As a machine learning (ML) and natural language processing (NLP) researcher, I build probabilistic and statistical models to simulate and analyze human behaviors from their conversations. Unlike other data such as image, video, and sound, natural language is mainly made by humans. So when analyzing texts, we need to think about who creates it, and on the contrary, understand people through texts. Following these principles, I research in NLP by focusing on the relationship between humans and texts. As data, I mainly look at the conversation. The conversation is a typical communication between two people. And its context depends on the speaker. For example, a speaker may have different conversations with different conversational partners. This difference is an important factor in understanding the person, and in contrast, the person makes the conversation more understandable.

In my research approach, I aim to 1) develop conversation models that generate human-like responses 2) investigate human behaviors from their conversations by novel ML models.

**Conversation Models for Generating Human-like Responses**

One of the goals in artificial intelligence research is creating an intelligent agent that acts like humans. Turing suggests the test to answer the question, “Can machines think?” by Turing test. In the test, a human has open-domain conversations that are no restriction about domains or topics with the intelligent agent with only texts. The agent generates human-like responses to the conversations. When the human does not look distinguishable whether the conversational partner is a human or an agent, the test is passed.

I researched on open-domain conversation modeling to generate conversational responses like a human. Specifically, I developed a neural conversation model that models speakers and generates personalized conversational responses. And, I developed a neural network model that evaluates generated responses automatically.

**Generating Personalized Conversational Responses**

In conversation response generation, modeling the speakers in addition to the utterances is important for generating appropriate responses. Knowing information about a speaker, such as her linguistic style or personal information can help predict her response, and knowing more about both speakers from their previous conversations can help predict the contents of their conversation. One more difficult and under-tackled problem in conversation response generation is the cold start problem, when the training data do not contain one or both of the speakers. It then becomes very difficult to predict the appropriate responses.

To incorporate the speakers into the neural conversation model, I developed Variational Hierarchical User-based Conversation Model (VHUCM) that is a variational auto-encoder based open-domain conversation model and models the speakers to generate personalized responses. The main idea of the model is that the conversational context depends on the speaker. For example, the same speaker pair is likely to have similar conversations. So, I set one latent global variable to represent the context of a conversation, and it is inferred by the conversation speakers' latent variables. VHUCM can generate personalized responses based on the speaker and conversation partner. Table 1 shows examples of personal questions and responses. The answer of A for question from B is interesting. From the other answers, we know that age of A is 19, and B's age is 18. The answer to the question is correct even it does not generate the exact age number. Additionally, I tested the new user situation that one of the conversation speakers never appears in the training data. To avoid this cold start problem, I inferred the new speaker variable from the conversation partners, and it shows better performance than other baselines including random. This project has been published at EMNLP 2019 [1].

**Evaluating Conversational Responses Automatically**

Evaluating the machine learning model generated responses for open-domain dialogue automatically is a difficult task. There are many possible appropriate responses given a dialogue context, and automatic metrics such as BLEU or ROUGE rate the responses that deviate from the ground truth as inappropriate.
For example, when the dialogue context is referring to a date plan, the appropriate responses can be accepting, rejecting, or suggesting other plans. However, BLEU and ROUGE fail to evaluate the appropriate response when it is acceptance, but the ground truth response is refusal. ADEM considers the relationship between the context and the generated responses, but it requires human-annotated scores to train the model.

To overcome these limitations, I developed Speaker Sensitive Response Evaluation Model (SSREM) that models the functions to compare the coherence between a given conversational context and a generated response without human-labeled data. The main idea of the model is that utterances from the same speaker are more difficult negative samples to classify the true response than random negative ones. I adopted a noise contrastive estimation technique to train the model. More, I built diverse negative samples by considering speakers rather than random negative ones. This is because random negative samples are easy to be distinguishable from the true response, so it makes the model to poor performance. SSREM shows a higher correlation with human judgments than existing baselines. Figure 2 shows the results. The red line is a linear regression line, and the coefficient of the line is a higher positive correlation with human judgment than the other models. SSREM has also applicability whether the training corpus and test corpus are different. This project will be published at ACL 2020 [2].

Statistical Models for Analyzing Human Behaviors in Texts

To make a human-like acting intelligent agent, understanding human behaviors in texts is important. Human is a social animal. They want to make social relationships between others. The activities using texts are related to social interaction. For example, people talk, write, call, or text friends, families, neighbors, or colleagues. These communications increase the closeness between people and make people co-work with other colleagues.

I researched on modeling to identify human behaviors and find important factors of the behaviors from conversations. Specifically, I developed a Bayesian model to identify self-disclosure in casual conversations. And I developed a neural network model to identify decision making process in a discussion corpus.

Modeling Self-Disclosure Behavior

Self-disclosure is an important and pervasive social behavior. People disclose personal information about themselves to improve and maintain relationships. A common instance of self-disclosure is the start of a conversation with an exchange of names and additional self-introductions. Another example of self-disclosure where the information disclosed about a family member’s serious illness is much more personal than the exchange of names. However, most researches are using a survey or human annotations to figure out self-disclosure. These methodologies are biased by participants’ memory and cannot apply to large datasets.

To investigate the self-disclosure behavior in large conversation corpus, I developed Self-Disclosure Topic Model (SDTM) that is a Bayesian topic model with external prior knowledge. It classifies the self-disclosure level into three categories, low, mid, and high disclosure. The self-disclosure behavior can be modeled using a combination of simple linguistic features (e.g., pronouns) with automatically discovered semantic themes (i.e., topics). To identify high disclosure themes, I built the external prior knowledge by extracting seed words and phrases from an external corpus of anonymously posted secrets. SDTM outperforms baseline models to identify self-disclosure behavior. And it shows a correlation between self-disclosure and the closeness of relationships that supports previous results in social psychology research. Figure 3 shows one of the results. Conversation length noticeably increases over time in the medium and high self-disclosure level groups, but only slight in the low self-disclosure level group. This project has been published at ACL 2012 [3] and EMNLP 2014 [4].
Modeling Decision-Making Process Behavior

Decision making in groups refers to the process of making choices to resolve issues by discussing the issues with group members. Social psychologists note that decision making affects the group performance and the satisfaction of its members, and that leadership plays a role. However, most research about decision making process are using a survey or doing in lab-environment that are biased by participants.

To investigate the decision-making process behavior, I built discussion records from the annals of the Joseon dynasty (AJD). The AJD consists of the historical records of kings who governed the Korean peninsula from 1392 to 1910. In the AJD, the kings discuss national issues with government officials and decide upon a course of action such as ordering or accepting. To identify the leaders’ decisions from a discussion, I developed Conversational Decision-Making Model (CDMM) which is a hierarchical RNN model with attentions.

It incorporates words in an utterance with the speaker and predicts the leaders’ final decision. CDMM outperforms baseline models and clarifies the keywords and key members to identify the king’s final decision. Figure 4 shows the one of the example results. CDMM gives a high attention score to the word “Okay” for Accept decision as compared to the other decisions when the speaker is king. However, when officials use this word, CDMM assigns a high attention value to the word in the Order decision. This project has been published at LaTeCH-CLfL 2015 [5] and EMNLP 2018 [6].

Future Research Directions

Open-domain conversation modeling has many challenges. The main reason is that the problem is too huge - no boundaries of the domain. Recently, Google and Facebook researchers suggest the methodologies that use various and large conversation corpora with complex structural models [7, 8]. These models are hard to identify the reason of generating non-appropriate responses because these are like a black-box.

To overcome this limitation, we need to investigate the conversations by answering these questions at first: “What, Who, Where, When, Why, and How do people have conversations?” From these characteristics of the conversational behaviors, we can understand the struggles in the conversation modeling and make ideas to solve them. My research will continue to investigate human behaviors in a huge amount of texts. The analysis will help I and other researchers have a better understanding of conversations and will be served as insightful ideas for conversation modeling.

Topics of Conversations

In the near future, I plan to investigate what people are talking about in conversations. People have casual conversations about various topics such as politics, economics, or sports. As part of the potential direction, I now investigate the degree of difficulty in generating responses based on the topics. A person who participates in the conversation is easy or difficult to answer depending on the topic of the conversation. For example, it is easy to say about a yesterday sports game, but, answering political issues is hard. I aim to build ML models that identify the difficulty of answering based on the topics. The results will figure out the relationship between the difficulty of answering and the topics, and lead to make conversation models that can answer specific topics fluently.

Intentions of Conversations

There are various reasons why people have conversations with each other such as managing relationships, exchanging information, or solving problems. When a person participates in a conversation, he/she expects responses from the conversation partner. To generate appropriate responses, the conversation model should identify the intentions of the conversation. I aim to build ML models to identify the intentions of conversations, and incorporate them into the conversation model. I plan to bring the definition of intentions from the discourse analysis research and build the computational approaches to figure it out.
Multimodality of Conversations

A conversation is not only consisted of texts. It has various metadata such as speakers, time, location, and voice. Especially, AI speakers such as Amazon Alexa and Google Assistant have a conversation with humans by voice. I have studied that combining voice and text together is important to identify emotions [9]. I aim to build ML models that take additional metadata to understand texts and human behaviors better.

Beyond Conversations

People communicate with others by texts, and turn-taking conversation is not the only way. There are many types of texts such as articles, letters, and comments, etc. Even I focused on turn-taking conversations, I open to investigate NLP research problems with the same principles. Especially, I aim to solve the text summarization problem since it is a similar structure to the conversation modeling, understanding existing texts, considering authors/readers, and generating appropriate sentences.

I also interested in multilingual NLP research. Most NLP research work is in specific languages such as English or Chinese. Even the ML models are language-independent, considering language-dependent linguistic and cultural characteristics are important. I have built a human in the loop system to identify and expand keywords in Indonesian tweets [10]. With this experience, I aim to investigate NLP research problems, especially in low resource languages.

These research directions are inherently interdisciplinary. Social scientists investigate conversational behaviors qualitatively, while machine learning researchers analyze it by developing computational models and applying large corpus. These qualitative and quantitative study results can inspire the idea to both researchers. I have collaborated with political scientists [11][12]. I am ready to collaborate with people from various fields, and I will contribute to both research fields.

References

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