Emotion in Future Intelligent Machines

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Abstract
Over the past decades, research in cognitive and affective neuroscience has emphasized that emotion is crucial for human intelligence and in fact inseparable from cognition. Concurrently, there has been a significantly growing interest in simulating and modeling emotion in robots and artificial agents. Yet, existing models of emotion and their integration in cognitive architectures remain quite limited and frequently disconnected from neuroscientific evidence. We argue that a stronger integration of emotion in robot models is critical for the design of intelligent machines capable of tackling real world problems. Drawing from current neuroscientific knowledge, we provide a set of guidelines for future research in artificial emotion and intelligent machines more generally.
Emotion is critical for the flexible, intelligent behavior of biological organisms. Accordingly, multiple attempts to model emotion in robots and artificial agents have been described in the last decades. Yet, how emotion is modeled and how it interfaces with “cognitive architectures” remains poorly developed. We argue that current shortcomings are due to the design of artificial emotion in a manner that is largely disconnected from recent neuroscientific evidence.

Several robotics and artificial intelligence proposals take inspiration from biological cognition (e.g. Mnih et al., 2015; Cully et al., 2015; Moulin-Frier et al., 2017; Doncieux et al., 2018). In many of these, reinforcement learning is used as a model of autonomous learning and decision-making, providing good examples of fruitful interactions between neuroscience and artificial intelligence (Neftci & Averbeck, 2019). However, the framework of reinforcement learning does not encompass critical components of natural emotion; it primarily addresses processes related to operant learning and simple forms of decision-making (see review by Moerland et al., 2018). More generally, and as argued in the present piece, emotion is not sufficiently incorporated into robotics.

Here, we begin by reviewing the literature on emotion modeling in robots and artificial agents. We discuss existing proposals with respect to five criteria: embodiment, behavior, architecture design, theoretical approach, and goal. Our proposed classification is aimed at bridging the gap between computational models of emotion employed in robotics and the neuroscience of emotion. Critically, we emphasize recent findings in brain science that reveal how emotion and cognition are integrated at multiple levels of the brain. We then translate such insights into guidelines for the development of future models of emotion in intelligent machines capable of tackling real-world problems.

1. Virtual and robotic models of emotion

Over the past few decades, there has been growing interest in simulating and modeling emotion in machines like robots and virtual artificial agents across multiple research fields, including affective computing, social robotics, neurorobotics, and computer animation. Due to the specificity of each discipline in terms of their engineering perspective and research goals, existing proposals are fairly disconnected from one another. However, progress in the field requires identifying common themes while understanding particular requirements and/or goals of the approaches adopted. We propose that the existing research landscape be understood in terms of five criteria, as follows.

1.1. Embodiment: physical vs. virtual

A straightforward dimension of artificial emotion is to consider agent embodiment: physical embodiment (robot) or virtual embodiment (e.g. animated virtual character). Kismet (Breazeal, 2003), Berenson (Karaouzene et al., 2013), and EMYS (Correira et al., 2016) are expressive robots designed to interact with humans. They have actuators controlling eye and mouth movements with enough degrees of freedom to mimic stereotypical emotional facial expressions. While some platforms are based on more anthropomorphic robot faces (e.g. Wu et al., 2009), simpler ones display facial expressions on a screen (e.g. Masuyama et al., 2018). Another aspect that applies to physically embodied but non-expressive robots pertains to developing “behavioral regulation” capabilities during task performance (e.g. Avila-Garcia & Cañamero 2004; Krichmar, 2013; Belkaid et al., 2018).
However, while benefiting from real physical embodiment, robotic models suffer from limited behavioral repertoires given the inherent difficulties of movement generation in mechanical systems.

In the domain of virtual embodiment, 3-D animated avatars exhibit rich non-verbal behaviors (gestures, postures, and facial expressions), in addition to verbal utterances that convey socio-emotional cues to human users. Several computational models of emotion have been implemented on conversational virtual agents (e.g. Gratch & Marsella, 2004; Gebhard, 2005), and Greta (Pelachaud, 2009) and MARC (Courgeon & Clavel, 2013) are well-established platforms. To increase the feeling of immersion, animated virtual agents can be integrated in virtual reality (Martin et al., 2011; Ochs et al., 2016), giving users a sense of situated interaction. Nevertheless, these applications suffer from limitations due to the absence of physical interaction with the real world.

### 1.2. Behavior: social vs. non-social

Another distinction can be made in terms of the nature of the behavior exhibited by the machine. The majority of artificial emotion models focus on social behavior for the purpose of facilitating human-machine interactions: selecting verbal utterances for customer service chatbots (Yacoubi & Sabouret, 2018), interacting with and learning from museum visitors (Karaouzene et al., 2013), and mixing verbal and non-verbal behaviors in companion robots (Saint-Aimé et al., 2009; Correira et al., 2016) or virtual trainers (Gratch & Marsella, 2004). But there is a lot more to emotion than just social behaviors, and some models address questions such as approach and avoidance behavior in foraging (Krichmar, 2013), as well as competitive foraging (Avila-Garcia & Cañamero 2004). Another example is the modulation of attention by emotion-related factors in visual search (Belkaid et al., 2017).

### 1.3. Architecture design: modular vs. integrative

Modularity is an important engineering design principle. Many cognitive architectures, like other designed systems, are modular (e.g. Breazeal, 2003; Courgeon & Clavel, 2013; Correira et al., 2016). Accordingly, when emotion is added to the overall system architecture, frequently it takes the form of a separate module which interacts with other components. In this context, emotion is often conceived as a simple “bias” mechanism that up- or down-regulates other system functions; for example, sensory processing might be increased, or cognitive functions may be deemphasized. In contrast, integrative approaches highlight the interdependence between emotion and cognition in the system (e.g. Avila-Garcia & Cañamero 2004; Belkaid et al., 2018). The modularity of the overall architecture of intelligent systems is an essential design decision, and a growing literature provides evidence for the integration of emotion and cognition in the brain (Phelps and LeDoux, 2005; Pessoa, 2008; 2013; Grossberg, 2018).

### 1.4. Theoretical approach: top-down vs. bottom-up

Some computational models of emotion take direct inspiration from emotion theories developed by psychologists, and explicitly instantiate theoretical principles in what can be referred to as a top-down fashion. For example, the ALMA model (Gebhard, 2005) is based on a combination of two theoretical models, the cognitive-based framework developed by Ortony and colleagues (Ortony et al., 1988) and the Pleasure-Arousal-Dominance scheme by Russell and Mehrabian (1977). The EMA model (Gratch
Marsella, 2004) implements the appraisal and coping theory proposed by Lazarus (1991), and TEATIME (Yacoubi & Sabouret, 2018) implements the action-tendency theory proposed by Frijda (1986). In contrast, artificial emotion can be approached in a bottom-up fashion by focusing on the implementation of specific aspects of natural emotion. For example, Avila-Garcia & Cañamero (2004) propose a hormone-like mechanism as part of homeostatic action selection processes to address the problem of resource competition (see also Krichmar, 2013). In another application, Boucenna and colleagues (2014) investigated how a robotic system can learn to recognize facial expressions in an unsupervised fashion (i.e. without explicit labels). We note that bottom-up approaches can actually complement and inform existing emotion theories by providing concrete implementations of processes that are otherwise outlined descriptively (Belkaid et al., 2018).

1.5. Research goal: application-oriented vs. modeling-oriented

In general terms, artificial emotion systems can be distinguished based on their research goal. A subset of the literature is application-oriented, with the goal of generating human-like reactions in order to enrich interactions with a human user (e.g. Breazeal, 2003; Pelachaud, 2009). Particular applications include elderly care (Correira et al., 2016) and high-stakes decision-making (Gratch & Marsella, 2004). A complementary goal is to model mechanisms of natural emotion to evaluate and test existing frameworks (e.g. Krichmar, 2013; Belkaid et al., 2018). As discussed below, we believe computational and robotic models will play an increasingly important role in advancing the understanding of the neural basis of emotion.

2. Natural emotion: brain, body, and behavior

How emotion-related processes are modeled in robot and artificial agents often contrasts sharply with current knowledge about biological emotion. In the following, we summarize key findings of the neuroscientific literature that highlight the gap between natural and artificial emotion. In particular, we stress the integration between emotion and cognition in humans and animals at multiple levels: brain, body, and behavior.

2.1. Emotion and the brain

Historically, the brain basis of emotion was conceptualized in an area-centric manner. For a long period, the hypothalamus was believed to be the emotion center, shifting to the amygdala in the 1980s. In the last decades, not only has the number of regions of the “emotional brain” increased steadily, but how they function via complex circuits is starting to be unraveled. These regions include the medial prefrontal cortex, the orbitofrontal cortex, the cortex of the insula, the thalamus, and many more. Critically, rather than being functionally localized in specific areas, emotion-related processes are implemented by distributed neural circuits that rely on multiple structures at the same time (Pessoa, 2017; Tovote et al. 2015; Lindquist and Barrett, 2012).

More broadly, the classical separation between emotion and cognition has been gradually eroded. Behind the blurring of their boundaries is the notion that mental processes are implemented via large-scale, distributed networks (Sporns, 2010). The networks that have been uncovered in the context of cognitive processes share many nodes (i.e. regions) with those that are important for emotion (Najafi et
Thus, neural computations underlying behavior are implemented via overlapping networks. In this manner, specific brain areas affiliate, or group with, multiple large-scale networks depending on behavioral demands.

Even more generally, the separation between mental domains such as perception, cognition, action, motivation, and emotion, while possibly suitable for a textbook organization, does not reflect the organization of the brain. To understand how the brain generates complex, flexible, and adaptive behaviors it is necessary to understand how brain circuits disrespect standard boundaries. In a very real sense, the domains cannot be separated.

2.2. Emotion and the body

Intelligence is not a mere collection of computations occurring in the central nervous system but result from the coupling of the brain, the body, and the environment (Varela et al., 1992; O’Regan & Noë, 2001). From this perspective of embodied cognition, emotion is rooted in homeostatic processes that guarantee bodily integrity, and the associated construction of bodily representations capturing the state of body at any instant. These key functions engage both subcortical and cortical areas. Thus, neuroscientifically grounded theories of emotion attribute a central role to the body in emotion-related processes. For example, in the core affect theory, bodily states are central to emotional experience (Russell, 2003). In the somatic marker theory, associations between particular situations and patterns of elicited physiological and emotional reactions are established, and help shape behavior (Damasio et al., 1996).

2.3. Emotion and behavior

Emotion expressions, including those such as facial expressions, gestures, and postures, are an important feature of the relationship between emotion and the body (de Gelder et al., 2015; Cowen et al., 2019). The variety and complexity of processes involved in emotion expression and recognition underlines their importance in human social behaviors.

Emotion-behavior coupling is not limited to communicative functions but is also strongly related to motivation and action generation (Frijda 1986; Blakemore & Vuilleumier, 2017). In living organisms, motivated behaviors are represented in terms of approach and avoidance. Even ostensibly simple behaviors like escape leverage complex cognitive-emotional processes (Evans et al., 2019). More generally, survival – and autonomous function – depends on the ability to generate flexible behaviors and to adapt to dynamical environments. In sum, how an organism acts in its environment is a key problem that depends on emotion-related processes, which therefore is not confined to generating expressive behaviors for communication.

3. Toward better models of emotion

The brief review of the previous section points to several promising research directions. We propose four principles for the development of artificial emotion in the next generation of intelligent machines:

- Emotion models should account for emotion-cognition integration
- Emotion models should subscribe to principles of embodiment
Emotion models should support both social and non-social behaviors

Emotion models should inform research on natural emotion

**3.1. Account for emotion-cognition integration**

Consider a traditional architecture with standard components such as perception and decision-making (Figure 1A). Recognizing the utility of considering affective information, models have included an emotion component that interfaces with some of its processing components. We argue, however, that emotion and cognition should be integrated in the overall architecture such that emotion is involved in all cognitive processes (Figure 1B). In other words, emotion cannot be implemented as an “add on” to an existing cognitive machine, for example, where it boosts certain perceptual and decisional components based on urgency or threat.

Although Figure 1B illustrates the need to blur the boundary between emotion and the rest of the architecture, emotional computations must be specified at a sublevel that is sufficiently granular to allow the translation of this principle into concrete implementations. Consider the example of attention, a central cognitive operation. A fruitful way to conceptualize attention is in terms of priority maps (Itti et al., 1998). In particular, the priority of a to-be-attended visual item depends on a series of factors, including stimulus salience and top-down control, which can respectively labeled as perceptual and cognitive factors. Critically, priority also depends on affective and motivational factors (Anderson and Phelps, 2001; Anderson et al., 2011). For example, an item paired with aversive consequences in the past will acquire negative significance, and gain prioritized processing so that it can be adequately handled. Likewise, an item paired with reward in the past will acquire motivational significance. Combined, the determination of priority integrates multiple factors that are needed to determine overall object relevance (Figure 1C).

As another example, consider executive control (also called “cognitive control”), which includes operations involved in maintaining and updating information, monitoring conflict and/or errors, resisting distracting information, inhibiting prepotent responses, and shifting goals. A useful way to conceptualize executive control is in terms of a set of processes, including inhibition, updating, and shifting (Miyake et al., 2000). Insofar as value, relevance, significance, and so on, need to be taken into account for proper executive control, emotion/motivation participate in these processes. In other words, objects or contexts that influence cognitive control processes such that rewards (respectively, punishments) ensue, become positively (respectively, negatively) relevant. Why is the architecture in Figure 1A not sufficient? After all, information about what is emotionally/motivationally relevant will be conveyed to the particular architecture components. The central reason is that influences must be bidirectional (Figure 1D). For example, dealing with an emotional stimulus or situation requires multiple adjustments, including “updating” to refresh the contents of working memory, “shifting” to switch the current task subgoal, or “inhibiting” to cancel previously planned actions. In this manner, resources are coordinated in the service of proper function.
3.2. Subscribe to principles of embodiment

To stress the importance of embodiment for artificial intelligence, roboticists often use arguments related to morphology and physical interaction with the environment (Brooks, 1991; Pfeifer et al., 2007). As an example, consider a system that must learn the concept of a “chair”. Purely vision-based approaches (e.g. using deep neural networks) would need a massive amount of data and would only be
able to recognize chairs by shape. In contrast, a humanoid robot able to sit on a flat surface could learn that sitting minimizes energy loss and thus start to learn the functional aspects of chairs. In other words, disembodied machines cannot make sense of the world the same way humans do. As far as emotion is concerned, the same reasoning applies. For instance, facial expression recognition should be embedded in a system that can produce expressive behavior and associate it with its own internal states in order to process what is being expressed by the system itself or others. Otherwise, it is little more than a detection device of stereotypical patterns labeled as ‘happy’ or ‘afraid’.

When addressing emotion embodiment in artificial systems, there has been a focus on how emotion is expressed through the body (e.g. emotion recognition in computer vision, face actuators in social robotics, synthesis of social cues in computer animation). But, for models of emotion and cognition to be more truly embodied, the behavior they implement must be driven by core bodily signals of pleasure, pain, satiation, energy depletion, and so on (Figure 2A; see also Froese & Ziemke (2009) and Man & Damasio (2019)). Indeed, in the previous section, we stressed how emotional/motivational factors of value, relevance, and significance are important for proper autonomous function. This type of information is rooted in the bodily responses that a stimulus or event elicits: reward is processed through signals of pleasure, harm avoidance stems from the sensation of physical pain and the drive to preserve physical integrity, such that the successful execution of higher-order goals partly depends on the association between a set of actions with the physiological responses they trigger. Therefore,

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**Figure 2**: Embodiment and emotion for intelligent robots. **A**) As embodied intelligent machines, robots are able to acquire information about, and to act upon, the world through a variety of sensors and actuators. The notion of embodiment also includes the processing and regulation of bodily signals such as pleasure, pain, satiation, and so on, which is crucial for emotion and for autonomous behavior. **B**) By integrating emotion in robotics architectures, we can design machines able to generate and coordinate intelligent behaviors for survival, exploration, and high-level goals. The illustration of iCub robot in A) was reproduced with permission from Antoni Gracia.
building a robot capable of autonomously and intelligently exploring an unknown environment requires mechanisms to monitor energy level, avoid physical harm, develop a preference for safe locations, attend to objects which are relevant to goals/plans, and switch between goals and behaviors depending on current own and external states (Figure 2B), all of which rely on embodied emotional-cognitive processes.

3.3 Support both social and non-social behaviors and interactions

Models of emotion tend to focus on either social or non-social interactions. For example, facial expression recognition on the one hand and autonomous navigation on the other. Frequently, engineers are interested in simulating socio-emotional competence to make human-machine interactions more user-friendly. Although social interaction is a major domain in which emotion is involved, we believe emotion modeling should encompass both social and non-social behaviors. Indeed, the examples developed previously highlight the key role of emotion in autonomous, flexible behaviors.

Considering both social and non-social emotional processing can be beneficial. For example, how to process social and non-social stimuli that are self-relevant (Figure 3A), how to switch between social and non-social goals, and how to learn which actions are more goal-conducive from both social and non-social signals (Figure 3B). From an engineering perspective, autonomous cars could be safer for humans if they had the capacity to interpret social cues (e.g. pedestrian patterns and interactions); industrial robots could be more efficient if they were able to manage both independent and

![Figure 3](image-url)

*Figure 3: Social and non-social interactions with the environment. Emotion is key to intelligent behavior, both in social and non-social contexts. It is important for models of emotion to implement mechanisms that handle adequately both social and non-social stimuli (A), and to process both social and non-social rewards (B).*
collaborative tasks; and companion robots could be more engaging and fun if they could develop a “personality” from both social and non-social experiences.

### 3.4 Inform research on natural emotion and cognition

While it is in theory possible to engineer intelligent machines differently from living organisms, we believe it is enormously beneficial to take cues from how biology gives rise to intelligent behaviors. To go a step further, we advocate that machines be conceived as models which can further our understanding of human intelligence through the process of recreating it. Can we build a machine able to process different types of stimuli and events, to safely explore an unknown environment, to self-regulate and adapt its behavior to a variety of contexts, to develop long-term knowledge, preferences, goals and relationships? In doing so, designing intelligent machine can benefit not only from but also to the study of natural intelligence.

Models can inform research on human emotion and cognition at four levels: 1) testing existing theories, 2) proposing new theories, 3) proposing new experiments, and 4) creating opportunities for new experiments (Figure 4). For instance, does the current understanding of how we process social and non-social stimuli (e.g. threatening face vs. snake) suffice to implement similar mechanisms in a robot? This type of questioning allows the assessment of the current state of knowledge, revealing ambiguities and missing pieces of the puzzle (level 1). For example, how is processing prioritized when in the presence of various distractors? To which extent does the triggered response depend on learning? What series of computations leads to appropriate responses? The process of testing theories should be hypothesis-driven and based on scientific knowledge, rather than solution-oriented (i.e. engineering a functional system) to lead to new theories (level 2). The process can then suggest new experimental designs to test the validity of the proposed hypotheses (level 3). Furthermore, modeling intelligent behavior in machines enables innovative experimental research (level 4). An example of an emerging question is the investigation of factors that lead humans to consider machines as social agents (Wiese et al., 2017; Belkaïd et al., in preparation). More generally, robots offer a unique opportunity to create embodied real-time interactions to address questions about human social cognition.

### Conclusion

In this paper, we proposed a framework for designing intelligent, autonomous machines which is centered on the integration between cognition and emotion. Recent advances in neuroscience emphasize the importance of emotion in human intelligence, and stress their interdependent relationship, as well as the brain’s interactions with the body and the environment. Modeling emotion and fully integrating it in “cognitive architectures” is thus key to building robots able to function independently in diverse and challenging real-world situations. We hope our proposal helps in developing research guidelines for future research. More generally, we encourage a closer collaboration between roboticists, computer-scientists, and neuroscientists for the sake of fruitful cross-fertilizations between fields.
Figure 4: Schematic of how emotion modeling in robots can inform neuroscientific research. Four levels at which modeling can help advance neuroscientific knowledge: 1) testing existing theories, 2) proposing new theories, 3) proposing new experiments, and 4) creating opportunities for new experiments. Embracing an interdisciplinary approach will be beneficial to both the robotics and the neuroscience communities.

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