Affect-sensitive Dialogue Response Generation for Positive Emotion Elicitation

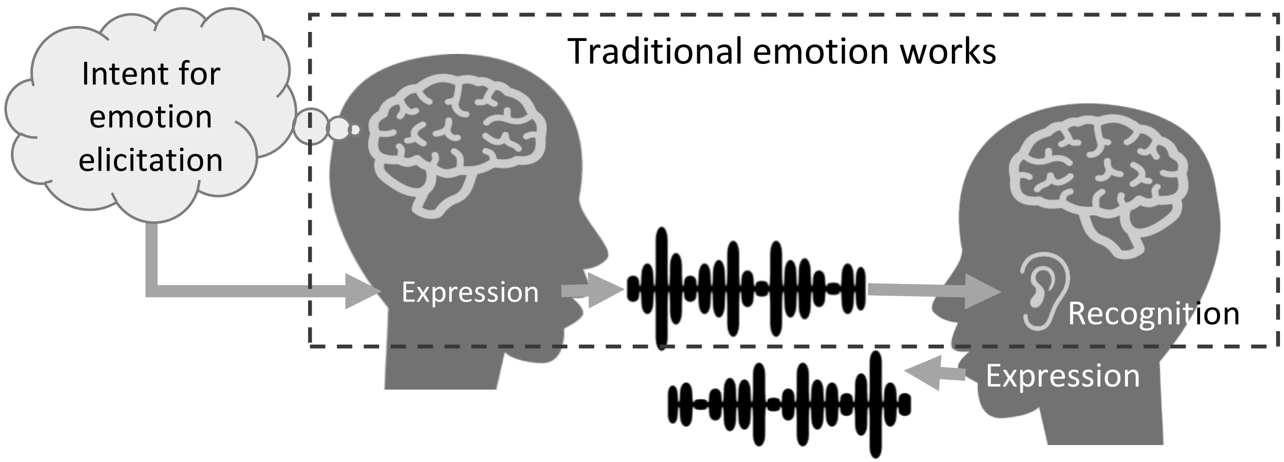
Nurul Fithria Lubis
Augmented Human Communication (AHC) Lab
Nara Institute of Science and Technology (NAIST)

Affective dialogue systems

High potential of dialogue systems to address the emotional needs of users

- Increase of dialogue system works and applications in various tasks involving affect
  - Companion for the elderly
    [Miehle et al., 2017]
  - Distress clues assessment
    [DeVault et al., 2014]
  - Affect-sensitive tutoring
    [Forbes-Riley and Litman, 2012]

Emotion elicitation



Emotion elicitation: eliciting change of emotion in dialogue

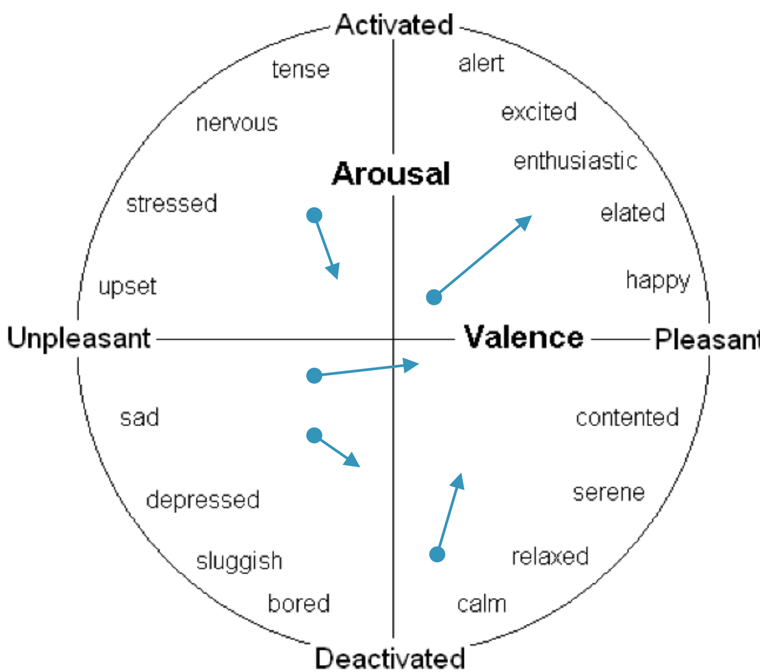
- Using machine translation with target emotion (Hasegawa et al., 2013)
- Using system's affective personalities (Skowron et al., 2013)

✗ Have not yet considered the **emotional benefit** for the user

Research goal:
Positive emotion elicitation

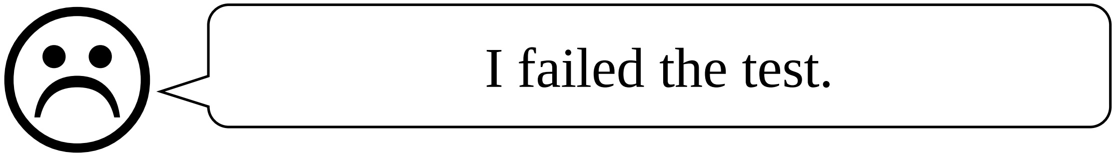
We aim to draw on an overlooked potential of emotion elicitation to **improve user emotional states**

- A chat-based dialogue system with an implicit goal of **positive emotion elicitation**

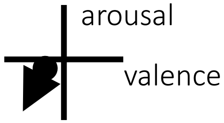


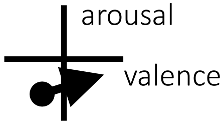
Circumplex model of affect [Russell, 1980]

Different responses elicit different emotions



User	I failed the test.	I failed the test.
System	**Oh, again?**	**You will do better next time!**
User	Yeah...	Thank you.
Emotional impact	*Negative*	*Positive*



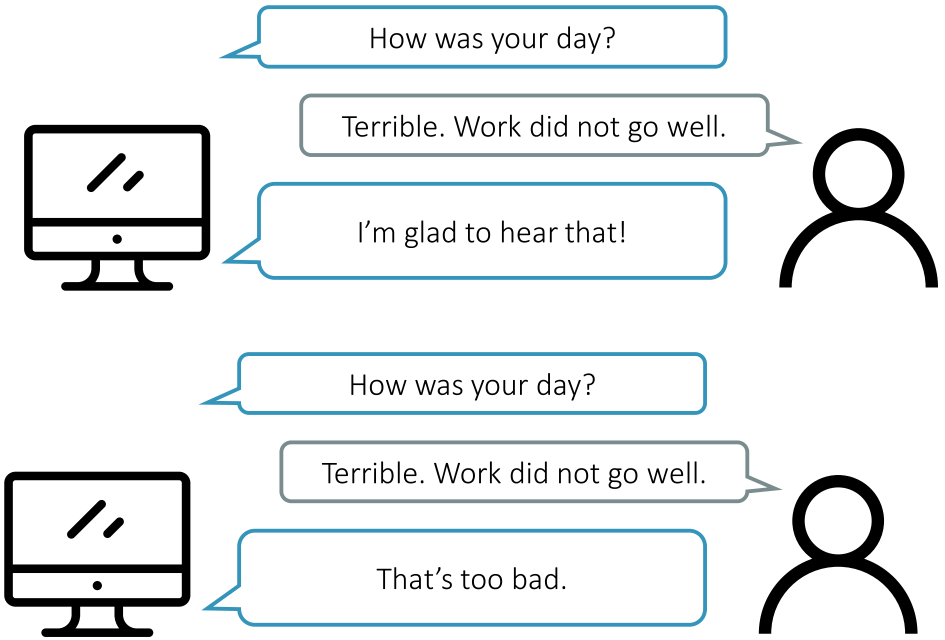


Positive emotion elicitation does NOT mean always responding with positive emotion

There are situations where "happy responses" can lead to negative impact

Expressing negative emotion can lead to positive impact

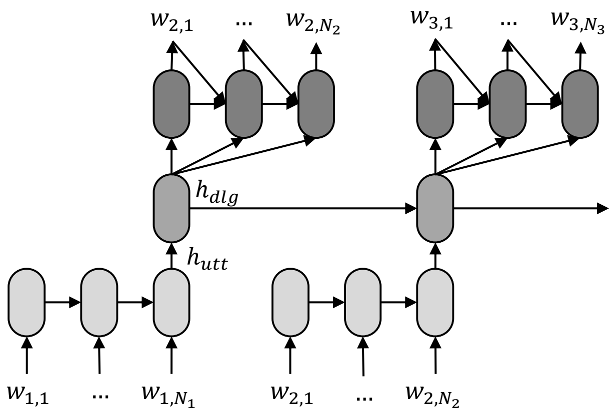
- System should learn the proper strategy



Neural chat-based dialogue system

- End-to-end modeling of chat dialogue
- RNN encoder-decoder [Vinyals et al., 2015]
- Hierarchical recurrent encoder-decoder (HRED) [Serban et al., 2016]
- Generating dialogue response with emotional expression [Zhou et al., 2018]

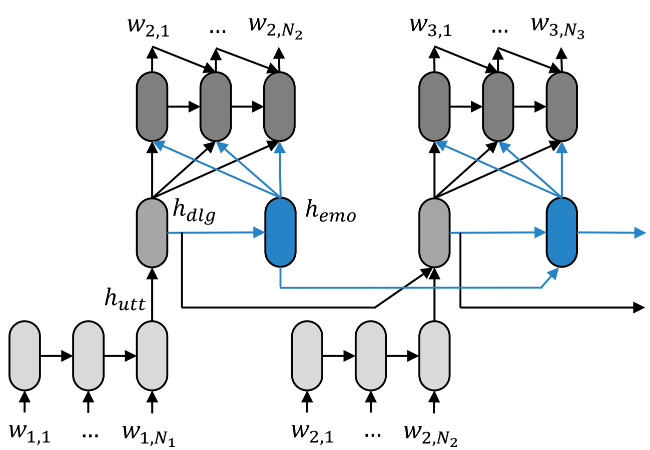
Not yet an application towards emotion elicitation



[Serban et al., 2016]

Proposed approach

Emotion-sensitive response generation: Emo-HRED



Encodes emotional context and considers it in generating a response

Train on responses that elicit positive emotion

Training Emo-HRED

Optimization

- Train on combined losses
  - Negative Log Likelihood (NLL) of target response
  - Emotion prediction error
    - The emotion encoder targets the emotion label of the dialogue turn
- The final cost is used to optimize the entire network
  - Adam optimizer

Pre-training and selective fine-tuning

- Emotion-annotated data is limited
- Start by **pre-training** HRED with large-scale conversational data
  - Learning semantic and syntactic knowledge
- **Selectively fine-tune** Emo-HRED with the emotion-annotated data
  - Only train parts that are affected by emotion context
  - Avoid over-fitting or destabilizing

NAIST 国立大学法人 奈良先端科学技術大学院大学 NARA INSTITUTE of SCIENCE and TECHNOLOGY

Datasets

Existing data

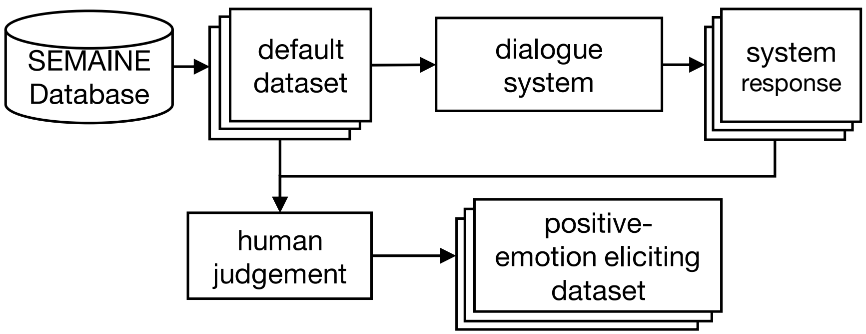
SubTle Database

- For pre-training
- Large-scale conversational corpus from movie subtitles (5.5M triples)

SEMAINE Database

- Small amount of conversation between user and listening agent in WoZ fashion (2K triples)

Positive-emotion eliciting data



SEMAINE-positive

- For fine-tuning
- Augmenting an existing corpus
- Contains positive-emotion eliciting responses

Evaluation

Objective evaluation: Perplexity

Pre-training: SubTle
Fine-tuning: SEMAINE-positive
Testing: SEMAINE-positive

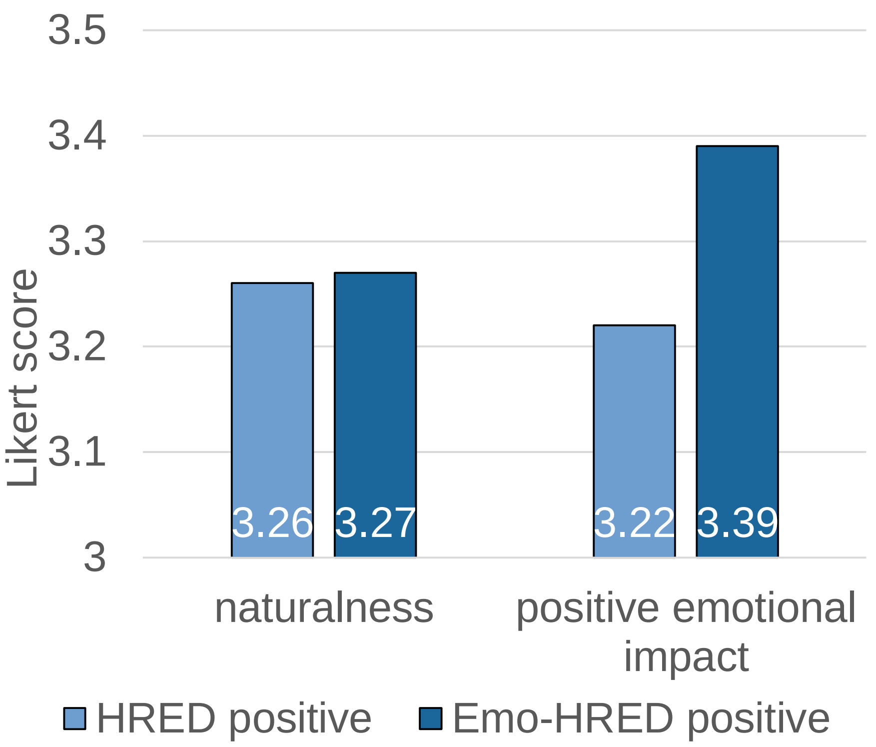
Model	**Parameter update**	**Perplexity** on SEMAINE-positive test set
Baseline HRED	standard	121.44
	selective	100.94
Proposed Emo-HRED	selective	**42.26**

Emotion information can be leveraged in response generation to reduce perplexity

Subjective evaluation

- Evaluation via crowdsourcing
  - 100 test queries, 20 judgments each
- Likert scale 1 to 5 (higher is better)
  - Naturalness
  - Positive emotional impact

The proposed model is perceived as more natural and significantly elicits a more positive emotion ($p < 0.05$)



Conclusion

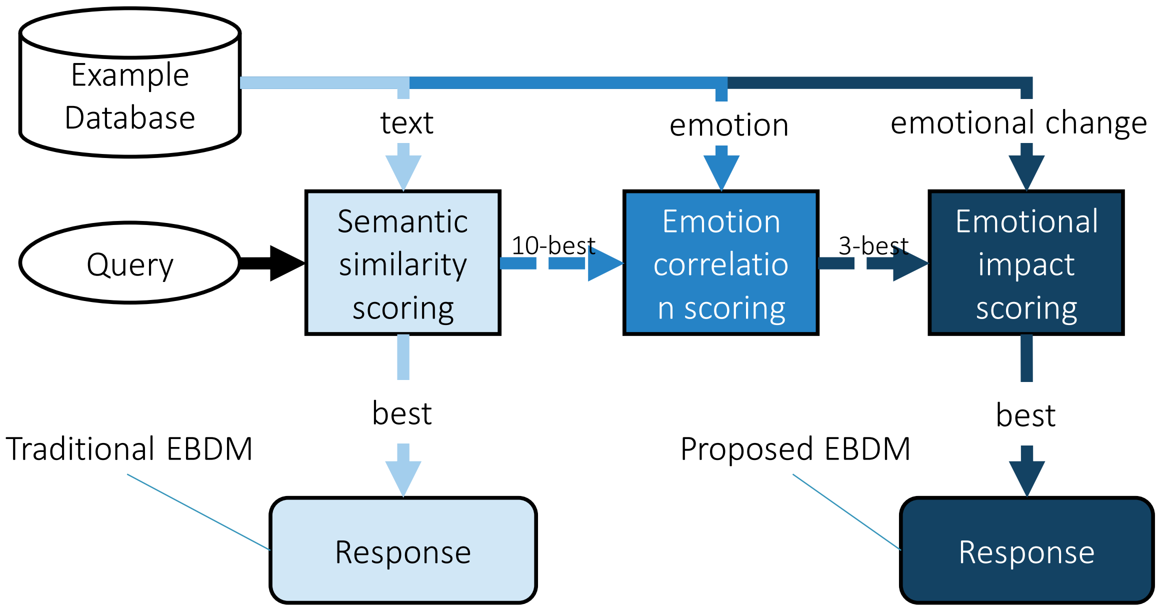
Conclusion

- We proposed: a dialogue response generator to elicit positive emotion
  - Considers emotional context of dialogue
  - Trained on constructed corpus that contains responses with positive emotional impact
- Subjective and objective evaluation show improvement over system that ignores emotion information
  - More natural
  - Elicit a more positive emotion impact
- Future work
  - Collect and utilize more emotion rich dialogue data
  - Richer dialogue context
    - Other modalities
    - Longer context

Thank you

Automatically retrieve responses with positive impact by utilizing example-based dialogue system approach

(Lubis et al., 2017) in Proc. IWSDS 2017



- Semantic similarity: text cosine similarity between query and example query
- Emotion correlation: valence & arousal Pearson's score between query and example query
- Emotional impact: valence change in the example triple

Evaluation shows that the proposed EBDM is perceived as **more natural** and **elicit a more positive impact**