

Week TODO: TODO

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Summary: Multimodal machine learning is the study of computer algorithms that learn and improve through the use and experience of multimodal data. It brings unique challenges for both computational and theoretical research given the heterogeneity of various data sources.

In week 2's discussion session, the class aimed to formalize a taxonomy of cross-modal interactions: various ways in which elements from different modalities can relate with each other and the types of new information possibly discovered as a result of these relationships. The following was a list of provided research probes:

1. Are emotions the same as emotional intelligence? How would you define emotions? How would define emotional intelligence? How do you relate these two concepts of emotions and emotional intelligence? Do we want AI systems to have emotions, emotional intelligence or both?
2. What would be the equivalent of this emotions vs emotional intelligence comparison when talking about social intelligence? Should we compare social intelligence to social interactions? Social behaviors? Or social skills?
3. Should we use the term emotional intelligence or emotional competence? Should we talk about emotional skills, in a similar way to our discussion about social skills?
4. Is it important to differentiate social intelligence from emotional intelligence? Similarly, should we differentiate social skills from emotional skills? Social competence vs emotional competence? Or should we integrate them? Or the union of all these concepts?
5. Can you identify examples and use cases where clearly a situation is referring to emotional intelligence and not social intelligence? Or vice-versa?
6. What are the skills and/or abilities would you expect an AI system to have so that we can call it emotionally intelligent? Is there a core set of skills/abilities that are particularly important? We could call them the "core skills/abilities". What would be the core set of abilities and skills for social intelligence? Social competence?

As background, students read the following papers:

1. (Required) What are Emotions? And How can They be Measured? [Scherer, 2005]. Klaus Scherer is arguably one of the most prominent researchers in emotion sciences. This paper nicely defines emotions, also contrasting them with other emotionally-related phenomena such as mood, affect and attitudes. Students should read at least pages 695-707 but it may be good to also take a look at the section on "How can emotions be measured".
2. (Required) Emotional Intelligence: Toward a Consensus of Models and Measures [Roberts et al., 2010]. This paper gives an historical view of research in emotional intelligence. It is not necessary to remember all proposed tests and theories, but students should have an understanding of trait, ability and mixed Emotional Intelligence models. An alternative to this paper would be the Emotional Intelligence chapter [Rivers et al., 2020] mentioned in the other relevant papers.
3. (Suggested) Componential Emotion Theory Can Inform Models of Emotional Competence [Scherer, 2007]. This is an interesting paper discussing links between emotion research and emotional intelligence. This is written by Klaus Scherer, who is from the emotion research community. The paper emphasizes

a list of emotional competence that is worth taking a look at.

4. (Suggested) Emotional Expressions Reconsidered: Challenges to Inferring Emotion From Human Facial Movements [Barrett et al., 2019]. Emotions are often linked to facial expressions. This comprehensive paper revisits the concept of emotional expressions linking facial displays and emotions. We selected this paper as an example of emotion models with displayed behaviors (in this case, facial expressions). The paper also makes a great summary of emotion theories linked with behaviors (e.g., Table 2).
5. (Suggested) Practical Intelligence, Emotional Intelligence, and Social Intelligence [Lievens and Chan, 2017]. This paper nicely relates emotional and social intelligence. The sections about emotional intelligence and social intelligence will be good reminders from your Week 2, 3 and 4 readings. The second part of the paper nicely discusses the different methods for measuring intelligence, which would be worth looking at (e.g., Table 15.1).
6. (Other) Emotional Intelligence [Rivers et al., 2020]. This chapter was from the same book ("Cambridge Handbook of Intelligence") as the Social Intelligence chapter from Week 2. It is good to understand at a high-level the trends in Emotional Intelligence, including how it is measured and its correlates. Students should not over-study the specific debates (e.g., ability vs mixed models), but read this paper with the goal of understanding similarities and differences between emotions and emotional intelligence.
7. (Other) Emotional Intelligence Measures: A Systematic Review [Bru-Luna et al., 2021]. If you are interested in a comprehensive list of all the measures of emotional intelligence, this article has a very long list, with good categorization.

We summarize several main takeaway messages from group discussions below:

1 Definitions

1.1 Emotions

In class, two interpretations of emotions were discussed: the first defines emotions as functional states that determine subsequent behaviors [Adolphs and Andler, 2018], and the second claims that emotions could be constructed in the moment by our brain [Barrett, 2017]. Emotions can have objective and subjective components, with emotions that function as states having more objective components and emotions that serve as labels for behaviors having more subjective components.

Measuring Emotions: Physiological sensors are commonly used in studies on emotions in order to capture neuroactivity and physiological signals that occur in response to stimuli [Harley, 2016]. However, the considering physiological measurements solely as objective measures in the context of emotions may not be true. This is because self-awareness can influence how individuals perceive their emotions, potentially leading to different physiological reactions influenced by other affective processes. While emotions studied in psychology may have objective components such as neuroactivity and physiological signals, experiences of emotions can be heavily subjective [Barrett et al., 2001]. Differences can also exist between self-reported mental states and observations.

1.2 Emotional Intelligence

Emotional intelligence can be defined as a combination of the modules of skills and competence related to perceiving, expressing, facilitating, understanding, and managing emotions [Roberts et al., 2010]. It is context-dependent and involves connecting emotions to situations, empathy, and regulation of emotions, both for oneself and others. All four branches of emotional intelligence - perception and expression, facilitation, understanding, and management - are context-dependent.

1.3 The Critical Role of Context in Understanding Emotions

The complexity and dynamic nature of emotions make them heavily situation-dependent, making context crucial for understanding and analyzing them. Work such as Mesquita and Boiger [2014] and Mesquita and Walker [2003] proposes models of emotion which centers around interactions, relationships, culture, and context. This is particularly true when it comes to AI, which needs to have a context to detect emotions

accurately (an example task is the EMOTIC data set [Kosti et al., 2017]). Similar characteristics may be present in the facial expressions of various emotions; moreover, sometimes it is difficult to perceive subtle changes in facial expressions.

Context is also essential when regulating the emotions of others, as the social and cultural norms that surround an emotional situation play a significant role in how those emotions are perceived and interpreted. Understanding emotions, connecting them to situations, and having empathy for others are all crucial skills in emotional intelligence, and they are all heavily influenced by context.

1.4 The Roles of Emotions in Human Context

The utilitarian and existential views of emotions suggest that emotions are necessary for human existence and performance. Humans have evolved to possess emotions as they are essential for existence and survival [Keltner et al., 2006]. People use feelings or emotions to confirm their existence; moreover, when faced with threats or danger, the body secretes adrenaline, which leads to feelings of excitement and prepares the body for a fight or flight response.

Although in contemporary society where the frequency of facing threats is much lower than earlier human periods, emotions remain an essential aspect of human experience. Emotions can play a role in humans' reward system, which motivates us to do certain things. Some individuals even prioritize maximizing their happiness, which remains a valuable heuristic for some. Moreover, the differences in emotions and how we utilize them are what contribute to the diversity among humans.

2 Emotions and Artificial Social Intelligence

To begin this section, we ask the question “*why should we build ASI with emotions*”? Those in favor of emotionally intelligent ASI would argue that the role of emotions in ASI is to enable machines to understand, perceive, and respond to human emotions to enhance their social interactions and relationships [Picard, 2004]. In particular, we may desire emotions in ASI to aid performance gains on different tasks, such as engaging in conversation. Furthermore, ASI with emotions would be able to understand affective signals from the real world. It can process affective information and give affective cues to humans. However, do all A.I. tasks need to be achieved through emotion signals? In this section, we raise questions on how we should *implement* emotional intelligence in ASI, how we can *evaluate* emotional intelligence in ASI, and *when* should ASI have emotional intelligence.

2.1 Implementing Emotions in ASI

Emotional ASI and the “Human” Factor: Imagine that we built the “perfect” AI system that can understand human emotions. Is there still a “human” factor missing from the AI? One “human” factor that would be missing is the internal feeling of emotions. To answer this question, we first note a distinction between emotions and emotional intelligence [Roberts et al., 2010]. While ASI may be able to learn emotional intelligence (i.e., correctly reasoning about emotions and output appropriate emotions), there is no internal physiological process. Work such as Arbib and Fellous [2004] aims to separate emotions from physiological processes in order to create a set of “robot emotions”. However, a lack of internal emotions may not necessarily be detrimental to ASI. If ASI is built from a utilitarian viewpoint, then we only need the AI to simulate emotions to signal its goals and to satisfy an interaction without internal feelings. For example, while the Paro robot does not feel emotions, it can still use emotional signals provide therapeutic interactions to humans [Hung et al., 2019]. Therefore the “human factor” may not need to be reflected in ASI.

Understanding Emotions to Build ASI: A subsequent question from the previous section is: while internal human feelings do not have to be reflected in ASI, do we need to first fully understand human emotions in order for it to be sufficiently implemented in AI? On the one hand, we are unsure how emotions arise and are processed in humans to achieve emotional competence [Scherer, 2005]. Therefore, it would be difficult to assume emotion competence in AI if we cannot understand our own emotions. In contrast, we also revisit the idea that AI is often utilitarian. Thus, a deep understanding of internal human emotions may not

be important for emotional competence in ASI. Furthermore, we note that there are people who may not experience certain emotions [Twenge et al., 2003]. However, they may mimic these emotions as output to fit societal norms. Thus, even if there was an established human construct of emotions, it may not apply to all humans, and hence not all ASI.

2.2 Evaluating Emotions in ASI

Given that we do not fully agree on a human taxonomy of emotions, how do we evaluate emotional competence in ASI? To answer this question, we can first consider defining a series of tests to evaluate emotional understanding and reasoning in ASI. We note that emotional tests for humans are correlated [Roberts et al., 2010]. Therefore, we can make a benchmark for ASI which correlates well with an emotional task for humans, and this in turn may make it sufficient to test ASI. Another idea is to use *goal-driven* evaluation. This is, we evaluate ASI based on its ability to complete a task. In particular, we consider two goal-driven evaluation methods: an internal evaluation (e.g., model reasoning) and an external goal driven evaluation for communication. An example that would fall into the latter category is a dialogue system would can successfully use emotions to persuade a user to perform an action [Wang et al., 2019].

However, is a task-oriented view of emotions sufficient to achieve emotional competence in ASI? On the one hand, it may be enough for ASI to simply predict and signal emotions during a specific interaction, such as a service robot [Kwon et al., 2007]. However, it can also be beneficial for an ASI agent be able generalize to different domains, situations, or cultures. Furthermore, a task-oriented assessment of emotional intelligence can bypass the need for emotional reasoning. For instance, ChatGPT may pass a Turing test involving emotions. However, is its emotional reasoning truly sound?

2.3 Personalization in ASI

Another major point of discussion is if we need AI to have all-encompassing emotions or only for specific tasks (e.g., robot waiter with emotions). To examine this question, we first look at a real-life situation: Let's say you have a car that can recognize your emotion and affective states, and takes over driving when you feel down. Would that be appropriate?

First, we note that this is also a HCI-centered problem. While some users may like this gesture, other users may be annoyed which leads to perceived error [Tian and Oviatt, 2021]. Thus, partial emotional skills and goals in ASI seem appropriate (e.g., automatically taking over a dangerous driving etc). Furthermore, personalization in emotional understanding in ASI can also be desirable. For example, some people express more emotions than others. If ASI can understand an individual's emotional states and personality, then ASI can be an good aid [Ghandeharioun et al., 2019].

As previously mentioned, it may not necessary for ASI to possess emotions, but it should have the ability to recognize, interpret, and respond to emotions. In some cases, ASI with errors in emotional interaction may be bypassed [Tian and Oviatt, 2021, Salem et al., 2015]. However, for AI systems employed in medical care and mental health, precise emotional measurement is essential when dealing with sensitive situations.

We conclude that specific emotional skills in ASI for specific scenarios is appropriate. We don't want ASI to be overly humanized [Mori et al., 2012], but we still want it to show emotion in an appropriate way. While studies such as Breazeal and Brooks [2005] have looked at mapping human emotions to robot emotional skills, future research can benefit from understanding how much emotional skill is optimal for ASI and human interaction.

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