Towards Emotionally Intelligent Machines: Taking Social Contexts into Account

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Abstract. Emotion is considered a critical component in human computer interaction and intelligent interfaces. However, the social context in which the emotion is manifested is rarely taken into account. In this paper, we present a set of two empirical studies, taking a social network perspective to examine the contextual effect on emotional expression. In study 1, we conducted a scenario-based experiment to examine people's intention to express in social networks with different structural properties. Study 2 investigated the actual expression on Facebook, and the roles of social network structure and personality traits play in the process. Altogether, it is found that an individual's tendency for expressing positive emotions and negative emotions is affected by the size and density of the social network he/she belongs to, and the effects vary with individual personality traits. Drawing on these findings, we propose to add the role of social context into existing emotion models, the context profile can be defined by each individual's social network structure. For different personality traits, the weightage of social context on the outcome expression will be adjusted accordingly. Implications on human-centered design are discussed.

Keywords: Emotion · Social network · Personality · Facebook

1 Introduction

Emotional intelligence enables people to have the capability to perceive, understand, and regulate emotions [32]. In the past decades, there is an increasing interest in humanizing machines by incorporating emotional intelligence to improve human-computer interaction. Specifically, emotion-related mechanisms have been considered and implemented in intelligent systems for enhanced functionalities, such as sensing and predicting users' affective states [47], generating human-like social behaviors among virtual characters [19,37], fostering lasting human-agent

relationships [21, 23], and facilitating negotiation and decision-making [1, 2, 22, 33, 46]. In these works, a multitude of computational emotion models are developed to define the processes that activate emotional states and expressions in artificial agents [39, 40, 45]. However, most of them focus on the internal states of the agents and the direct external triggering factors (i.e., the particular incidents that cause the emotional responses). The social context in which the emotion is to be manifested has not yet received much attention.

The effect of social context on people's emotions has been an important research topic in the field of psychology. Ekman and Friesen [7] posited that certain emotions are constrained by the etiquettes that define proper behaviors in a given society. People tend to conform to such social rules so as to maintain a favorable image in front of others [9]. The presence of an audience may either facilitate or inhibit affective expressions, depending on the emotional content and the relationships between the emotion discloser and the audience [5]. For example, affective expression is more frequent and detailed between people who are intimately familiar than who mere acquaintances [28, 31]. Overall, people are used to adjust their emotional expression according to audiences' different levels of significance and preferences.

However, social context has not yet been well incorporated into computational emotion modeling although some preliminary research started to addressed the importance of this issue. Endrass and colleagues [8] studied the agents' social and cultural signals in maintaining their believability and sustaining their relationships with people. The work demonstrates the role of social context in human-computer interaction. However, the context is defined at a macro level and the communication occurs in a simple human-agent setting. Ptaszynski [29] proposed a context-aware system to evaluate the appropriateness of user's emotions in a certain context. The system focuses on emotion recognition and the appropriateness of context that is defined by common associations between words. In general, what is lacking in existing computational emotion modeling literature is a way to quantify a particular social context and an implication beyond mere emotional perception.

Attention is needed on a complex interaction environment where multiple machines and/or multiple human users are involved, given the nature of complexity of human world and state-of-art systems. A better understanding of emotional expression in such a complex social context is meaningful for two reasons. First, social networks comprise important parts of individuals' societal life, hence it is necessary to understand not only the individuals but also their social relationships. Second, with better understanding about the contingency of affective expression, we can create a supportive context for beneficial disclosure of emotions.

To this end, the first step is to identify critical variables that can capture the important features of social context in influencing emotional expressions. Therefore, in this paper, we present two empirical studies, taking a social network perspective to demonstrate the contextual effect on emotional expression.

2   Related Work

Several psychological emotion models have been widely used in affective computing. The PAD emotional state model places emotions in a space with three continuous dimensions [20]. The dimensions represent the *pleasure* (P), *arousal* (A) and *dominance* (D) of each emotion. In parallel with the 3-dimensional approach, models classifying discrete emotions have been proposed. For example, the OCC model [25]–one of the most widely used models–proposes a hierarchy classifying 22 emotion elicitation conditions through appraising the emotion triggering event in terms of parameters such as desirability and likelihood. Based on the OCC model, a particular emotion can be triggered in an agent during an interaction and actions can then be taken accordingly. Models of this kind allow intelligent agents to identify elicitation conditions for a given emotion. In other words, whenever an incident occurs, it can be mapped onto a particular condition and trigger a corresponding emotion.

In addition to emotion appraisal highlighted in above-mentioned models, context is the other important source of information that accounts for the differences of emotional expressions in different scenarios [30]. Several studies have shown that by including contextual elements, systems can demonstrate better performance in various domains. For example, by considering the temporal dynamics of emotional states, virtual agents can not only better sense emotions in human-agent interactions [48], but also perform a variety of behaviors at different points in time in real-time interactive systems despite receiving the same stimuli [36]. In addition, a conversational agent with the detection of contextual appropriateness of emotions yields better emphatic capability and helps users to manage their emotions [29].

According to López and colleagues' [18] definition of context, these works mainly address the personal and environmental contexts, leaving another important context–social contexts–understudied. One study showed that culture, which is a representation of social context, can affect small talk behaviors in human-agent interactions [8]. It is an early attempt to bring social contexts into computational emotion modeling. An artificial agent attempting to integrate social contexts into the process of comprehending emotion and triggering appropriate emotion responses can benefit from a more in-depth understanding of how social contexts influence people's emotional behaviours. For this purpose, we conduct research reported in this paper to provide a premise for future work on social context-aware emotional intelligence for human-computer interaction.

3   Study 1

The social network perspective provides an approach to understand a social context [16,18]. It focuses on the relationships (also known as ties) that exist between individuals, as well as the interactions and outcomes of these relationships [38]. An ego-centered social network analysis examines a local network quantitatively from the viewpoint of a person at the center. Specific structural

indices can be computed to indicate an ego's network structure, and contextual differences are thereby comparable among egos [14]. In other words, individuals who have structurally equivalent networks are supposed to exhibit similar responses by virtue of the similar facilitators and constraints in the context [3].

Past research has established several metrics to describe a personal social network, among which network size and density are two fundamental ones. The network size is defined as the number of nodes in a network, and the network density is defined as the ratio of existing relationships in the network over all possible relationships. The values of network density range from 0 to 1, ranking networks from completely sparse in which none of the members knows each other, to completely interconnected so that everybody is linked to everyone else. The two metrics capture distinct dimensions of a social network. Network size determines how many resources one can gain from the network, reflecting the quantity of connections [12]; while network density is usually interpreted as cohesiveness and closure of the network, reflecting the quality of interpersonal relations [13]. By investigating the effect of network size and density, we expect to gain insights into divergent dimensions of social context and their influence on people's tendency to express emotions.

3.1 Method

A between-subject design was applied with network size (10/50/200) and network density (sparse/dense) as two factors. Participants consisted of 296 (98 males and 198 females) undergraduate students. Their average age was 21.92. Each participant was randomly assigned to one of the six conditions.

During the experiment, participants were given a cover story stating that the purpose of this study was to evaluate a feature of Facebook, with which they would share their status updates to only a designated group of audience. Then, participants were presented with a description about the characteristic of the network:

> "This group has some characteristics: It involves *only 10 / 50 / 200* of your friends, *only a few / most* of them know each other."

We did not exactly define "a few" or "more" but left it to the participants to their own subjective interpretation. Next, following the scenario rating task paradigm [34], participants were asked to read the six scenarios (as shown in Table 1) that were adopted from [24, 34]. Each scenario was 30–60 words long. Participants were instructed to imagine as if they were to encounter these situations. After each scenario, they were prompted to indicate how much they would be willing to share this emotional experience with the specific group on a 7-point Likert scale ranging from 1 (very unlikely) to 7 (very likely).

3.2 Results and Discussion

A repeated measure analysis was conducted with network size and density as two between-subject factors and the valence of emotion as the within-subject factor.
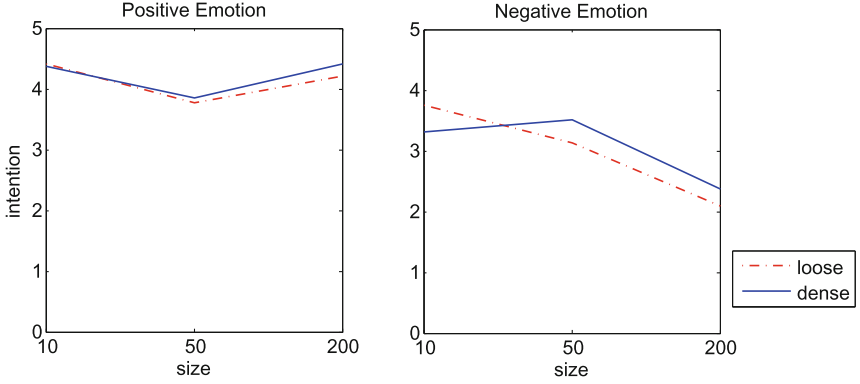
Table 1. Scenarios in study 1

Positive emotion	Negative emotion
I had some important job to do in my student organization. Last night, after having worked almost day and night for about a week, I finally finished my part	I had a paper due in one of my classes, and the night before my computer crashed.
My brother's birthday was coming up. So, I went to the store he likes, and found a gift that I think he would love	A friend of mine and I decided that we would go to a movie; But, my friend forgot about it, and didn't show up.
I found a summer job that would look really good on my resume. Getting a good summer job was really important to me because I am graduating this December, and I need good experiences to get a good full-time job	I am the president of the debate team this year. A freshman who joined our team this fall. After today's practice, I told him that his performance was very bad. Now I feel I shouldn't say that

Table 2. The main effect and interaction of network size and density on expression intention

Factor	F	df	p
Positive emotion			
Size	5.15	2, 290	0.006
Density	0.25	1, 290	> 0.05
Size × Density	0.17	2, 290	> 0.05
Negative emotion			
Size	33.26	2, 290	< 0.001
Density	0.31	1, 290	> 0.05
Size × Density	0.304	2, 290	0.049

In general, results showed that positive emotions on average were more likely to be expressed than negative emotions. More important, as shown in Table 2, network size has a main effect on expression of both positive emotions and negative emotions. Figure 1 shows that the intention to express positive emotion was significantly stronger in network size condition of 10 and 200, compared to that of 50. Regarding negative emotions, both network sizes of 10 and 50 afforded significantly higher intention to express than network size of 200.

Therefore, it suggests that social context which individuals interact with plays a key role in deciding emotional expression. In either a very small or a very large network, individuals are more likely to express positive emotions, compared to those in a network of medium size. In a very large network, broadcasting own emotions may raise a major concern about self-image. As the audience size grows, the need to be perceived as popular and competent (i.e., the impression concern) increases [17].

Fig. 1. Expression intensity as a function of network size and density.

To foster a desirable image, individuals are inclined to display positive emotions. Due to the same impression concern, people in a large social network would hesitate to express negative emotions. By contrast, individuals in a very small network may tend to exchange internal feelings as a means of bonding, because a small network is likely to offer more focused social attention and affirmation that are anticipated when sharing pleasure. Indeed, negative emotions are not always damaging. Expressing negative emotions when necessary, but not continuously, can be a demonstration of trust [26, 35, 43] and to improve intimacy [11]. This explains why negative emotions are acceptable in small networks where individuals' intimacy need is well supported and the impression concern is less intense.

In sum, the results presented a strong evidence for adding context variable in affective models. An expressed emotion is not only a reaction to the triggering event itself but also a decision made by taking the environment around into consideration.

4   Study 2

While Study 1 demonstrates how the social network around a person affects his/her intention to express emotions, how can the social context be added on to existing models that have incorporated personal attributes such as expression inclination in communication context [47]? This raises another empirical question about whether the contextual effect is homogeneous across individuals. In view of this issue, we conducted Study 2 with personality traits included as the individual attributes. Meanwhile, we analyzed the network structure and actual behaviors to provide convergent results to Study 1.

4.1   Method

One hundred and seventy-two undergraduate students (57 males, 115 females, mean age = 21.05) were included in this study. Upon their consent, we retrieved

their most recent status updates as well as their network structure through the Facebook API. Then, they were asked to fill up a survey about their personality.

We used an application called "NameWebGen"[1] to access participants' information on Facebook. This application generates a text file listing all of one's Facebook contacts and the connections among these contacts. Then, these text files were imported into the social network analysis software UCINET 6 [4] which computes the egocentric network size and density based on the connections within a given social network.
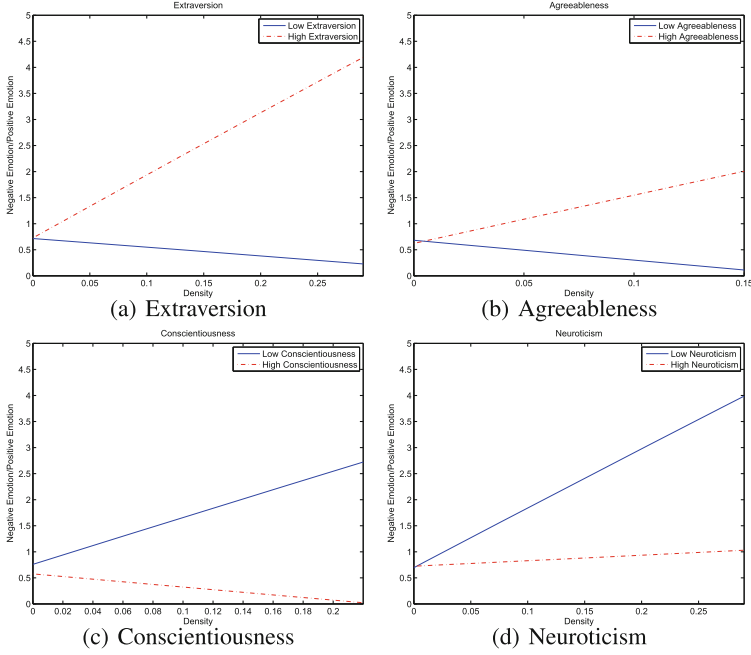
The 100 most recent status updates of each participant were retrieved from Facebook through the API provided by Facebook. The frequency of positive and negative emotional words was computed by the test analysis program–Linguistic Inquiry and Work Count (LIWC2007) [27]. The core of LIWC is its internal default dictionary which defines a total of about 4,500 words and word stems falling into approximately 70 word categories. Given a writing sample, LIWC searches each word in the text and counts the frequencies of the words that are defined in the dictionary. The word frequency in each category is taken as a percentage of the total word count in the text sample. With regards to emotional disclosure in particular, LIWC contains two word categories that predominantly signify different expressions of emotions: positive emotions (e.g., love, nice, sweet) and negative emotions (e.g., hurt, ugly, nasty). These two categories of emotion words have been used to indicate temporal pattern of individual's happiness on Facebook and Twitter [6] and emotional fluctuations over time on Twitter [10]. In the current study, the ratio of negative emotion word frequency over positive emotion word frequency is taken to indicate the overall pattern of emotional expression.

Participants' personalities were measured by the Big Five Inventory [15] which is a widely used personality measure to classify people's personalities into the five dimensions: openness to Experience (e.g., being curious and imaginative), conscientiousness (e.g., being responsible and organized), extroversion (e.g., being outgoing and sociable), agreeableness (e.g., being cooperative and helpful), and neuroticism (e.g., being anxious and moody).

4.2   Results and Discussions

Linear regression analysis shows that there is no significant interaction between network size and personality traits (p's > 0.05), suggesting that the effect of network size did not differ between individuals. Interestingly, network density shows statistically significant interaction effects with four personality traits, namely, extroversion ($b = 1.44$, $SE = 0.22$, $p < 0.001$), agreeableness ($b = 1.55$, $SE = 0.32$, $p < 0.001$), conscientiousness ($b = -1.20$, $SE = 0.31$, $p = 0.002$), and neuroticism ($b = -1.10$, $SE = 0.26$, $p < 0.001$). In other words, the effect of network density on emotional expression pattern varies across people with different personality traits.

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[1] http://namegen.oii.ox.ac.uk/fb/.

Fig. 2. The effect of network density on emotional expression varies with the personality. Lines are fitted by linear regression models. "Low" is defined as 1 standard deviation below the mean of the given trait, and high is defined as 1 standard deviation above the mean of that trait.

This can explain why network density has shown no contribution to emotional expression in Study 1. The effect of network density is high on some individuals yet low on others, resulting in null effect on average. As Fig. 2 shows, a person scoring high on extroversion is more likely to be affected by network density (i.e., the denser the network is, the more likely the person would like to express negative emotions over positive emotions). The effect is reversed for people who scored low on extroversion, though to only a mild extent. This patten is applicable to the trait of agreeableness, too.

Regarding individuals who scored high on conscientiousness, the network density showed a negative effect on expressing negative emotions. In contrast, for those scored low on conscientiousness, their tendency for expressing negative emotions increased as networks became denser. As for the neuroticism trait, network density increases the ratio of negative emotions over positive emotions for individuals who are less neurotic. For those who are highly neurotic, network density showed slight influence only.

It suggests that a closely connected network can support extroverted and agreeable individuals' tendency to share negative emotions, probably through fostering a safe environment to bear socially undesirable expressions. In contrast, a loosely connected social network may increase people's concern about self-image.
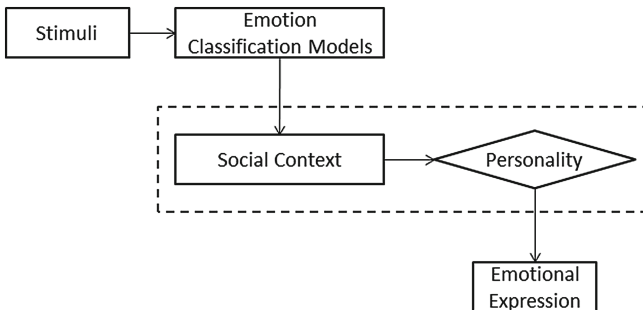
For conscientious individuals, they may care about others' feelings more in an interconnected network. Thus, they may inhibit their expression of negativity. In contrast, neurotic individuals may always express negative emotions due to their internal distress. They are the least affected by the social context. Those who are less neurotic may feel more comfortable to express negative emotions in a well-supported dense social network.

Taken together, this study provides convergent results to Study 1, supporting the effect of social context on emotion expression. Nonetheless, in some circumstances, the context does not affect individuals uniformly. Rather, it interplays with the personality traits. Particularly, network density, but not network size, makes variant influence on individuals with different personality traits. It implies that individual differences should be jointly considered with the social context, to accurately predict or generate emotions.

5   Implications for Affective Computing Research

In summary, both studies show that social contexts, in terms of the size and density of the social network which a person belongs to, determine the tendency of emotional expression. Meanwhile, the effect of network density differs across individual personality traits.

Drawing on these findings, we suggest adding the component of social contexts into existing emotion models. As illustrated in Fig. 3, previous emotion model directly links the stimuli to emotional expressions without considering social contexts. Based on our results, social contexts can be added between the emotion classification model and emotional expressions to provide another level of filtering. For a given emotion, social contexts will determine the extent to which it should be expressed. In particular, the context profile can be defined by each individual's social network structure. Following the computation of social contexts, an individual's personality profile can be included to determine the direction and magnitude of social context effects on the emotion expression.

Fig. 3. A framework for integrating social contexts into emotion models. Components in the dashed box were overlooked in previous models.

Here, we use two instances of an intelligent agent to illustrate how the social context-aware framework can be applied in practice.

This framework can be used in intelligent agents. For a believable and empathetic agent, one of the core attributes is that the agent can understand and simulate how people feel. Based on our framework, agents should generate emotion in accordance with the social contexts. In a communicatively coordinated collaboration, multiple agents cooperate by using and responding to intentional acts [30]. Each agent may consider the impact of expressing positive or negative emotions as a function of the number of agents it needs to interact with over the long term. Meanwhile, each individual agent's personality trait can be pre-defined through specification of roles and abilities. If the communication takes place within a small network, the agent can safely express both negative and positive emotions in order to build trust with each other [41,42,44]. If the agent is designed as a conscientious one, it is expected to express less negative emotion in a sparse network.

The model can also be utilized for managing an online social network (e.g., discussion group, virtual game). Given that positive emotional expressions in a big social network are more expected than negative emotional expressions, there could be a mechanism that can remind the users, who are in a negative mood, to avoid strong negativity in their public expressions. An opposite strategy can be applied in a dense network, where users can be encouraged to disclose more negative emotions to seek social support. Alternatively, the system can intervene the social context formation to adapt to users' needs. For example, an online health community is expected to encourage people to share their distress or problems so as to receive attention and help. If it is detected that the community is too big such that negative emotional expression is very likely to be hindered, the system can generate new schemes to divide the community into smaller groups. According to the design objectives of different social networks, the system can take actions accordingly by releasing more connection resources for network expansion or putting constraints on it.

6   Conclusions and Future Work

This research is driven by concerns about the understudied variable–social contexts–in human computer interaction. As an empirical study, it always starts from a simple design, to eliminate confounding explanations and produce generic knowledge. Therefore, we only discuss the emotion valence in this paper. A finer categorization of emotions is expected in the future to integrate the concerns of discrete emotions into the examination of contextual effects. Also, by choosing two fundamental social network metrics (i.e., size and density), our studies demonstrate the initial step towards taking social contexts into account when modeling emotions. The proposed theoretical framework provides a promising starting point for integrating social contexts in computational emotion models. Future work will look into other social network metrics to develop a more comprehensive profile of social contexts. Meanwhile, the next step could include

building up a computational model with the variables of social network size, density and personality for applications such as conversational agents. Eventually, this line of work is expected to establish an elaborative social context-aware affective model that can be applied to various infocomm applications.

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