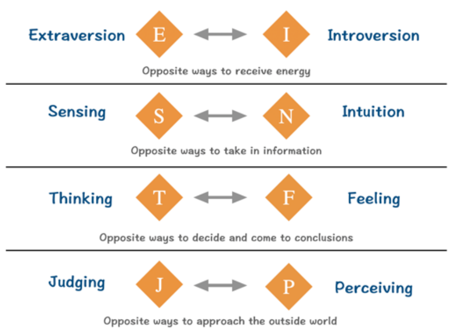


Fig1: The four MBTI pairs

The traditional way to get a personality model is by finishing a questionnaire containing a set of behavioral questions. Trained psychologists made a great effort to set questions to reveal aspects of an individual's character or psychological makeup, but such a method is usually costly, laborious, and error-prone. The intrinsic drawbacks of using the questionnaire make researchers exploit other methods. Some techniques have made progress in detecting personality with various data sources with a certain degree of accuracy. For example, some researchers have tried to approach the problem of personality recognition through some non-linguistic cues, such as face recognition [8] [9], signature, handwriting recognition [10]; speech acts [11], smartphone data [12]; and so on. Another group of researchers focused more on

1 Graduate School of Engineering, The University of Tokyo, Bunkyo, Tokyo 113-8656, Japan
2 Information Technology Center, The University of Tokyo, Kashiwa, Chiba 277-0882, Japan
a) tanhaoyue@g.ecc.u-tokyo.ac.jp

linguistic cues, like conversations, text, blogs from social media [13], fine emotion features extracted from essays [14].

Among those results, linguistic cues received more attention because people's words reflect who they are, and language has long been considered to have a profound correlation to personality traits [15] From the psycholinguistic perspective, it has been shown that different styles in language usage characterize each personality dimension. For example, extrovert people use more positive emotion words and less formal language than introvert people [16] [17]. There are two main methods for personality detection--using psychological lexicons with machine learning algorithms or training deep learning-based models with state-of-the-art natural language processing techniques. Since social media is becoming an increasingly significant role in our lives, providing massive corpora in a short time. Volume and linguistic naturalness make social media data a good fit for personality detection models. Section 2 will discuss how the two main approaches mentioned above use social media for personality detection [18] [19] [20].

Many companies conduct a personality test when interviewing candidates, but a chatbot could do this repetitive and bias-prone task. Little research focuses on building sentiment-aware chatbots to fulfill this complicated task. This paper will introduce how to build a sentiment-aware chatbot that can detect users' MBTI personality types by realizing two things:

- Train a deep learning-based personality detection model to obtain better accuracy.
- Build an interview chatbot that provides users engaging conversational experiences while analyzing their personality type with the trained model.

2. Related Work

2.1 Personality detection from text

Personality Detection with Psychological Lexicons

Exploration of the relationship between the use of language and personality identification dates back to the end of the 20th century. Based on the assumption of language psychology, the words use choices of people reflect who they are. In the beginning, many remarkable studies focused on personality detection using psychological lexicons. Pennebaker et al. developed a linguistic inquiry and word count (LIWC) [21] method, categorizing the words into 81 psychologically relevant categories. Then, counting the word use of each category will get the Big 5 personality traits. With LIWC constructed, Golbeck et al. used Twitter data to calculate the Pearson correlation values between language feature scores and personality traits scores, then applied machine learning algorithms - ZeroR and Gaussian Processes - to predict personality values [22].

Similarly, Yin et al. studied the relationship between negative textual information and Big Five personality traits [23]. They found that user interaction with Weibo for certain personality traits helps predict the spread of negative Weibo messages. Since language use is unpredictable on social media, others also mentioned that interpreting the results requires a tremendous psychological language background. To solve that, Poria et al. pointed out that using common sense knowledge with affective and sentiment information improves the accuracy of the existing frameworks [24] They used SenticNet [25], a popular tool to extract common sense knowledge and the associated sentiment polarity from the text, leading to an accuracy improvement on personality detection.

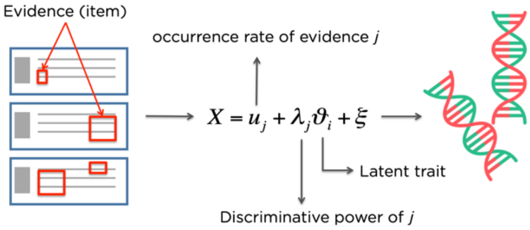


Fig2: Personality detection with psychological lexicons

Personality Detection with Deep Learning Approach

Using psychological lexicons has some inevitable drawbacks, such as the size of LIWC cannot be large enough to cover all the words. Automatic personality prediction has become a widely discussed topic for researchers in the NLP community. NLP is a field of linguistics machine learning focused on understanding everything related to human language. NLP tasks include classifying whole sentences, generating text content, extracting an answer from a text requiring models to understand the context instead of single words. The breakthrough of word embeddings has encapsulated more information in a vector, making it possible for machines to understand ambiguous natural language more deeply.

Moreover, social media is becoming an increasingly significant role in our lives, especially during this pandemic when people are hard to meet in person. Giant social media platforms, like Facebook, Twitter, or Weibo, users tend to reveal more information about their daily lives in linguistic or non-linguistic ways, providing massive corpora in a short time. Substantial social media data has become an excellent data source for building recommender systems or community detection. Further, previous studies have shown that people on Facebook and other social networks barely lie to reach impression management (IM) but rather stretch the truth. Training deep learning models on sizeable natural language social media datasets is worth trying to improve personality detection accuracy.

Transformers

Existing personality detection models attempted to use deep learning and open vocabulary feature extraction to improve classification accuracy [26]. However, since the pre-defined corpus is limited in size, the number of extracted contextual features is relatively small. To address the issue mentioned above, applying pre-trained language models like Bidirectional Encoder from Transformer (BERT), which enables models to generate more complex word characteristics to compare word semantics, is a good solution. BERT is a way of learning text representations with the encoder part of the Transformer. As the name says, BERT uses only the Transformer model's encoder, suiting for tasks requiring an in-depth and comprehensive understanding of the complete sentence.

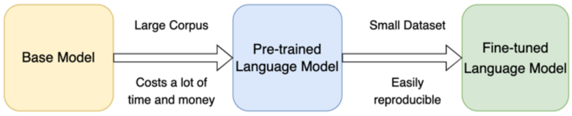


Fig3: Pretraining and fine-tuning

The Transformer is an architecture that significantly uses attention [27] to improve deep learning NLP translation models' performance. It quickly became a leading architecture for most text data applications. Numerous projects, including Google's BERT and OpenAI's GPT series, have built on this foundation and published performance results as language models. They have been trained on a massive dataset in a self-supervised way and then developed a statistical understanding of the language they have been trained on but are unfamiliar with a specific task. Based on that, the original pre-trained models can go through a transfer learning process, where the model can be fine-tuned in a supervised way. Fig3 shows the characteristics of pretraining and fine-tuning. Based on the previous studies, this research will use linguistic data from social media, apply BERT models for the sentence-level embedding and then build the classification with a multi-layer perceptron (MLP) or SVM.

2.2 Chatbot as a novel data collector

In traditional personality assessment, self-report questionnaires on the web survey are crucial to discover latent traits of people. However, In a web survey, users can easily hide their true feelings by selecting different buttons. Even if users are truthful to the questionnaire, other surveys have multiple scale options, and people also turn to scale things in various ways. The drawbacks of web surveys usually lead to unreliable and inaccurate user responses. On the other hand, studies show that chatbots are an excellent platform for eliciting high-quality distinct and self-disclosure user responses [28] [29].

Further, the chatbot market is growing astonishingly, from 4.2 billion dollars in 2019 to 15.7 billion dollars by 2024. A wide range of applications, including e-commerce, clinic, tourism, is applying chatbots to collect data and release humans from tedious work. Giant companies like Google, Microsoft, and Facebook have built chatbot platforms, making it easy for developers to design chatbots for special needs.

Some studies in NLP have been focusing on building emotionally-aware chatbots to provide users with an engaging conversation experience. Pamungkas concluded some state-of-the-art EACs, proving that adding emotional information can contribute to a more positive interaction between machines and humans [30]. Many efforts were made to build large and complicated sequence to sequence models, leading to improved accuracy of individual tasks, but hard to adapt or reproduce in other projects. It remains challenging to build EAC because of the uncertainty of conversation flow and the lack of emotion-labeled datasets that focus on specific tasks.

3. Approach

3.1 Training deep-learning-based personality detection model

The Kaggle Personality Dataset

Datasets containing personality types are sporadic. The Kaggle personality dataset is one of few datasets containing both social media raw text and MBTI labels. It is consists of 8,675 records of users' information from the PersonalityCafe forum. Each record contains: Type: The user's MBTI personality type. Posts: The last 50 posts an individual posts on the website (separated by "|||").

Fig4 gives a general distribution of each personality type, and the dataset contains a severe imbalance problem. Also, the imbalanced distribution reveals that people with personality type "IN" tend to express their feelings and ideas online, but the "ES" type of people enjoying the real-world social. It also depicts the words per post of each personality type, and it seems to fluctuate between 25 to 30 for most of the classes. It gives an insight into how many words the chatbot should collect to make a personality prediction.

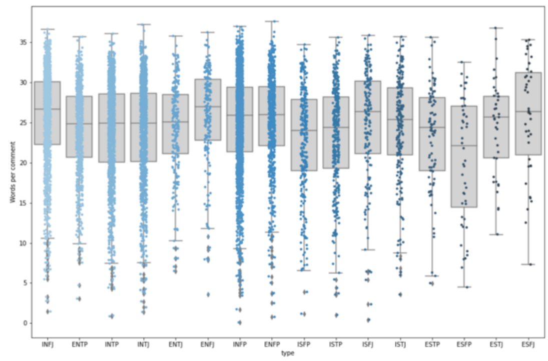


Fig4: Words per post for each personality type

The goal of the personality prediction model is to input raw texts of a person and output the MBTI personality type of that person. To realize it, it requires training four classifiers (I-E, N-S, T-F, P-J) to predict the tendency of each dimension, and the combination of the predicting result of each classifier contributes to the final personality type.

Training Flow

Multiple language models exist, such as BERT, Albert, and Robert, but the performance varies a little [31]. Hence, this research only applies BERT-base and BERT-large to extract language features and generate sentence-level embeddings. Fig 5 gives an overall look at the training process.

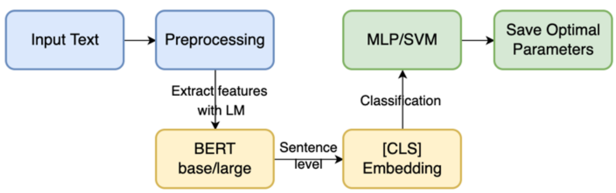


Fig5: Training flow

Preprocessing

Posts collected online are in irregular format, and it may be difficult for the machine to process, so some steps are necessary before modeling. Fig6 and fig7 show the comparison before and after preprocessing. The preprocessing procedure includes：

- Remove URLs and "|||" between posts.
- Put every word lowercase.
- Lemmatize each word.
- Remove MBTI profile strings.

Word clouds are generated for data visualization to understand better what specific words each personality dimension prefers. Words for each indicator were from the posts with the most extreme class probability (500 for each binary class). Some words shared between both types of a given dimension are removed to exploit particular word uses of different MBTI types. Fig8 illustrates the generated word clouds, where the size of each word is proportional to its appearance frequency in the corresponding extracted posts. It reveals the correlation of unique language use of each dimension and personality traits.

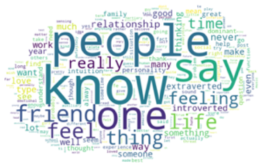
```
Before preprocessing:
 'Well! This happens to be my area of expertise :cooler: Just kidding, but I did have the pleas
ure of rooming with two ISFJs, an ESFP, and an ENFP this year at college (One ISFJ and the ESFP
together...|||I was reading this article the other day https://www.theatlantic.com/health/archive/2015/0
9/people-love-the-myers-briggs-personality-test/404737/ and it made me feel so not like an INFJ. It cou
ld've...|||I had the same feeling around the same age and am still getting used to my new fac
e.. I think it has more to do with my dealing with depression and the depersonalization symptom
s that can go along...|||I assume you've already checked out articles on 6 vs. 9 online, but th
is is a short blurb that seems pretty straightforward: https://www.enneagraminstitute.com/misidentifying
-6-and-9/ Since you've...|||So my little brother has tried to find his MBTI type many many time
s. He comes out with a different result every time after taking pretty much every test on the w
eb. I've even tried going
```

Fig6: Before preprocessing

```
After preprocessing:
  well this happens to be my area of expertise cooler just kidding but i did have the pleasure
of rooming with two s an  and an  this year at college one  and the  together i wa reading this
article the other day and it made me feel so not like an  it could ve i had the same feeling ar
ound the same age and am still getting used to my new face i think it ha more to do with my dea
ling with depression and the depersonalization symptom that can go along i assume you ve alread
y checked out article on v online but this is a short blurb that seems pretty straightforward s
ince you ve so my little brother ha tried to find his mbti type many many time he come out with
a different result every time after taking pretty much every test on the web i ve even tried go
ing through the careful about idealizing any type i used to want to be an  because i knew one w
ho i wa obsessed with but now that i ve distanced myself from her and stopped comparing myself
to her i m a lot i haven t really heard of u havi
```

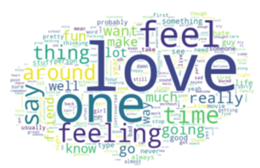
Fig7: After preprocessing


(a)E (b)I

(c)S (d)N


(e)T (f)F

(g)J (h)P

Fig8: A Word cloud visualization of the most prevalently used by specific classes of each personality dimension.

Posts of users after preprocessing step are ready to generate vector representations to feed into language models. First, extract features of the preprocessed text by passing it through BERT-base or BERT-large, storing the training features in a pickle file. This experiment chooses sentence-level embedding (CLS). As shown in fig10, BERT-base takes 12 hidden layers, each having 768 dimensions, while BERT-large uses 24 layers with 1024 dimensions. Since extraction is the most computationally expensive section, training was done on Colab's Tesla K80 GPU. Then, finetuning the model with multi-layer perceptron (MLP) or simple machine learning algorithms like SVM. Finally, use Adam optimizer with a binary cross-entropy loss function for each indicator.

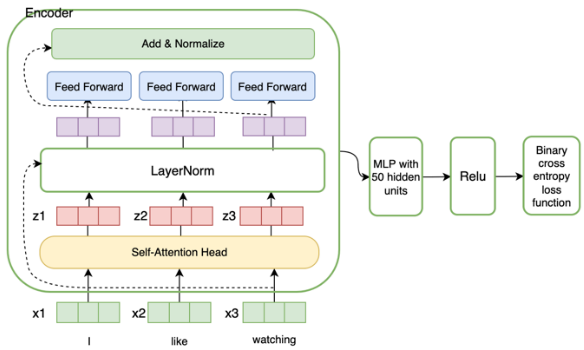


Fig9: The structure of training model

Fig9 gives an overall look at the architecture of the training model, and fig10 adds some details of generating sentence-level embeddings. Fig11 gives a visualization of the BERT encoder on input text, from which the weight of each attention head is shown in different colors.

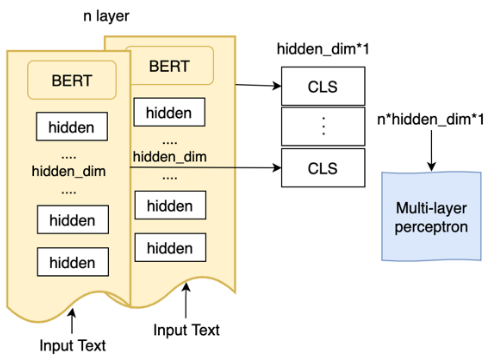


Fig10: Training detail

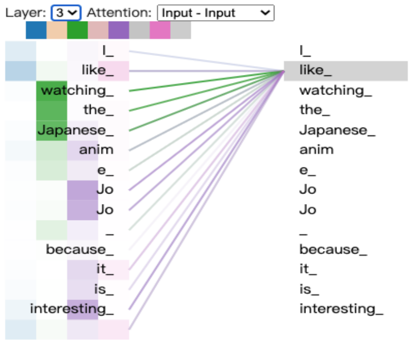


Fig11: Multi-head attention visualization

3.2 Sentiment-aware interview chatbot

Building a well functional chatbot requires interactions of several parts. The following are some terminologies for building a chatbot:

- **Natural Language Understanding (NLU)**: a process by which a conversational agent understands meaning from text and represents it to allow computation.
- **Intents**: in a given message, a user is trying to convey or accomplish (e.g., greeting, specifying a location).
- **Slots**: a means to fulfill a request, storing information as key-value to track information for a conversation.
- **State Tracker**: an NLU component that keeps tracking all the information over multiple terms of dialogue.
- **Dialog Policies**: a set of algorithms to predict the best following action for the conversational agent to take from the state tracker.

This project uses the Rasa framework [32] to design conversation flows and customize chatbot actions to enable the interview chatbot to ask users questions and store received answers. One of the difficulties of building up the interview chatbot is splitting the intent training dataset so that the users' intent inferred during conversation will not conflict. To avoid the mentioned problem, this research carefully divides users' input into more than ten possible intents, including greeting, inform, chitchat, and so on. Also, the chatbot will ask more than ten psychologically meaningful questions, and users' natural language answers will be stored in slots, helping the chatbot keep track of the conversation flow. For example, fig12(c) shows the interaction between different modules. For each input text, NLU detects users' intent and extracts necessary entities. The dialog management module will check intent and extracted entities, usually stored in a slot, to decide the next action.

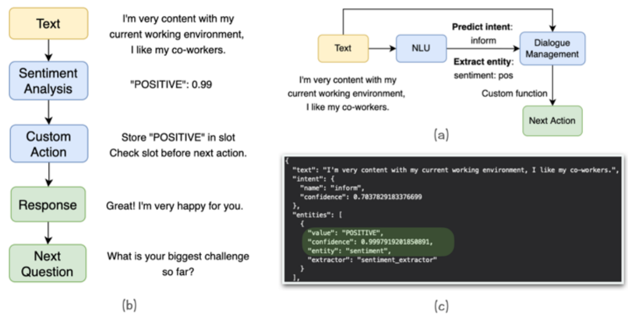
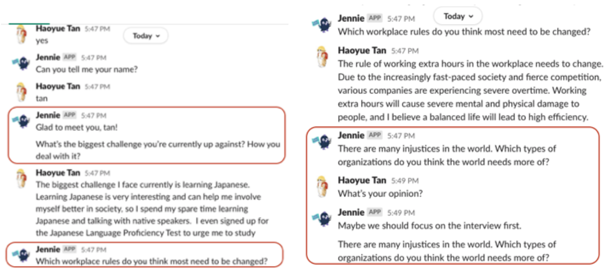


Fig12: (a) shows interactions between different modules; (b) shows how to add customized sentiment analysis function into dialog; (c) shows sentiment prediction of the NLU module.

The biggest challenge in building a chatbot is building a humanizing machine to improve user engagement. However, there is still little work focusing on emotionally aware chatbots. This research attempts to make the chatbot detect users' sentiment correctly and react to it. Specifically, the chatbot can achieve sentiment-aware with customized functions with NLTK Vader [33] model. For each input interview answer, the model will give a prediction value of text, pos or neg or neu, which will be stored in a slot. Fig12 shows how the chatbot reacts by the sentiment value before asking the following interview question. For each input text, the customized sentiment analysis model of NLU will predict sentiment with confidence, storing it as an entity and providing information for the dialog management module. So far, the designed chatbot can conduct an interview, ask interview questions in order, handle some unexpected situations, store users' responses, as shown in fig13(a) and fig13(b).



(a) (b)

Fig13: Basic functions of the interview chatbot, including ask questions (a) and detect chitchat (b) and get users back to the conversation.

4. Results and Discussion

Experiment

Experiment settings include the following steps:

- Extract language features of each preprocessed text (a users' 50 posts on social media) with language models BERT-base or BERT-large. As mentioned in section 3.1, hyperparameters settings of BERT-base are 768 hidden layer dimensions and 12 layers of attention, and that of BERT-large is 1024 hidden layer dimensions and 24 layers of attention.
- Use extracted language features to train models for each

personality trait (I-E, N-S, T-F, P-J) by applying a 10-fold cross-validation method. Because the dataset is imbalanced, this experiment uses stratified k-fold cross-validation to split the dataset into train and test sets.

- The accuracy of the MLP training model is obtained by minimum binary cross-entropy through 10 epochs, and the accuracy of the SVM model is obtained by running the classification algorithm SVM on split sets.

The model achieved good accuracy on the Kaggle datasets. As Table1 shows, as expected, language model-based approaches far outperform the traditional method of using psychological lexicons with machine learning algorithms. BERT-large + MLP achieved the best accuracy on four indicators, but the P-J model remains a poor performance. The imbalance of the data set may be the reason, and further reasons should be discussed.

Model	I-E	N-S	T-F	P-J
BERT-large + MLP	**79.12**	**86.98**	**76.61**	**70.62**
BERT-large + SVM	77.04	86.27	74.62	61.82
BERT-base + MLP	77.97	86.38	71.66	63.02
BERT-base + SVM	77.04	86.27	71.54	60.43

Table1: Results (accuracy %)

Chatbot Deployment

The interview chatbot is deployed on the web using Rasa X. It is a handy tool for conversation-driven development. Since the number of visits will not be very high, the selection server will be started locally, and through Ngrok, users can access the chatbot deployed on the web. As shown in fig14, we can easily see the dialogue flow and value changes at each step.

Every time a user inputs a message, the chatbot will calculate the most likely intent of the input text while extracting or calculating possible entities. The dialogue flow, consisting of intents and actions, can be seen on the upper right cube, and different slot values are shown on the lower right cube. Besides viewing each user's conversation, we can also annotate the user's input, enriching the examples of each intent. This platform can help developers collect unexpected user inputs to efficiently design and tune models.

Discussion

Compared to training machine learning algorithms with psychological lexicons, using language models like BERT for personality detection improves the overall accuracy to a great extent. However, the J-P indicator remains at low accuracy. Stajner and Yenikent [34] have experimented by asking a computational linguist and a psychologist to rate their certainty on each MBTI dimension based on users' posts. The annotator with the psychology background focused more on the user's overall impression. In contrast, the other annotator focused more on the linguistic clues, the content words, and the style. According to the result, J-P and S-N were the two dimensions for which the annotators did not find any signal in many instances, meaning that purely text is hard to detect people's personalities on those dimensions.

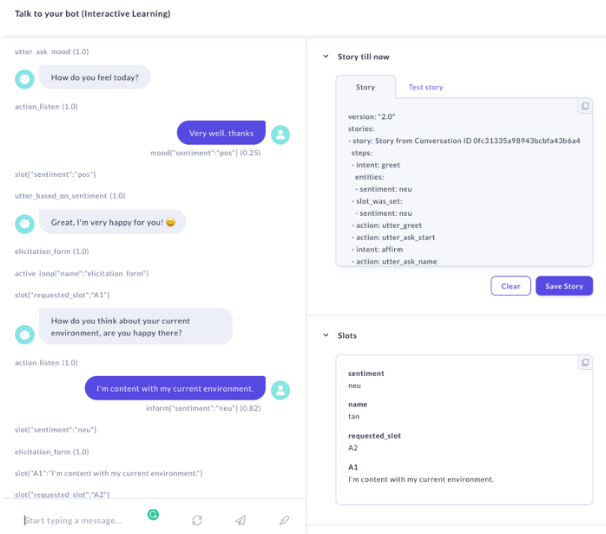


Fig14: Deploy the interview chatbot on web with interactive learning

On the other hand, since emotional words correlate with certain personality traits, it is worth applying sentiment analysis to text and embedding sentence-level vectors. For example, The SenticNet5 [35] dictionary can effectively extract certain words' emotional tendency (positive/negative) and give the corresponding polarity score between -1 to 1. Concatenating the emotional score to extracted BERT features might lead to better accuracy.

As for the sentiment-aware chatbot, the pre-trained model Vader performs poorly when making sentiment predictions for long sentences. Hugging Face also provides a sentiment analysis pipeline trained on massive datasets, providing a better accuracy on longer sentences. Future work can also connect this module with the currently built chatbot to detect and react to user input better.

5. Conclusion

Combining personality computing models and chatbots is relatively new, and it requires knowledge from both natural language processing (NLP) and human-computer interaction (HCI). Designing chatbots is very interesting but also requires tremendous prior knowledge and experience. According to previous research, sentiment-aware chatbots can significantly improve users' interaction experience, but it is rather challenging to ensure chatbots can react to sentiment while maintaining the conversation. Also, personality detection from text has drawn much attention due to the importance of personality and the emerging raw text on social media. Language models like BERT have improved detection models' performance significantly. Using technology to assist with personality analysis is very meaningful, but some discussions remain necessary to take.

Future work will enable the chatbot to detect not only sentiments but also more complex emotions (tired, busy, etc.) and give more human-like responses. Afterward, experiments will be conducted to allow more users to chat with the chatbot and give out specific comments. Evaluation of chatbots, both subjective and objective, will also be better studied and designed out.

Acknowledgments This research was supported in part by JSPS KAKENHI Grant Number 19H04150.

Reference

[1] Z. Xiao, M. X. Zhou, W. Chen, H. Yang, and C. Chi, ”If I Hear You Correctly: Building and Evaluating Interview Chatbots with Active Listening Skills.’ In Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems (CHI ’20). Association for Computing Machinery, New York, NY, USA, 1–14.

[2] Y. C. Lee, N. Yamashita, Y. Huang, and W. Fu, “I Hear You, I Feel You”: Encouraging Deep Self-disclosure through a Chatbot.” In Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems (CHI ’20). Association for Computing Machinery, New York, NY, USA, 2020, 1-12.

[3] J. Li, M. X Zhou, H. Yang, and G. Mark. 2017. Confiding in and Listening to Virtual Agents: The Effect of Personality. In Proceedings of the 22nd International Conference on Intelligent User Interfaces. ACM, 275–286.

[4] S. Dhelim, N. Aung, M. A. Bouras, H. Ning and E. Cambria, “A Survey on Personality-Aware Recommendation Systems.” ArXiv abs/2101.12153 (2021): n. pag.

[5] O. P. John, L. P. Naumann, and C. J. Soto, “Paradigm shift to the integrative Big Five Trait taxonomy,” Handbook of personality: Theory and research, pp. 114–158, 2008.

[6] I. Briggs Myers, “Introduction to type: A guide to understanding your results on the myers-briggs type indicator (revised by lk kirby and kd myers). palo alto,” 1993.

[7] F. Celli and B. Lepri, “Is Big Five Better than MBTI? A Personality Computing Challenge Using Twitter Data.” in Proceedings of the Fifth Italian Conference on Computational Linguistics (CLiC-it 2018), 2018.

[8] S. S. Robin and E. KramerJames. 2011. King robert ward, identifying personality from the static, non-expressive face in humans andchimpanzees: Evidence of a shared system for signaling personality. Evolution and Human Behavior 32 (2011), 179–185.

[9] L. Liu,D. Pietro, Z. Samani, M. Moghaddam, L. Ungar, "Analyzing Personality through Social Media Profile Picture Choice." AAAI Digital Library (2016) Web.

[10] M. Gavrilescu, "Study on determining the Myers-Briggs personality type based on individual's handwriting," 2015 E-Health and Bioengineering Conference (EHB), 2015, pp. 1-6, doi: 10.1109/EHB.2015.7391603.

[11] A. D. Scott, E. J. Briscoe, H. Hayes, and R. L. Mappus. 2013. Towards automated personality identification using speech acts. In Proceedings of Workshop on Computational Personality Recognition (WCPR’13). AAAI Press

[12] G. Chittaranjan, Jan Blom, and Daniel Gatica-Perez. 2011. Mining Large-Scale Smartphone Data For Personality Studies. Personal and Ubiquitous Computing. Springer, Page 1.

[13] F. Mairesse and M. Walker. 2007. PERSONAGE: Personality generation for dialogue. In Proceedings of the 45th Annual Meeting of the Association for Computational Linguistics (ACL’07). 496–503.

[14] Saif M. Mohammad and S. Kiritchenko. 2013. Using nuances of emotion to identify personality. In Proceedings of the ICWSM Workshop on Computational Personality Recognition. Boston.

[15] G. Park, H. A. Schwartz, J. C. Eichstaedt, M. L. Kern, M. Kosinski, D. J. Stillwell, L. H. Ungar, and M. E. Seligman, “Automatic personality assessment through social media language.” Journal of personality and social psychology, vol. 108, no. 6, p. 934, 2015.

[16] F. Mairesse, M. Walker, M. Mehl, and R. Moore. 2007. Using linguistic cues for the automatic recognition of personality in conversation and text. Journal of Artificial Intelligence Research 30 (2007), 457–500.

[17] M. R. Mehl, S. D. Gosling, and J. W. Pennebaker. 2006. Personality in its natural habitat: Manifestations and implicit folk theories of personality in daily life. Journal of Personality and Social Psychology 90, 5 (2006), 862–877.

[18] G. Park, H. A. Schwartz, J. C. Eichstaedt, M. L. Kern, M. Kosinski, D. J. Stillwell, L. H. Ungar, and M. E. Seligman, “Automatic personality assessment through social media language.” Journal of personality and social psychology, vol. 108, no. 6, p. 934, 2015.

[19] V. Kaushal and M. Patwardhan, “Emerging Trends in Personality Identification Using Online Social Networks—A Literature Survey,” ACM Transactions on Knowledge Discovery from Data, vol. 12, no. 2, pp. 1–30, mar 2018. [Online]. Available: https://dl.acm.org/doi/10.1145/3070645.

[20] J. Golbeck, C. Robles, M. Edmondson and K. Turner. "Predicting Personality from Twitter." 2011 IEEE Third International Conference on Privacy, Security, Risk and Trust and 2011 IEEE Third International Conference on Social Computing, Boston, MA, pp. 149-156, doi: 10.1109/PASSAT/SocialCom, 2011.

[21] Y. R. Tausczik, and J. W. Pennebaker, "The Psychological Meaning of Words: LIWC and Computerized Text Analysis Methods." Journal of Language and Social Psychology. 2010;29(1):24-54.

[22] J. Golbeck and D. L. Hansen. 2011. Computing political preference among twitter followers. In Proceedings of CHI 2011. 1105–1108.

[23] C. Yin, X. Zhang, and L. Liu. 2020. Reposting negative information on microblogs: Do personality traits matter? Information Processing & Management, 57(1), 1–18.

[24] N. Majumder, S. Poria, A. Gelbukh,and E. Cambria. 2017. Deep learning-based document modeling for personality detection from text. IEEE Intelligent Systems, 32 (2), 74–79.

[25] E. Cambria, Y. Li, F. Z. Xing, S. Poria, and K. Kwok. 2020. SenticNet 6: Ensemble Application of Symbolic and Subsymbolic AI for Sentiment Analysis. Proceedings of the 29th ACM International Conference on Information & Knowledge Management. Association for Computing Machinery, New York, NY, USA, 105–114.

[26] AA. Marouf, MK. Hasan, H. Mahmud. 2020. Comparative analysis of feature selection algorithms for computational personality prediction from social media. IEEE Trans Comput Social Syst. 2020;7(3):587–99. https://doi.org/10.1109/TCSS. 2020.2966910.

[27] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, Ł. Kaiser, and I. Polosukhin. 2017. Attention is all you need. In Proceedings of the 31st International Conference on Neural Information Processing Systems (NIPS'17). Curran Associates Inc., Red Hook, NY, USA, 6000–6010.

[28] S. Kim, J. Lee, and G. Gweon, ”Comparing Data from Chatbot and Web Surveys: Effects of Platform and Conversational Style on Survey Response Quality.” In Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (CHI ’19). Association for Computing Machinery, New York, NY, USA, 2019, Paper 86, 1–12.

[29] Y. C. Lee, N. Yamashita, Y. Huang, and W. Fu, ””I Hear You, I Feel You”: Encouraging Deep Self-disclosure through a Chatbot.” In Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems (CHI ’20). Association for Computing Machinery, New York, NY, USA, 2020, 1–12.

[30] E. W. Pamungkas. 2019. “Emotionally-aware chatbots: A survey,” *arXiv*, arXiv:1906.09774.

[31] Y. Mehta, S. Fatehi, A. Kazameini, C. Stachl, E. Cambria and S.

Eetemadi, "Bottom-Up and Top-Down: Predicting Personality with Psycholinguistic and Language Model Features," 2020 IEEE International Conference on Data Mining (ICDM), 2020, pp. 1184-1189, doi: 10.1109/ICDM50108.2020.00146.

[32] T. Bocklisch, J. Faulkner, N. Pawlowski and A Nichol, "Rasa: Open Source Language Understanding and Dialogue Management." ArXiv abs/1712.05181 (2017): n. pag.

[33] C. Hutto, and E. Gilbert. 2014. VADER: A Parsimonious Rule-Based Model for Sentiment Analysis of Social Media Text. Proceedings of the International AAAI Conference on Web and Social Media, 8(1), 216-225. Retrieved from https://ojs.aaai.org/index.php/ICWSM/article/view/14550.

[34] S. Stajner, and S. Yenikent. 2020. A Survey of Automatic Personality Detection from Texts. Proceedings of the 28th International Conference on Computational Linguistics. https://aclanthology.org/2020.coling-main.553. 6284—6295.

[35] E. Cambria, S. Poria, D. Hazarika, and K. Kwok, "SenticNet 5: Discovering conceptual primitives for sentiment analysis by means of context embeddings," in AAAI, 2018, pp. 1795–1802.

