Brain mapping of semantic production and semantic intent

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Introduction

With the advance of brain decoding technique, studies have successfully identified neurocognitive representations into its neural and psychological components based on the underlying brain activation pattern. The computational models in those studies also demonstrated subject-independent properties and can be applied to words that did not contained in training data (Mitchell et al., 2008; Just, Cherkassky, Aryal, & Mitchell, 2010). With respect to time dimension, researches related to sequentially word-by-word neural representation, which mapped word-by-word vectors produced by the deep learning neural networks or language model and the word-by-word neural activity recorded by Magnetoencephalography (MEG), suggest that there is a relationship between the neural network constituent and its corresponding time/location brain process (Leila Wehbe, Ashish Vaswani, Kevin Knight, & Tom Mitchell, 2014; Fyshe, Sudre, Wehbe, Rafidi, & Mitchell, 2016). It is worth noting that the neural representation of higher order concept may be altered in some clinical population, for example, people with autistic spectrum disorder have altered neural representation of social self-concept (Just, Cherkassky, Buchweitz, Keller, & Mitchell, 2014). This characteristic could be served as a biomarker for the future application.

Recent neuroimaging studies have mapped large comprehensive semantic information across the entire semantic system (Huth, de Heer, Griffiths, Theunissen, & Gallant, 2016). A dual-stream model has been proposed that dorsal stream processing form-to-articulation and ventral stream processing from-to-meaning, respectively (Fridriksson et al., 2016; Hickok & Poeppel, 2007). Therefore, the processes that comprehending semantic information and that utilizing semantic information may not guarantee to active the same semantic representation in the brain. The aim of this research is to investigate the dynamic semantic processing in a contextual environment of dialog.

In order to a create a real-time conversational context that allows experimenters to mark each dialog event in the fMRI setting with precise timestamp while mapping between both receiving and producing semantic information and their corresponding brain activities, we implement an intelligent conversational bot with the functionality of natural language understanding and natural language generation that participants can have conversation with during fMRI scanning inside the MRI bore. In addition, an important functionality in the algorithm of dialog management is belief state tracking (Young, Gai, Thomson, & Williams, 2013; Wen et al., 2016; Hakkani-Tür et al., 2016; Yang et al., 2016; Chen, Hakkani-Tür, Tür, Gao, & Deng, 2016; Chen, Hakkani-Tür, Tür, et al., 2016; Wen, Miao, Blunsom, & Young, 2017), which can track the users goal online during the conversational interaction. These belief states included a predefined set of user intents, and this information will be extracted online from users expressing sentence based on either predefined rule-based or pre-trained neural-network models while users are having a conversation with the intelligent conversational bot. Whether or not these belief states that have similar intention will activate a consistent neuronal representation is an intriguing empirical question that will also be examined in this study.

To sum up, investigating the dynamic conversational process will not only provide chances to inspect the elements of receiving, producing semantic neuronal representation, and the neuronal representation of the user semantic intent but also the dynamic transition among them. Furthermore, it is possible to investigate the alignment between the neural network in each component of the chat bot module and the neurocognitive activation patterns in participants, and utilize the neurocognitive activation patterns as feedback for chat bot training and developing.

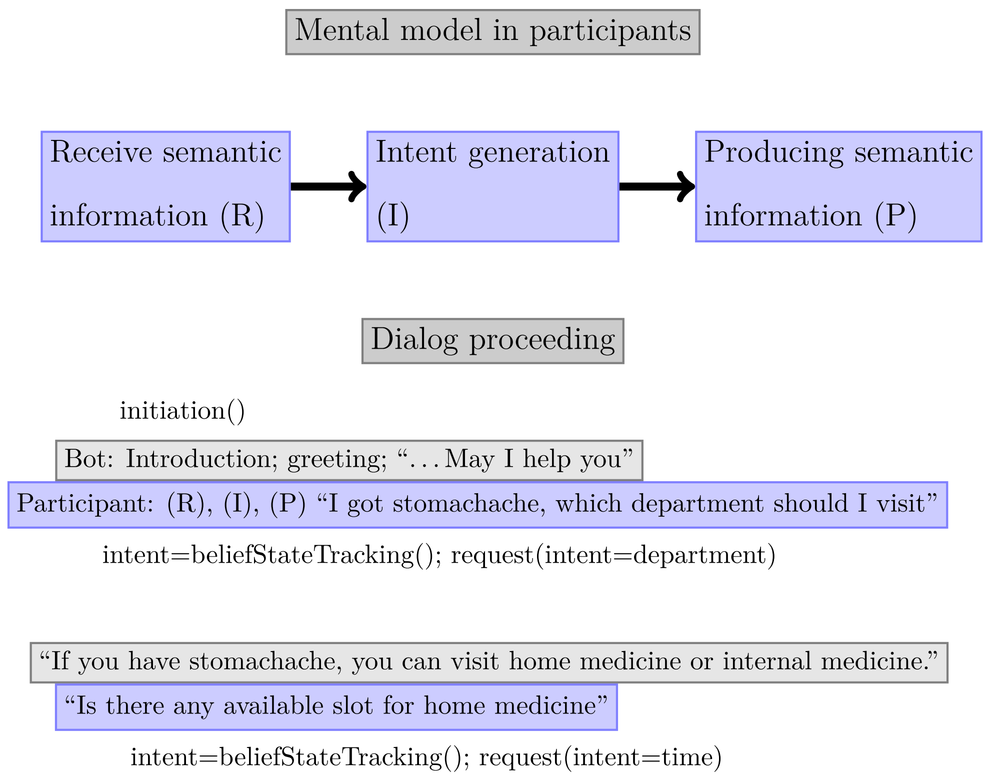

Figure 1. Mental model and example dialog

Method

Participants. 10 participants with normal or corrected-to-normal vision will be recruited.

Materials. Conversation content will include several themes that most people have related experiences, such as looking for doctor and booking tickets.

Procedure. In the functional MRI scan, at the beginning of each scenario, the bot will narrate an introduction containing the background story and the goals participants have to complete. A brief example is like that a person had seafood last night, then, next morning the person felt stomach. Now the participants have to look for doctors through conversation with the bot to request information and make a reservation. At the end of each scenario, participants will be invited to talk about their experience related to the current scenario. Once participants have completed a scenario, there will be five minutes rest followed by next new scenario.

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