A Virtual Counselor for Online Social Networks (or did I really want to send you my post?) *

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Abstract. It is well established by the scientific literature that a great part of Face-to-Face communication occurs at a non verbal level and also that this is partly obfuscated when the interaction takes place by Computer-Mediated-Communication (CMC). Fully aware we are simplifying the subject, we can say that the communication satisfies the need of humans to share their emotional experiences. Thus we can say that also the formulation and interpretation of messages exchanged in CMC is influenced by the emotions. Moreover the reduced physical presence in CMC implies a lack of social norms or social control which is amplified in the Online Social Networks (OSN) scenario. Motivated by these naïve considerations and the massive use of OSN, we introduce a Virtual Counselor as a contribution, from a technical point of view, to augment the quality of communication among users of OSN. The implementation of this Virtual Counselor is based on technologies by now mature like wearable devices to measure physical parameters, on artificial emotional intelligence, and on interactive tutoring systems, strongly used in online learning environments.

We propose an abstract model of the communication scenario in OSN containing the Virtual Counselor to help the interpretation of the messages and of the emotional states in order to improve the communication among parties. The goal is to align the emotional states of senders and receivers to form dynamic groups of target friends in the OSN to send the posts to. The dynamism of the groups is both spatial (that is the composition of receivers can change for a given sender and a given message) and temporal (for example the sending of a message can be postponed in time).

We think that this model is the basis for defining a new class of tools to improve the communication in OSN.

Keywords: Computer Mediated Communication · Online Social Networks · Emotion Representation · Artificial Emotional Intelligence.

1 Preliminaries

Positive and negative effects of massive use of technology have been thoroughly investigated by the scientific community (see e.g. [14]), but natural worries affects tech-scientists, and common sense people as well. In particular the overwhelming use of Online Social Networks (OSN) has changed the perception of the communication among individuals. All of us experience every day how Computer-Mediated Communication (CMC) through OSN sometimes is more difficult compared to the Face-To-Face communication. In this latter setting the nonverbal cues are a great part of the communication, see e.g. [6], though in CMC it has been shown that the emotions are not absent and are not even difficult to communicate, see [2].

In this paper we assert that the communication as is today in OSN occurs too often without being fully aware of the role, or better of the consequences, that the emotions can play. In particular in CMC usually there is no awareness of what are the post-effects of both the emotional state of the sender that in some way leaks through the messages we sent and of the emotional state of the receiver when she/he interprets the received message. The way the communication occurs today on OSN is, in a sense, blind. Meaning that a user u posts to all her friends/followers without having knowledge of the emotional state of her reader, but also without exposing her state. A consequence of this is that the receiver might misunderstand the original meaning of u's post.

Here we propose a model for a communication scenario in which there is a *Virtual Counselor* which can interpret the *emotional state* both of the senders and the receivers and of the message content as well. From this interpretation, the Virtual Counselor can give explicit suggestions both to receivers and senders to improve the interpretation of the message or even to determine which is the right subset of friends/followers to send the message or also to suggest when and if to send it.

The paper is organized as follows: in section 2 we sketch the model of the Virtual Counselor, in section 3 we discuss about technologies issues to implement the model and in section 4 we give some conclusions.

2 The model

The approach we propose starts from the model of Garrod and Pickering [9] represented in Fig. 1. Such a model clearly represents that in order to align the meaning of a message or, in general, of a dialogue it is needed to employ the work of at least four levels (from the bottom):

- the physical layer
- the syntactic-lexical layer
- the semantic layer
- the model layer

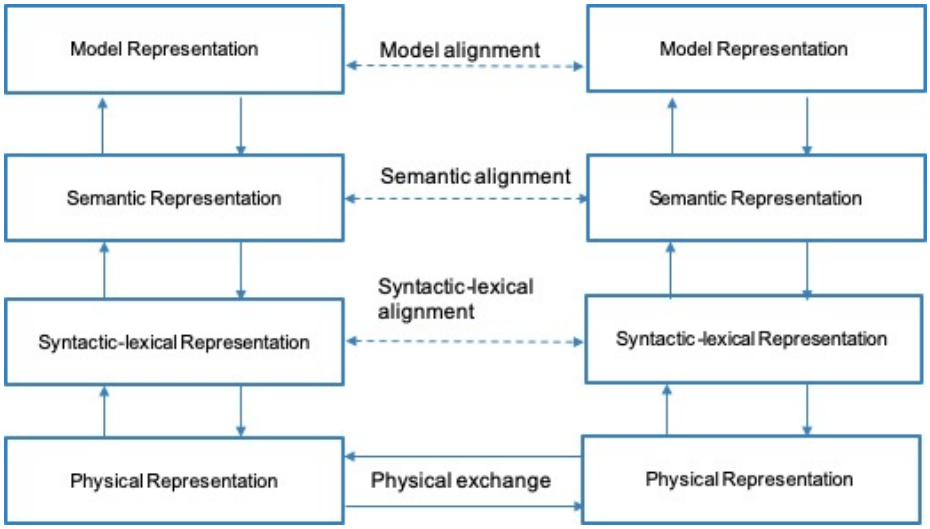

Fig. 1: Model of Garrod and Pickering [9]

The emotions may hinder the alignment task provoking negative side effects. The proposed approach focuses on improving the quality of communications in OSN and is based on the idea that it is possible to inject in such environment a *Virtual Counselor*, shortly VC. This latter resembles the Intelligent Tutoring Systems (ITS), often applied in e-learning scenarios, [12]. In particular, traditional ITS are software systems providing adaptive educational experiences for both students and teachers. Adaptivity is supported by ITS in several ways: i) providing students' learning activities coherently with their current knowledge and skills, in order to foster meaningful learning; ii) providing individualized feedbacks, able to stimulate next learning activities and avoid frustration, demotivation and disengagement due to unsuccessful performances; iii) providing hints helping students during the execution of their learning tasks. Therefore, our aim is to introduce a sort of adaptive tutor, dealing with emotions, in a communication context (in the place of the learning context), where the task is not *learning* but *communicating*, and in which we have not learners but participants to a message exchanging activity. Its main contributions are: i) supporting the sender in selecting a suitable group of receivers with respect to the emotional aspects, ii) providing alerts to the sender when his/her emotional state and the emotions expressed in his/her text message are not compliant with the context of the discussion, iii) prompting the receiver to support the right comprehension of the message, and iv) suggest the sender to possibly postpone in time the sending of the message. In our model, see Fig. 2, the VC constructs its knowledge about the emotional states of senders and receivers, extracts affective elements from the messages (outgoing or incoming) and applies rules to suggest emotion-based

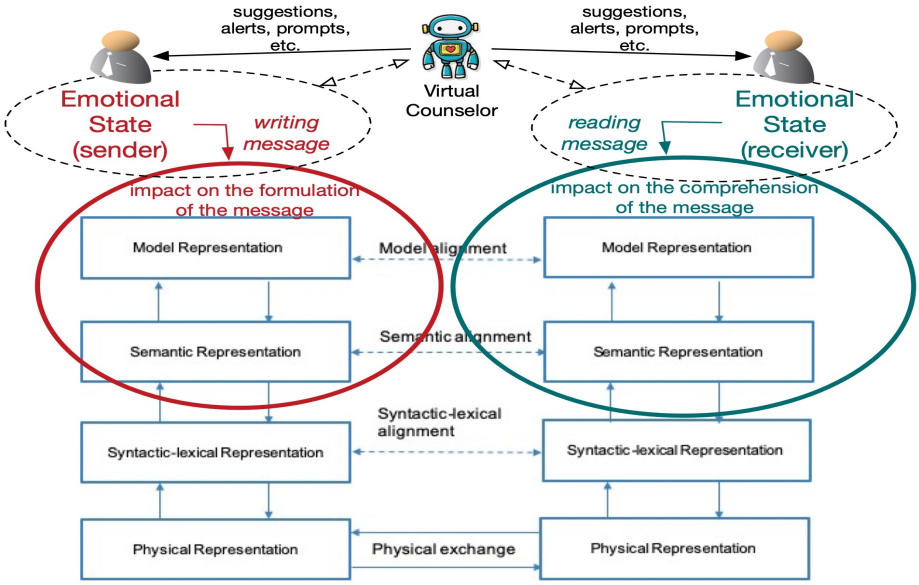

Fig. 2: Sketch of the proposed approach.

actions to reduce misunderstanding and negative side effects in communication tasks in the OSN.

In order to implement our model, we need to represent emotions as discrete elements belonging to a set E. Therefore, it is useful to refer to the Plutchik's discrete emotion model, [11], that maps eight basic emotions into a wheel: *joy, trust, fear, surprise, sadness, disgust, anger and anticipation*, see Fig. 3, for a simplified version. An alternative might be represented by the model proposed by Lang [7] that categorizes emotions in a 2D space by *valence and arousal*, see Fig. 4. For example, anger has negative valence and high arousal while sadness has negative valence and low arousal.

In order to define the behaviour of the VC we now define the communication scenario in which it operates.

Definition 1. *Given an alphabet Σ, a set of users U and a set of emotions E, a Communication Scenario C is a 6-tuple $C = (S, R, t, ctx, \sigma_h, \sigma_m)$ where*[1]

- $S \subseteq U$ is the set of senders;
- $R \subseteq U$ is the set of receivers;
- $t \in \Sigma^*$ is a text-message string;
- ctx is the context in which the communication takes life (e.g., the thread of the discussion, the topics of the dialogue);

[1] Given a set A, the symbol $\mathcal{P}(\mathcal{A})$ denotes the power set of A, that is the set of all subsets of A.

– $\sigma_h : U \to \mathcal{P}(E)$ returns the emotions of a user $u \in U$;
– $\sigma_m : \Sigma^* \to \mathcal{P}(E)$ returns the emotions expressed in t.

In what follows, for simplicity, we will consider only the case where $|S| = 1$, that is in the communication scenario there is only one sender for each message. The functions σ_h and σ_m return the emotions of the humans (the users) and of the messages, respectively.

Actually, the values of the functions σ_h are weighted with a value between 0 and 1 which expresses the *confidence* of the computed value. If this value is too low, a confirmation can be asked to the sender or to the receiver.

For the moment we will just give an hint on how the functions can be computed in section 3, in the extended version of the paper we will formalize the scenario.

Given the values returned by the emotional functions, the composition of these values determines the support for the decision or, better the *suggestion* of the Virtual Counselor.

Fig. 3: The Plutchik wheel

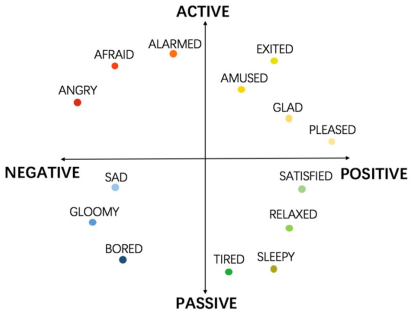

Fig. 4: 2D emotion space model of Lang

Definition 2. *A suggestion g is a statement of the following form:*

$$g := \{recommended \;\; action\} \cdot \{object\} \cdot \{explanation\}$$

For the moment let us give some examples of statements.

Definition 3. *Given a Communication Scenario $C = (S, R, t, ctx, \sigma_h, \sigma_m)$ and a set of emotions E, a Virtual Counselor for C is a mapping*

$$\mathcal{VC}_u : \mathcal{P}(E)^{|S|+|R|+1} \to G$$

that computes the suggestion $g \in G$ for the user u, based on the emotions of the $|S|$ senders, $|R|$ receivers and the emotion extracted from t.

Recommended action	Object	Explanation
send	t to $\bar{R}$	since emotional state of the sender/receivers are compliant
reflect on (before sending)	t and ctx	since emotional state of the sender and the emotions in the message are not compliant with the context of the communication
evaluate better	t and ctx	since the emotional state of the receiver is not compliant with the emotions expressed by the sender
confirm or deny (before sending)	t	since emotional state of the sender and the emotions in the message are not compliant

In words, the Virtual Councelor for a user u, is a function with $|S| + |R| + 1$ arguments: the first $|S|$ arguments represent the emotions of the senders, the other $|R|$ represent the emotions of the receivers and the last is the emotions of the message. Let us underline that the user u can play both the role of a sender or of a receiver, thus the VC behaviour is polymorphic and the role of u is indicated by $u^{\downarrow}$, when u plays the role a receiver, and $u^{\uparrow}$ when a sender.

Let us illustrate the framework above with an example.

Example 1. Let $U = \{s, r_1, r_2, r_3\}$, where s is the sender of the message t and r_i, $i = 1 \dots 3$, are the receivers (friends/followers in a OSN). The emotional functions are defined as follows: $\sigma_h(s) = \{excited\}, \sigma_h(r_1) = \{pleased\}, \sigma_h(r_2) = \{sad\}, \sigma_h(r_3) = \{glad\}$ and $\sigma_m(t) = \{amused\}$.

In this case, it is possible for the Virtual Counselor to suggest the exclusion of r_2 from the list of the receivers of the message t, given that the emotional state of s and the emotions expressed by t are not compliant with the emotional state of r_2. In this scenario, the compliance of the emotions is obtained by using the 2D emotion space model of Lang [7] and reported in Fig. 4. The suggestion is then:

Recommended action	Object	Explanation
send	t to $\{r_1, r_3\}$	since emotional state of $\{r_1, r_3\}$ are compliant with the one of s while that of $\{r_2\}$ is not.

3 Technological issues

In order to implement the functions defined in the previous section, we need to employ three technological assets.

In particular, σ_m can be supported by the first technological asset that is *sentiment analysis*. Sentiment analysis [1] is a very interesting field of Natural Language Processing. Sentiment analysis can be used to detect emotions in text messages exchanged between sender and receivers. Many existing approaches focused on word-level analysis of texts and are able to detect only explicit expressions of sentiment. Other techniques, recognized in literature, have been defined

to deal with emotions that are not expressed in the text by using words with an affective meaning. In these cases, the text describes real-life situations, which the reader is able to associate to specific emotions by using his/her commonsense knowledge.

Moreover, σ_h can be supported by the second technological asset that is based on the use of the *physiological signals* [13], which include the electroencephalogram (EEG), temperature (T), electrocardiogram (ECG), photoplethysmography (PPG), electromyogram (EMG), galvanic skin response (GSR), respiration (RSP), hearth rate (HR), hearth rate variability (HRV), to recognize emotions. In particular, studies like [8] assert that heart-related parameters, like HRV, can be exploited to detect emotions through the unobtrusive help of smart wearable devices and the application of machine learning techniques, typically for classification tasks. Moreover, HRV can be extracted from PPG [10] that is widely used in smart watches for this aim. A PPG sensor is non-invasive, in fact it uses a light emitting diode and a photo-diode to record the pulse waveform. More in details, the authors of [4] selected 5 features (Coefficient of variance of the pulse peak intervals, Respiratory sinus arrhythmia, Oscillation of the baroreflex, Ratio of low and high frequency, Standard deviation of the pulse intervals) from a total of 13 features to recognize 5 emotions (sad, angry, fear, happy, relax). The aforementioned paper reports that the highest accuracy has been achieved using a SVM classifier.

The third asset supports both the functions and consists in a computational ontology for semantically describing affective phenomena such as emotions, moods, appraisals and subjective feelings [3] [5]. In our approach, the ontology for emotions can be used to support classification tasks and to reason on emotions detected from both text messages and emotional states of sender and receivers.

4 Conclusions

We have presented, in a very preliminary way, our idea to improve the communication among users in OSN. The idea stems from the pervasive and massive and daily use of OSN to communicate. Often the communication leads to misunderstanding among the users due to a hasty writing of the message sometimes in a particular emotional state. Based on these considerations, we think that the users could be supported by a Virtual Counselor that can be implemented by means of mature technologies like sentiment analysis, NLP techniques, machine learning, and wearable devices.

A step forward of our research is to consider also feedback of the user's posts and apply learning techniques to improve the Virtual Counselor suggestion quality.

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