Emotion In Human-Computer Interaction

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Emotion

A neuroscience point of view of emotion

Emotion

Biological states associated with the nervous system

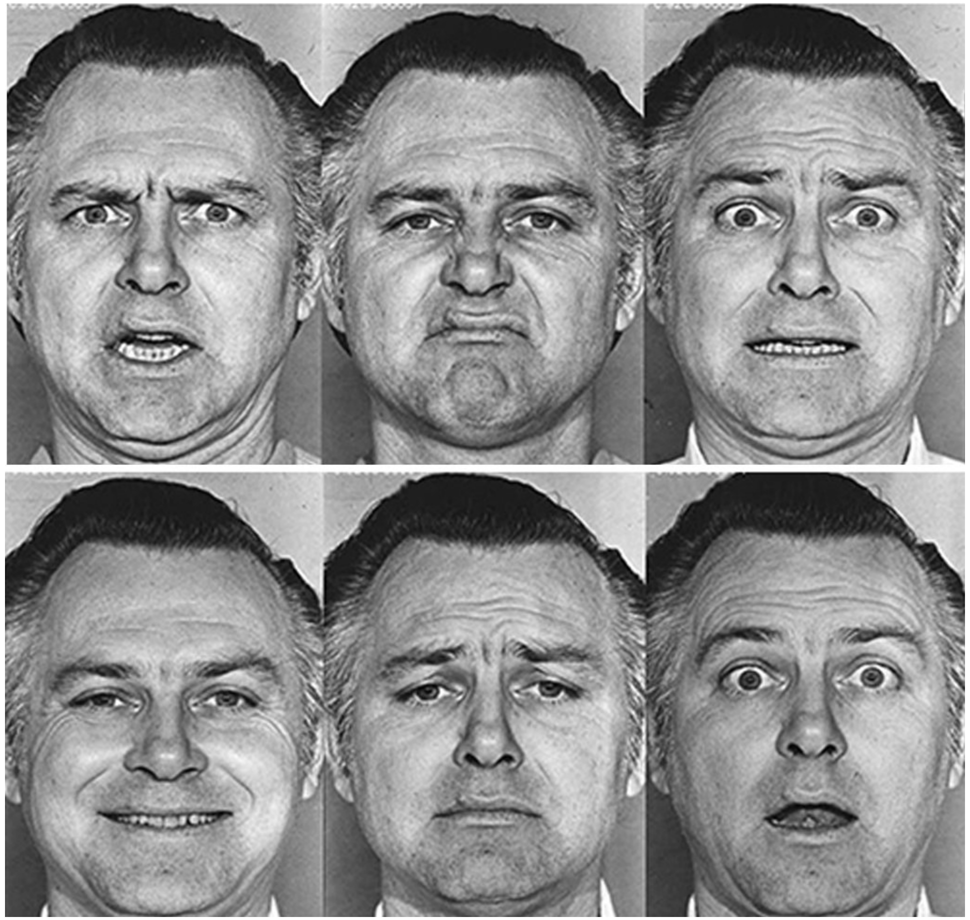
Arise from a variety of environmental reasons

Currently, no consensus on scientific definition

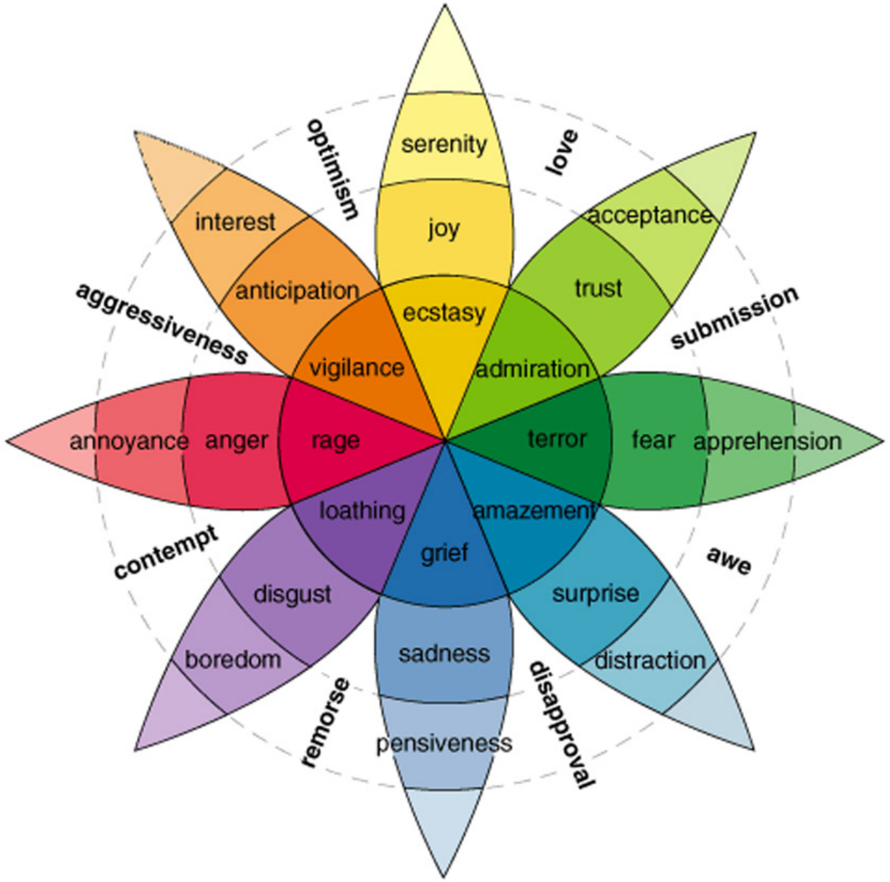
- Damasio: There are two types of emotions: primary and secondary emotions.
- **Primary** emotions are innate, processed in the lower level limbic system of the brain
  - We can feel fear before the we can reason or appraise the situation.
  - Important for survival!
- **Secondary** emotions arise from an understanding of a situation
  - Grief from the loss
  - Involves slow action and higher-level reasoning in the brain
- One situation can result in both types of emotions!

Ekman (1984)

- *There are 6 universal emotion based on facial expression:* ***fear, anger, sadness, happiness, disgust and surprise***
- There many proposals of “basic emotion” classes
  - Tomkins: Ekman + interest and shame
  - Johnson-Laird and Oatley: fear, anger, sadness, happiness, and disgust
  - Etc.
- In this regard, the most common set studied are **joy, sadness, anger, fear**

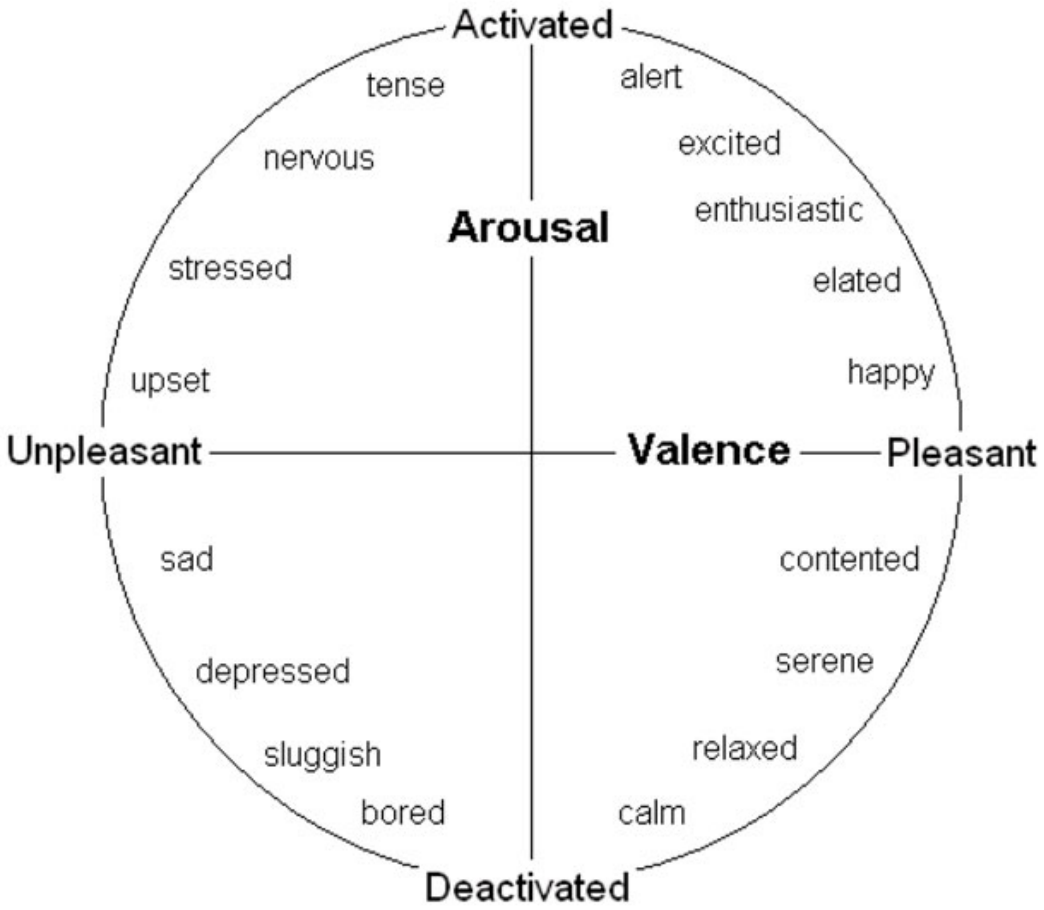


Plutchik (1980)



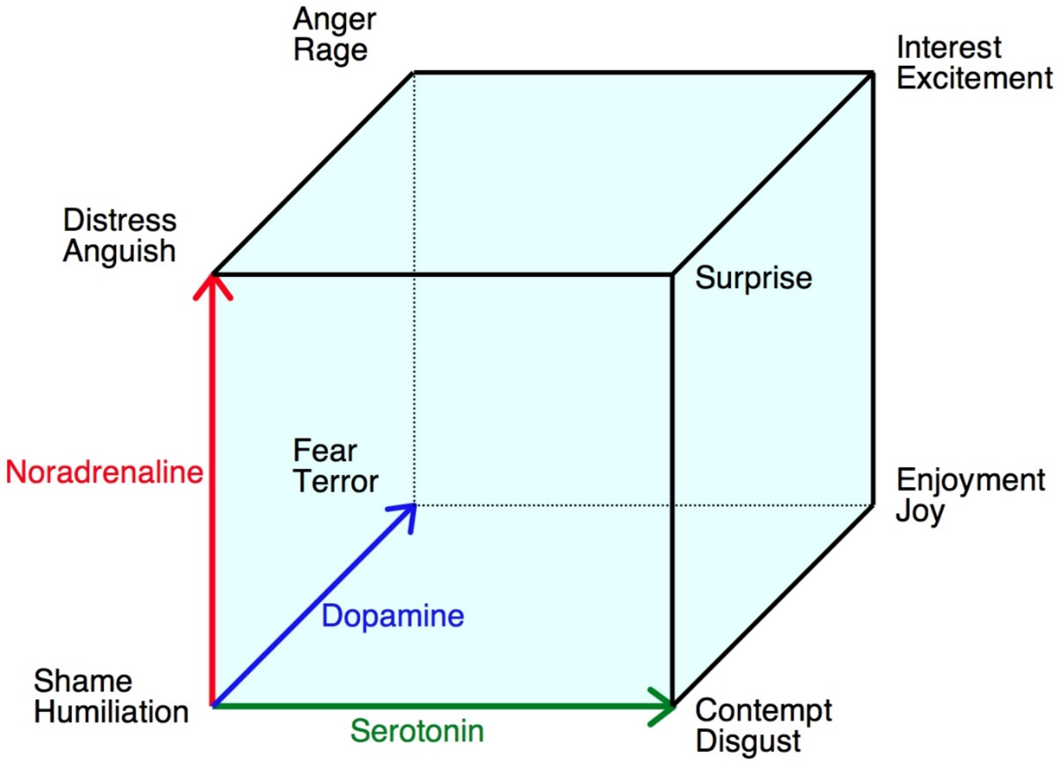
The Plutchik Emotion Circumplex
2D (left) and 3D (above) developed in 1980
by Robert Plutchik.

Russell (1980)



Fontaine et al. (2008)
+ Power/Dominance and expectancy

Lövheim (2011)



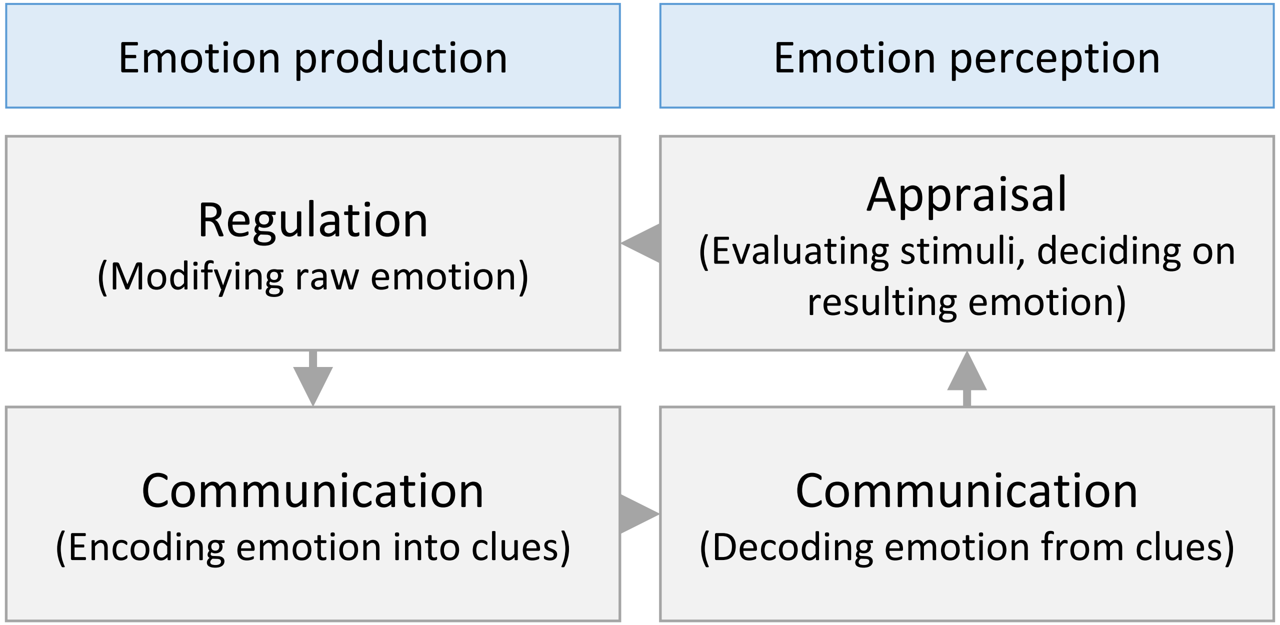
Other related terms

- **Sentiment:** feelings associated with opinions
- **Affect**: general word that covers phenomena involving all valenced (positive/negative) states, including emotion, mood, and preference
- **Mood**: lower in intensity, and last longer than emotions (several hours to days) and are not necessarily directed towards any clear object
- **Feeling**: private, mental experience of emotion. Unlike emotions, they are not observable
- **Empathy**: the ability to understand and share the feelings of others
- **Emotional contagion**: the tendency to automatically mimic and synchronize facial expressions, vocalizations, postures, and movements with those of another person's and, consequently, to converge emotionally,

Emotion in human communication

- Human communication evolved from the humans basic needs (Tomasello, 2010)
  - To request help, exchange information, and social bonding within a group
- Humans communicate for social reasons the majority of their lifespan (Light, 1997)
- Social communication and emotion are intertwined
  - To socially thrive, one must understand emotion
  - To emotionally thrive, one needs social interaction

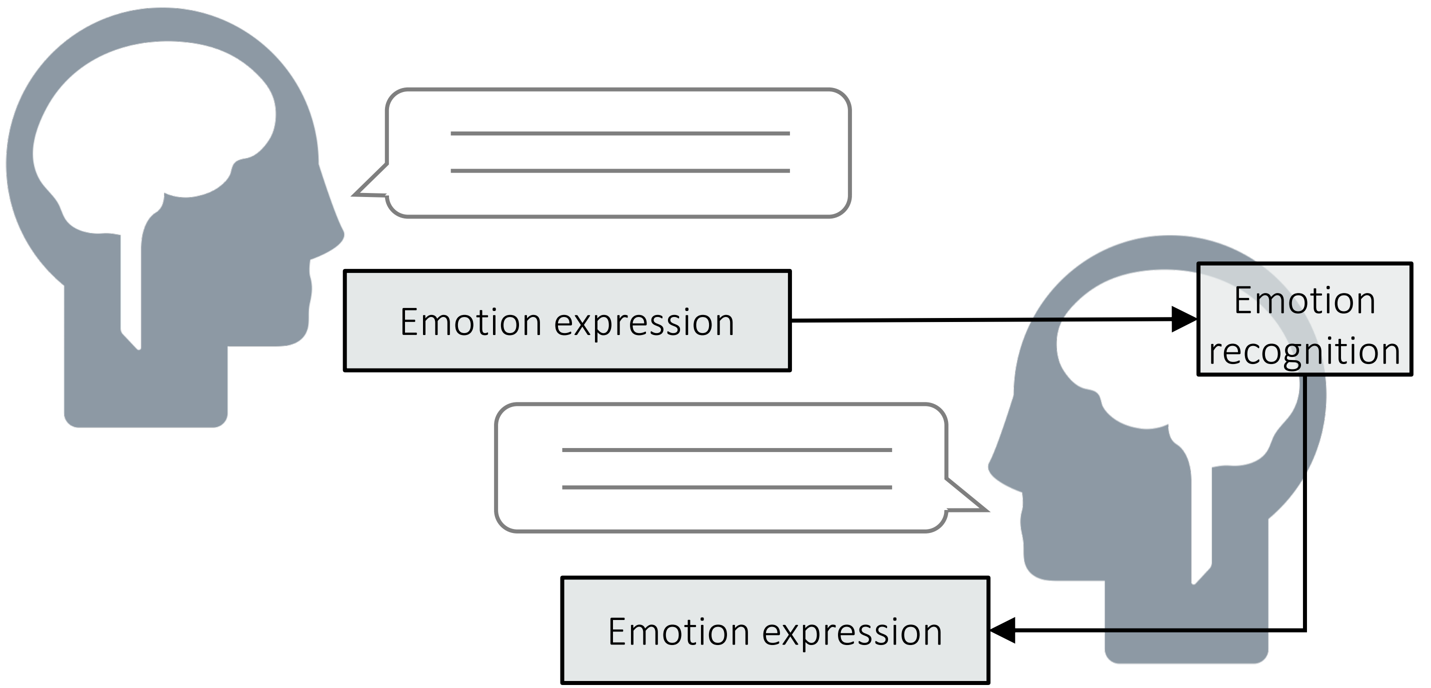
Appraisal theory of emotion (Scherer, 2001)



Affective computing tries to incorporate emotion into Human-computer Interaction (HCI)

Emotion in HCI

Traditional works on emotion in dialogue systems



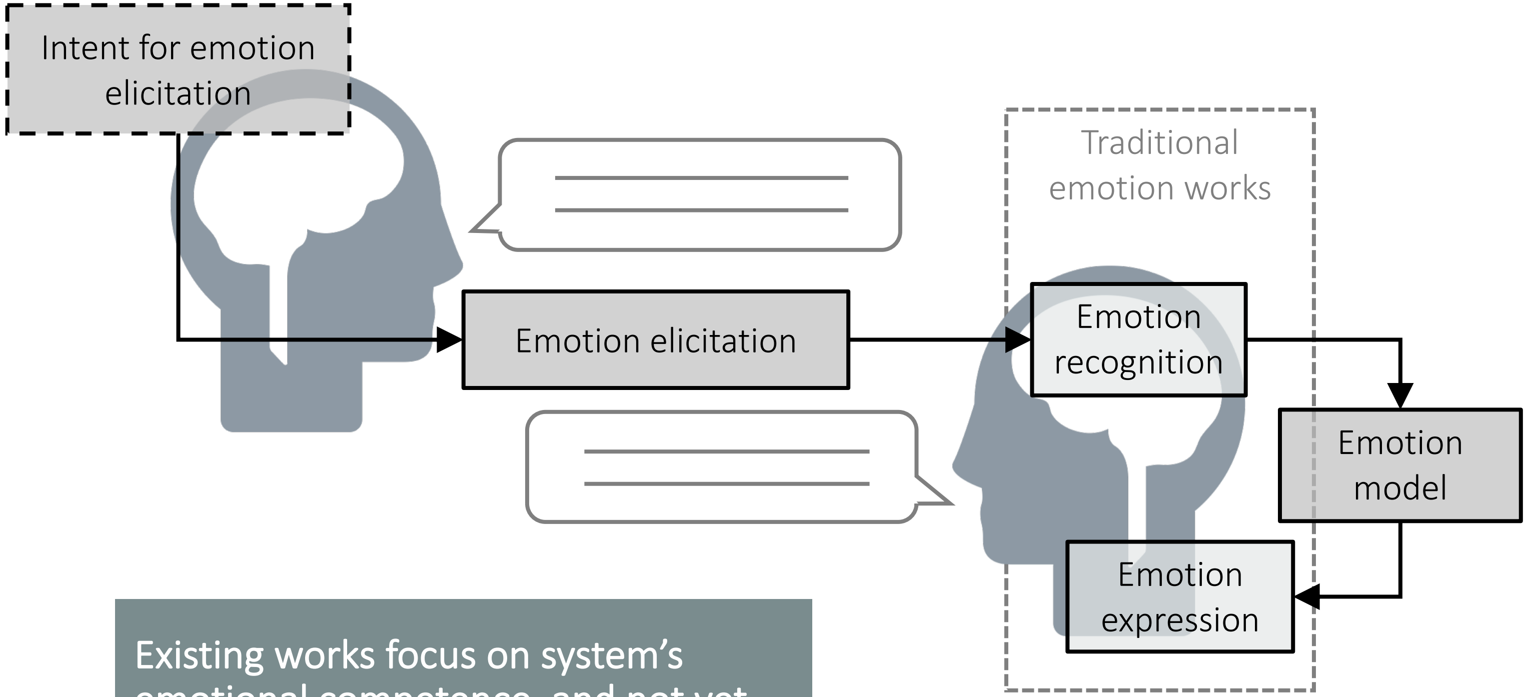
Emotion recognition

- Studied since 1940s
- Discerning emotional state of the user based on communication clues
- Increasing task success (Forbes-Riley and Litman, 2012)

Emotion expression or simulation

- Studied since the late 1990s
- Encoding feeling into communication clues
- Increasing closeness and satisfaction (Higashinaka et al., 2008)

Works on other emotion competences in dialogue systems



Existing works focus on system's emotional competence, and not yet

- Emotion processes as a whole
- Assist user's emotional process

Emotion modeling or appraisal

- Emotion model to guide system's emotional reaction (Gratch et al., 2001; Dias et al., 2014)
- The appraisal of emotion triggers into emotion responses (Lubis et al., 2015)

Emotion elicitation

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

Eliciting Positive Emotional Impact in Chat-Based Dialogue System

Work done at Nara Institute of Science and Technology

Limitations and challenges

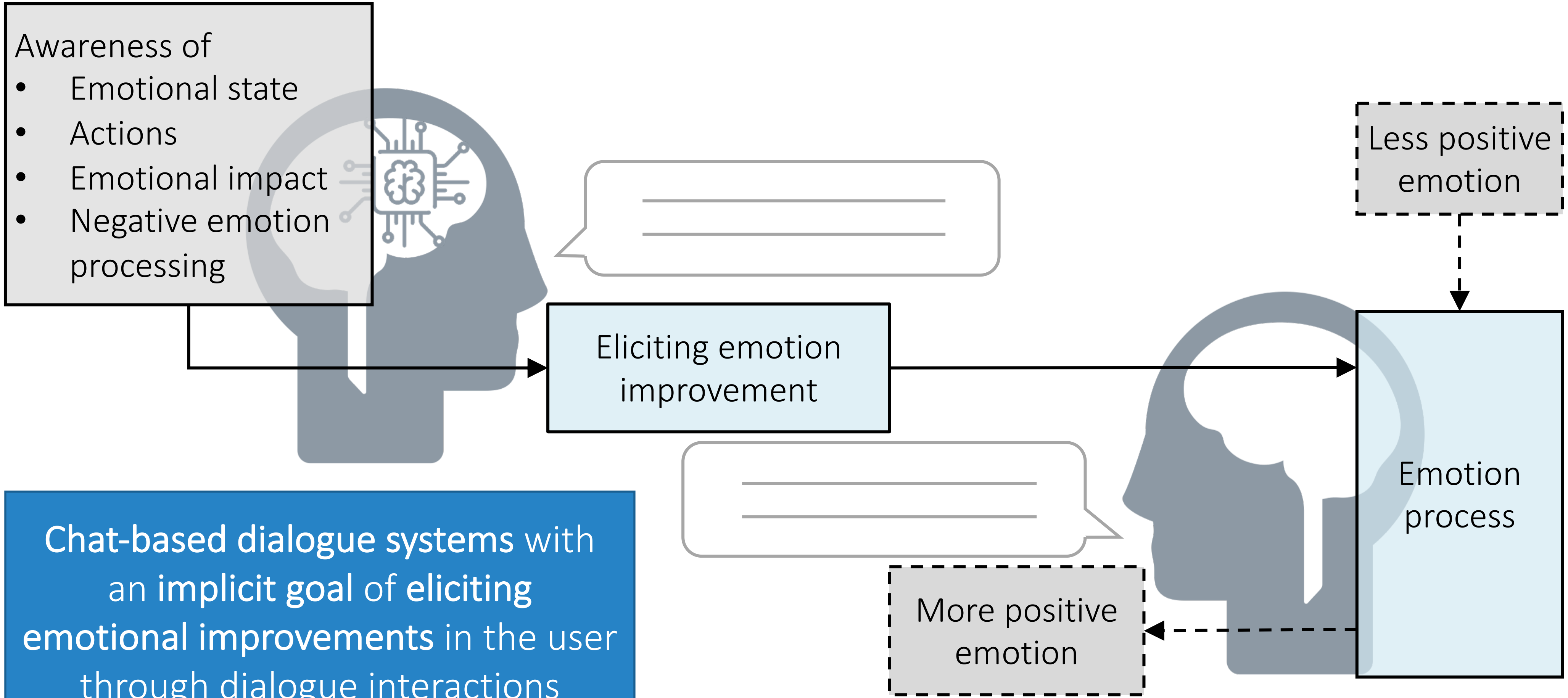
1. Lack of focus on emotional benefit of affective systems for users

- Humans are inclined to socially share emotional experiences, esp. negative ones (Luminet et al., 2000)
- Can human-computer interaction assist user in (negative) emotion processing to elicit improvement?

2. The absence of systems that address negative emotion common in everyday life

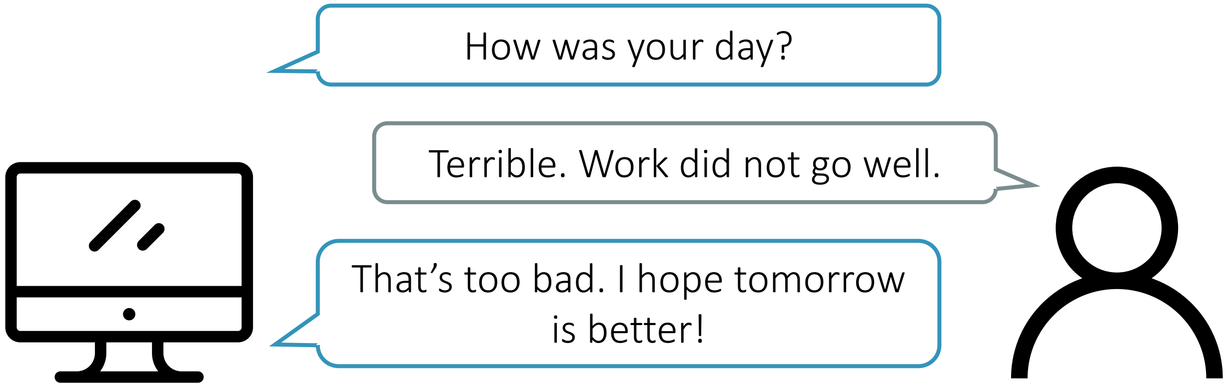
- Works on negative emotion largely focus on clinical disturbances
    - Distress assessment (DeVault et al., 2014)
    - Depression and suicidal tendencies (Cummins et al., 2015)
- Not applicable for the majority of computer users

Task Overview



Chat-based dialogue systems with an **implicit goal** of **eliciting emotional improvements** in the user through dialogue interactions

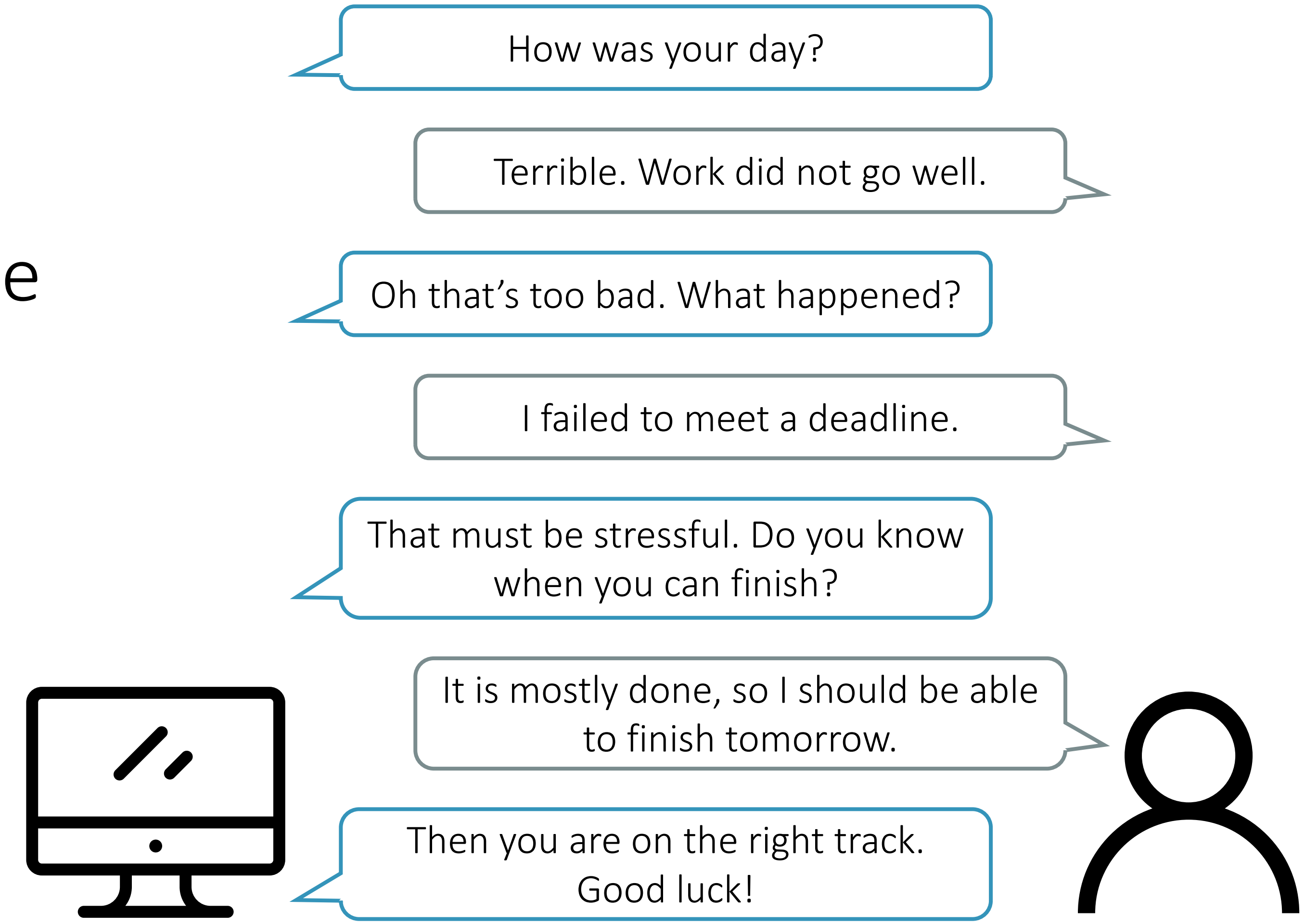
Short- and long-term emotion improvement elicitation



In **short-term**, the system tries to elicit emotion improvement on dialogue turn level

Short- and long-term emotion improvement elicitation

In **long-term**, the system considers the entirety of the dialogue to improve user's emotion

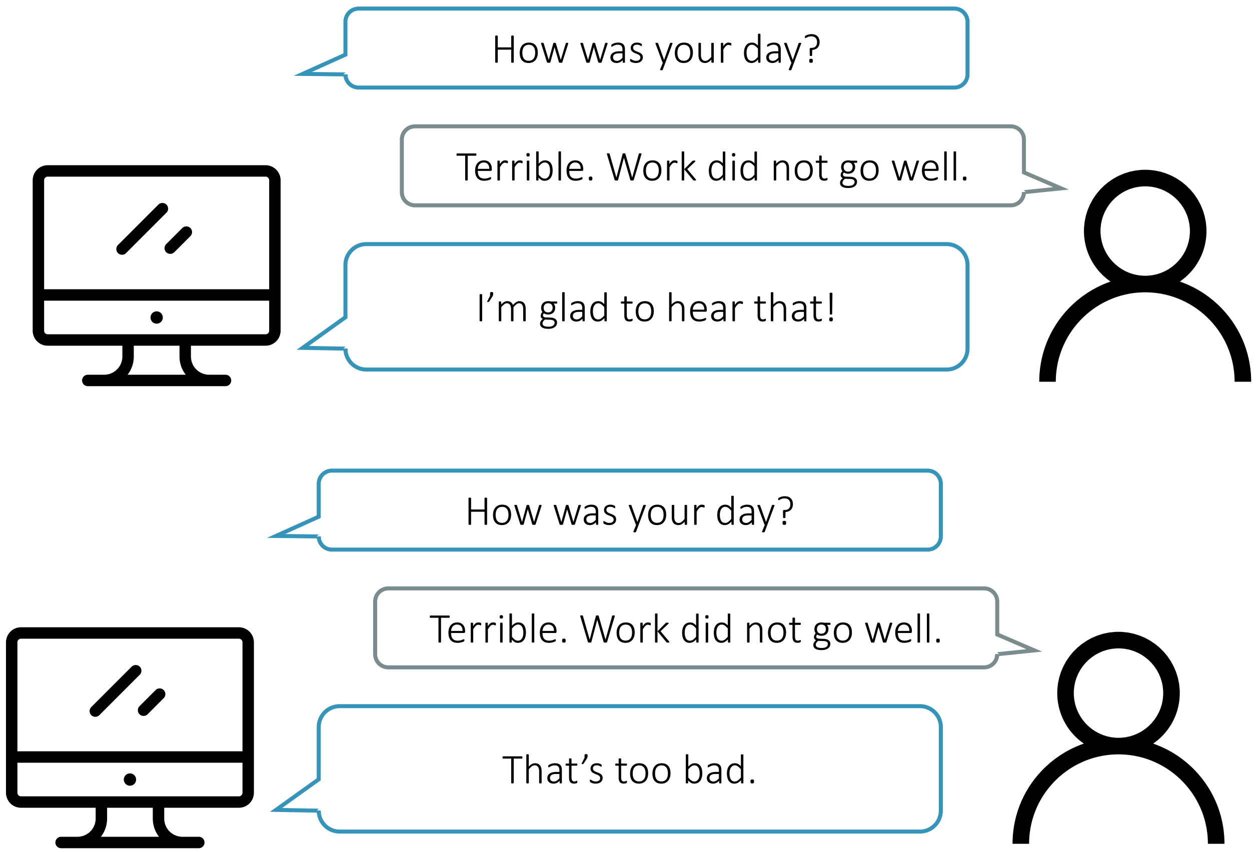


Positive emotion elicitation does NOT mean always responding with positive emotion

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



Research questions and contributions

1. Analysis of social-affective human communication

- How does improvement from negative emotion look like in human communication?

2. Emotion-sensitive response generation

- How can we consider emotion in dialogue system interactions?

3. Methods for short-term emotion improvement

- How can we elicit emotional improvements through dialogue system interactions?

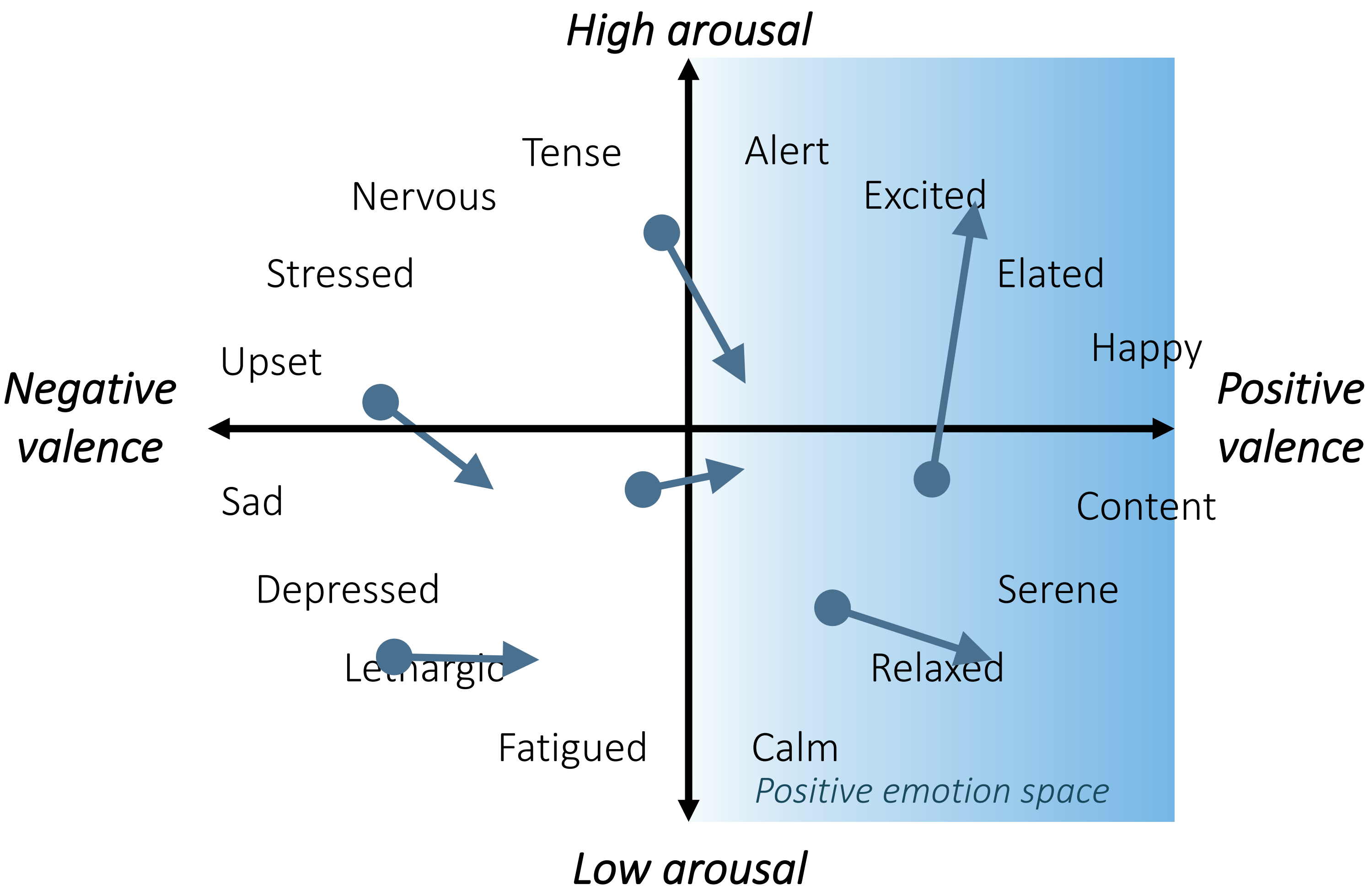
4. Study on long-term emotion improvement

- Can we identify the structure and simulate emotion improvements through dialogue?

Emotion elicitation in dialogue

Emotion

- Emotion
  - Dimensional model of emotion: **valence** and **arousal** (Russel, 1980)
- Positive emotion
- Emotion improvement
  - Synonymously, positive emotion elicitation



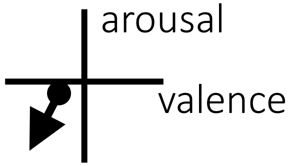
Different responses elicit different emotions

I failed the test.

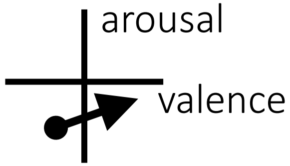
User	I failed the test.	I failed the test.
System	**Oh, again?**	**You will do better next time!**
User	Yeah…	Thank you.

Dialogue triples

Emotional impact *Negative*



Positive

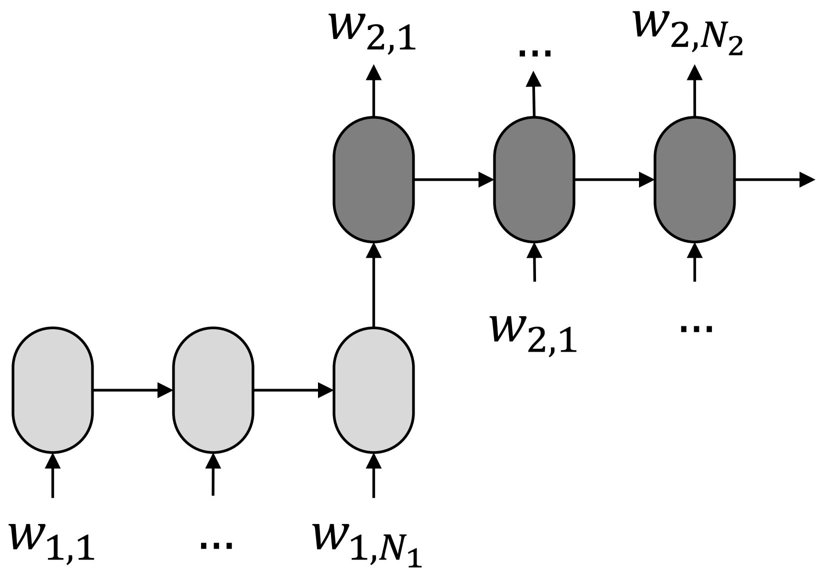


Proposal

- A dialogue system architecture that **tracks emotion** and **incorporates** this information in responding to user
- Methods to **train** chat-based dialogue systems to elicit positive emotion

Neural chat-based dialogue system for response generation

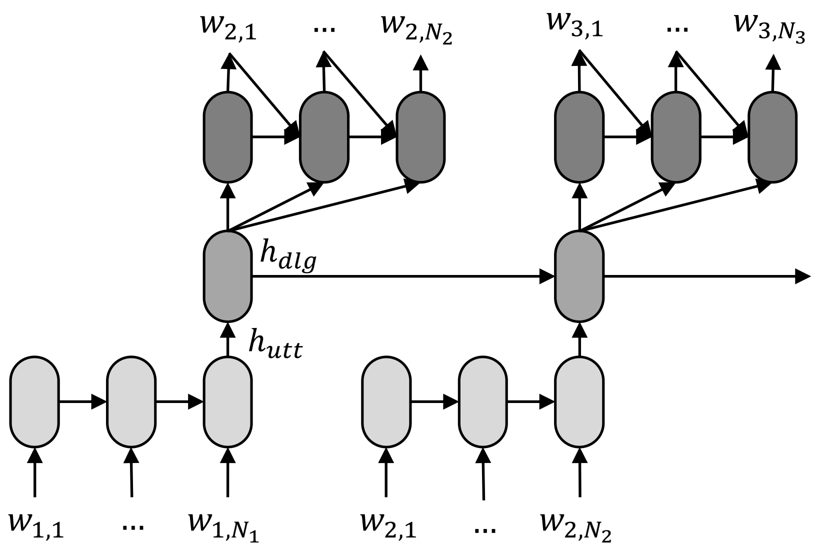
- End-to-end modeling of chat dialogue
- RNN encoder-decoder (Vinyals et al., 2015)



Neural chat-based dialogue system for response generation

- 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)

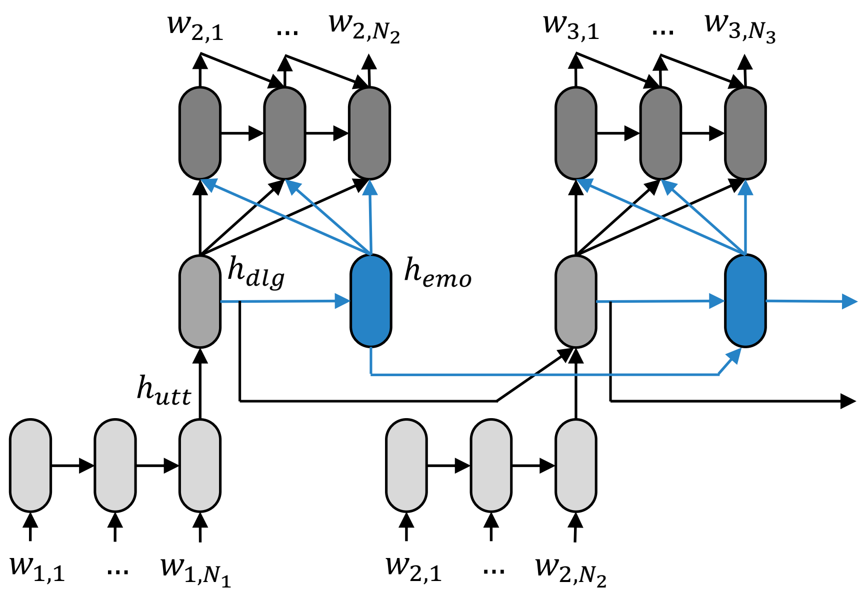
Not yet an application towards emotion elicitation



(Serban et al., 2016)

Proposed: Emo-HRED

(Lubis et al., 2018) in Proc. AAAI 2018



Emotion-sensitive response generation

- Encodes emotional context and considers it in generating a response

Positive emotion elicitation

- Train on responses that elicit positive emotion
  - SEMAINE-positive corpus

Training Emo-HRED

Optimization

- Train on combined losses, linearly interpolating
    - Negative Log Likelihood (NLL) of target response
    - Emotion prediction error
        - The emotion encoder targets the emotion label of the dialogue turn

$$cost = (1 - \alpha) \cdot NLL + \alpha \cdot error_{emo}$$

- The final cost is used to optimize the entire network

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
    - E.g. SubTle corpus (Ameixa et al., 2014)
- **Selectively fine-tune** Emo-HRED with the emotion-annotated data
    - Only train parts that are affected by emotion context
    - Avoid over-fitting or destabilizing

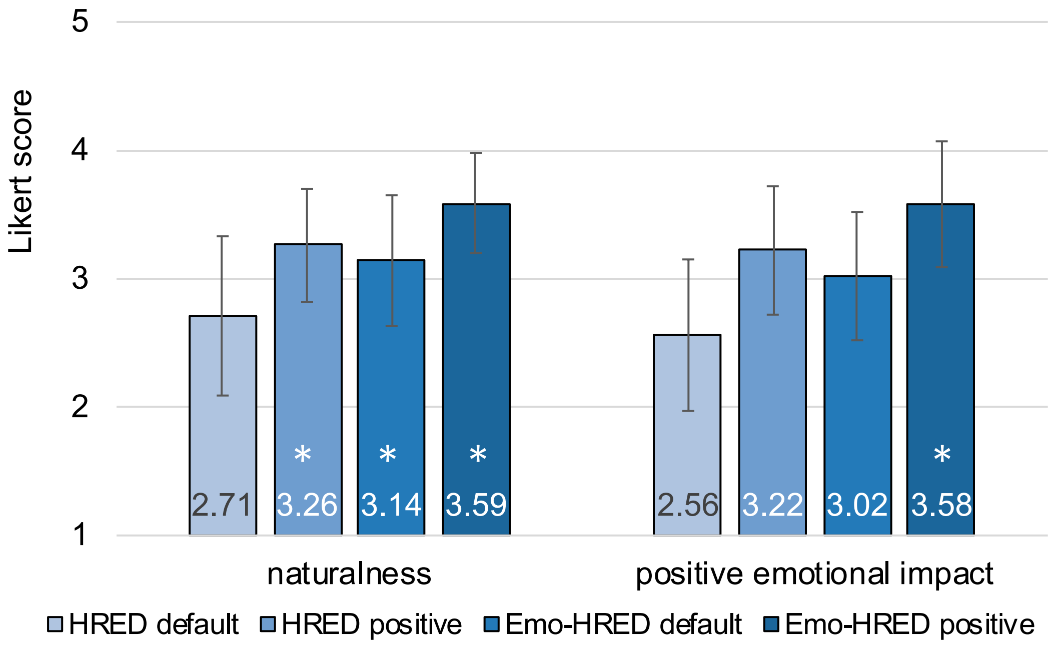
Objective evaluation: Perplexity

Model	Parameter update	Fine-tune data	**Perplexity** on SEMAINE-positive test set
Baseline HRED	standard	SEMAINE	185.66
		SEMAINE-positive	121.44
	selective	SEMAINE	151.77
		SEMAINE-positive	100.94
Proposed Emo-HRED	selective	SEMAINE	69.66
		SEMAINE-positive	**51.34**

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 elicits a more positive emotion

Limitations

1. Has not learned expert strategy

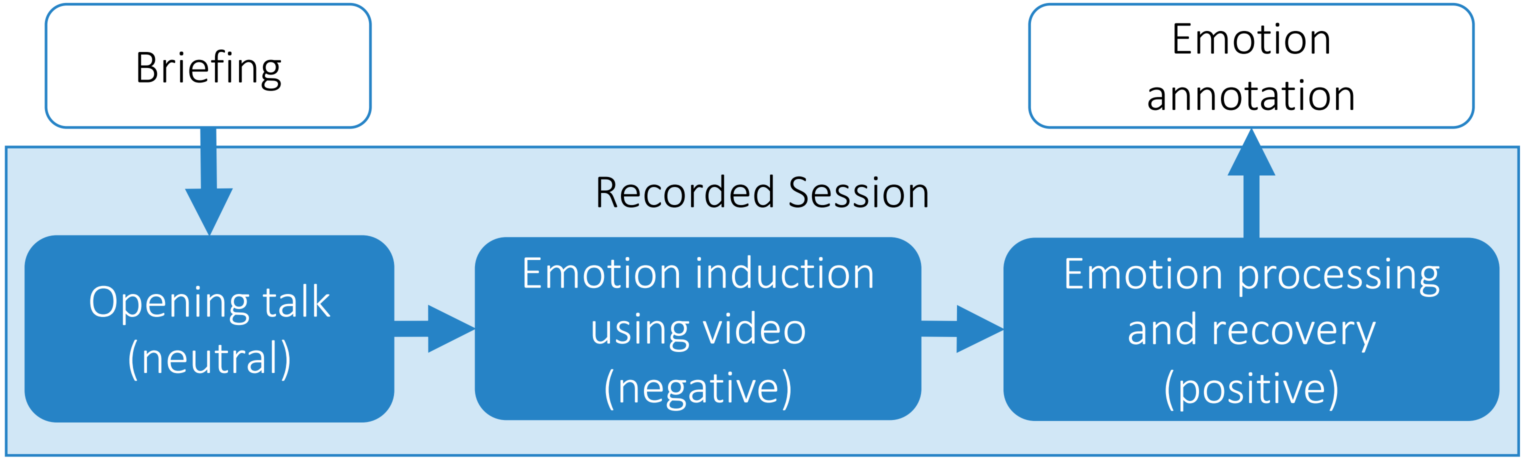
2. Short and generic responses

Unsupervised clustering for positive emotion elicitation

Negative emotion processing corpus

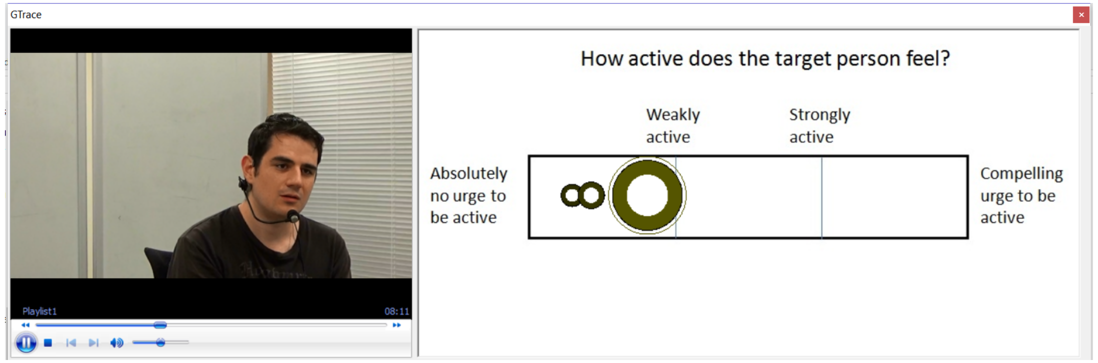
(Lubis, et al., 2017) in Proc. ACII 2017

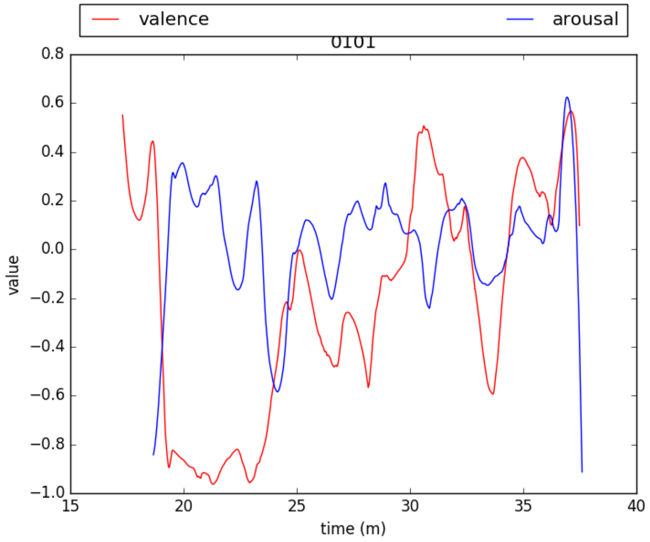
- Goal: observe expert strategy for eliciting emotion improvement
- Collect:
  - Interaction between an expert and a participant
  - Condition the interaction with negative emotion common in everyday situations
  - Expert guides the conversation to allow participant's emotion recovery and reinstate positive emotion

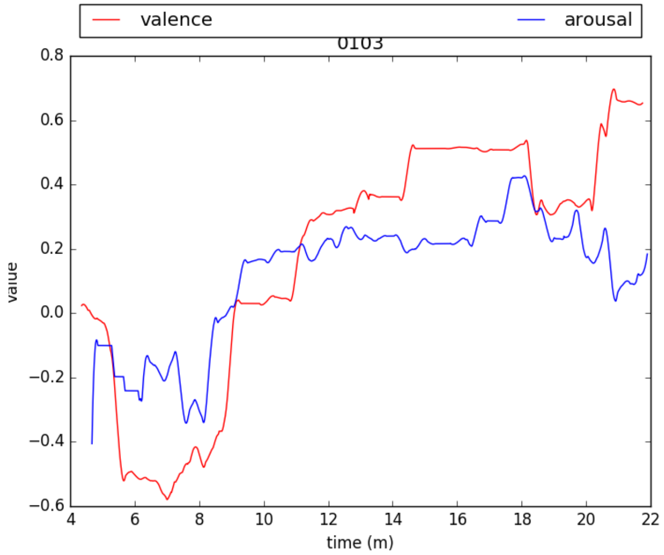


Data collection and annotation

- 60 sessions: 23 hours and 41 minutes of material
  - 1 counselor, 30 participants
  - 2 sessions per participant
    - 1 induced to anger
    - 1 induced to sadness
- Self-report emotion annotation using Gtrace [Cowie et al., 2000]
- Transcription







Counselor dialogue clustering

Goal:

- To find and utilize high-level information to compensate for data sparsity
  - categorizing responses and emphasizing this information in the training and generation process.
  - Information equivalent to dialogue acts
    - Specific to the dialogue scenario
    - Retaining affective intents

✘ Human annotation

- Expensive, labor intensive
- Not scalable
- Low reliability

✘ Standard dialogue acts classifier

- May not cover specific emotion-related intent in the data

✓ Unsupervised clustering

- No need to predefine the categories
- Requires minimal resource
- Scalable

Counselor dialogue clustering

Word2Vec embedding vectors
(Mikolov, et al., 2013)

- Words with similar meaning will have similar representation

K-Means

- Need to predefine how many clusters
- Choose K empirically

DPGMM

- No prior definition of model complexity

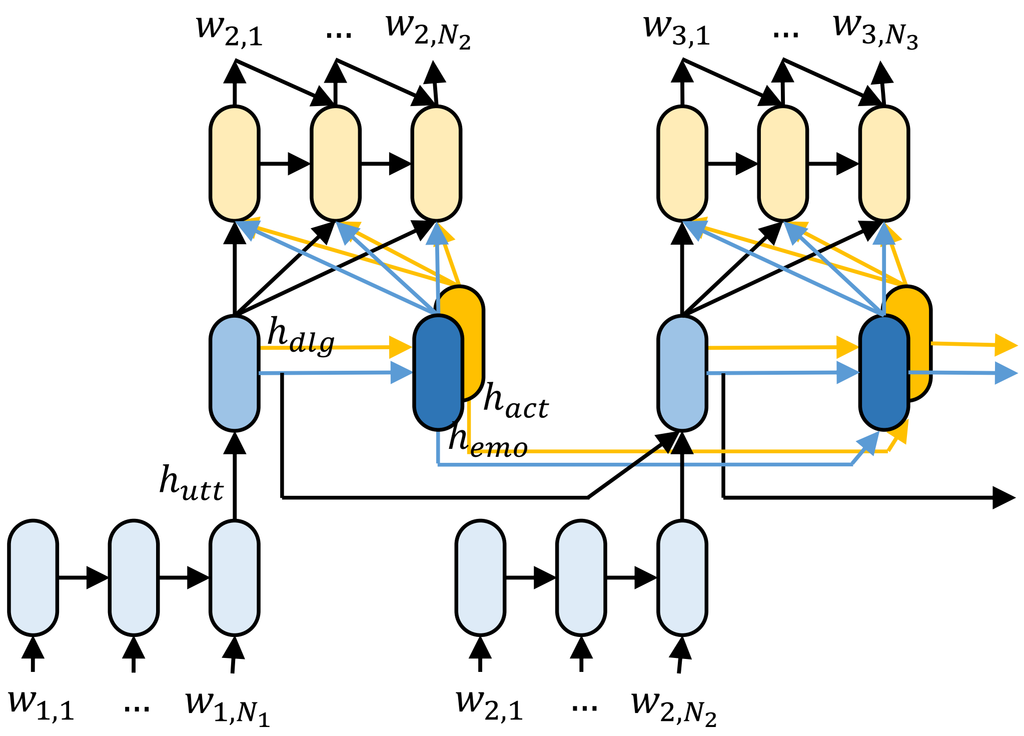
Analysis of found clusters show shared intention within clusters

Proposed: Multi context HRED (MC-HRED)

(Lubis, et al., 2018) on Proc. SIGDIAL 2018

A neural dialogue system which generate response based on multiple dialogue contexts

- Dialogue history
- User emotional state
- Response action label, i.e. cluster label



MC-HRED architecture.

Training MC-HRED

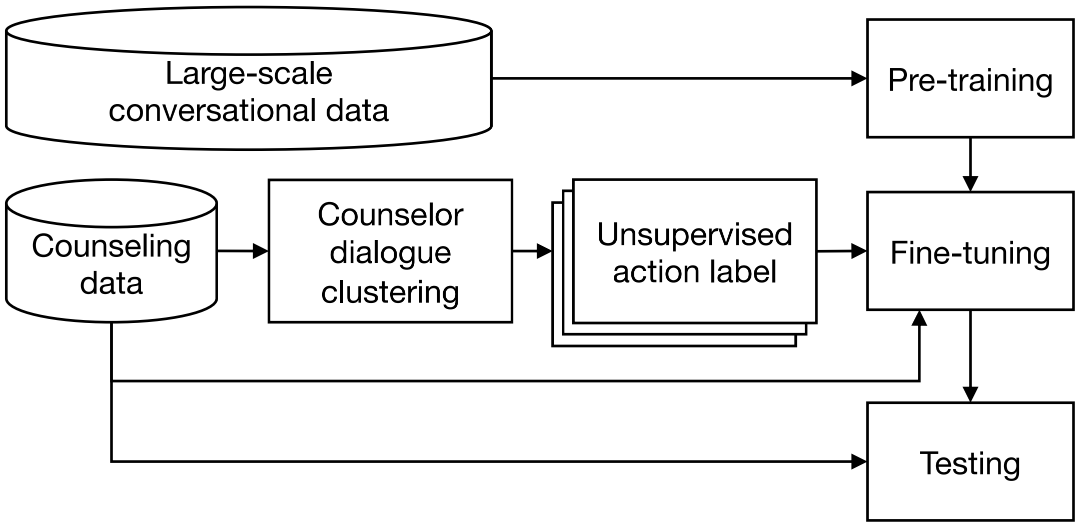
Optimization

MC-HRED is jointly trained on combined losses

- NLL of target response
- Emotion prediction error
- Action prediction error

Pre-training and selective fine-tuning

As with Emo-HRED



Objective evaluation: perplexity

Model	Emo	Action	Perplexity		
			all	short	long
Emo-HRED	yes	no	42.60	35.74	61.17
Clust-HRED	no	K-means	39.57	32.30	57.37
		DPGMM	30.57	24.79	42.25
MC-HRED	yes	K-means	**29.57**	**23.23**	**38.73**
		DPGMM	32.04	25.00	42.43

Objective evaluation

- MC-HRED with K-means obtains substantial improvement esp. on long triples
- The multiple contexts help, especially for long inputs

Subjective evaluation

- Improved engagement while maintaining the emotional impact and naturalness
- MC-HRED produce responses with 2.53 more words on average

Examples

U_1	oh how do you feel about that one.
U_2	yes i heard the story.
U_3 (Target)	you heard it before.
Emo-HRED	right.
MC-HRED	it’s a big thing.

U_1	are you a student here?
U_2	uh yes, actually I just got, er that's my lab over there in social computing yes (laughter).
U_3 (Target)	oh really. so you've been watching us going by.
Emo-HRED	Oh okay.
MC-HRED	(laughter) it’s nice to meet you.

More proposed methods for positive emotion elicitation

Training to maximize positive emotional impact

(Lubis et al., 2018) in Proc. SLT 2018

- Explicitly consider emotional impact in the training process
  - Not relying on training data to reflect positive emotion elicitation

Multi-modal emotion encoding for positive emotion elicitation

(Lubis et al., 2019) in IEEE/ACM TSLP

- Combine textual and audio features for emotion prediction
  - Catch emotional variations of identical utterances

Both models show performance consistently surpassing their respective baseline

Conclusion and future works

Conclusion

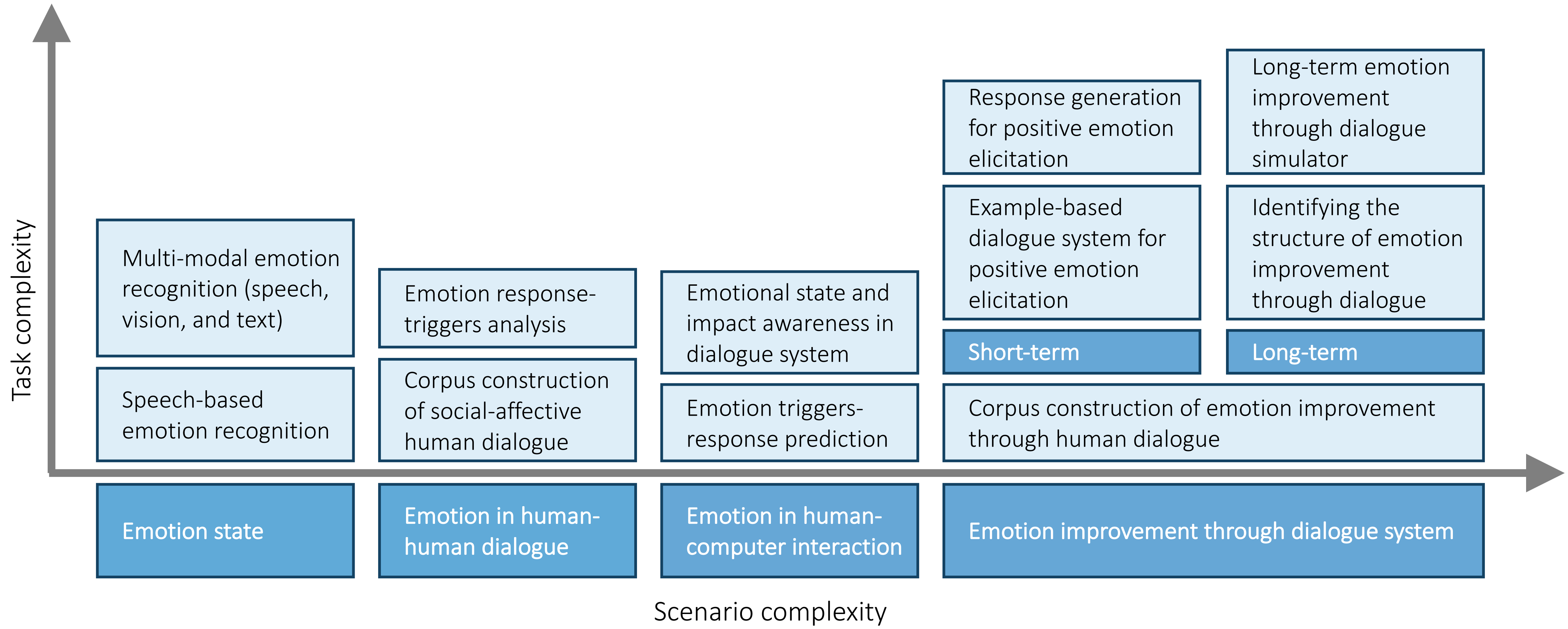
Existing works

- Focus on emotional competences of system
- Have not considered emotional benefit for user
- Have not considered negative emotion commonly encountered in everyday life

This work

- Human-computer interaction to emotionally benefit user
  - Assisting emotion processing
  - Emotion improvement elicitation
- Negative emotion in day-to-day conversations

Roadmap


Long-term emotion improvement through dialogue simulator
Response generation for positive emotion elicitation
Identifying the structure of emotion improvement through dialogue
Example-based dialogue system for positive emotion elicitation
Short-term
Long-term
Task complexity
Multi-modal emotion recognition (speech, vision, and text)
Emotion response-triggers analysis
Emotional state and impact awareness in dialogue system
Speech-based emotion recognition
Corpus construction of social-affective human dialogue
Emotion triggers-response prediction
Corpus construction of emotion improvement through human dialogue
Emotion state
Emotion in human-human dialogue
Emotion in human-computer interaction
Emotion improvement through dialogue system
Scenario complexity

Future Directions

- Learning dialogue strategy or policy for emotion improvement elicitation
  - User-adaptive dialogue strategy
  - Larger-scale corpus construction
  - Robust methods for limited and sparse data
- User study to observe the effect and effectiveness of affective systems
  - User reaction, long-term effect, relevant scenario or situation, etc.
- Application in task-oriented systems

Thank you