

The Emotional Machine

A Machine Learning Approach to Online Prediction of User's Emotion and Intensity

Amine Trabelsi, Claude Frasson

Département d'informatique et de recherche opérationnelle

Université de Montréal

Montréal, Canada

e-mail: {trabelam; frasson}@iro.umontreal.ca

Abstract— This paper explores the feasibility of equipping computers with the ability to predict, in a context of a human computer interaction, the probable user's emotion and its intensity for a given emotion-eliciting situation. More specifically, an online framework, the *Emotional Machine*, is developed enabling machines to “understand” situations using the Ortony, Clore and Collins (OCC) model of emotion and to predict user's reaction by combining refined versions of Artificial Neural Network and k Nearest Neighbors algorithms. An empirical procedure including a web-based anonymous questionnaire for data acquisition was established to provide the chosen machine learning algorithms with a consistent knowledge and to test the application's recognition performance. Results from the empirical investigation show that the proposed *Emotional Machine* is capable of producing accurate predictions. Such an achievement may encourage future using of our framework for automated emotion recognition in various application fields.

Automated Emotion Recognition; Computational model of Emotion; Machine Learning; Human Computer Interaction; Affective Computing

I. INTRODUCTION

Computers have become ubiquitous in our every day life. Therefore, the research field of Human Computer Interaction (HCI) has seen a pervasive growth. Recent works in HCI suggest that computers need to be proactive containing human-centered interfaces instead of being passive on responding only to user's commands [1]. In order to be proactive, these interfaces must have the ability to detect and track the user's behavior, especially his affective behavior, before starting an interaction build on this information [1]. Detection of the user's affective state enables machines to understand the user's needs and react accordingly. Give the computers this ability is also the aim of affective computing research field [2]. Thus, several works in HCI have incorporated affective computing (e.g., [3]). In these researches, computer's recognition of user's affective state is achieved by analyzing emotional expression channels such as facial expression, voice intonation, body posture and physiological responses, etc. Automatic emotion recognition has been applied in different areas such as Intelligent Tutoring Systems (ITS) [4], call

centers [5], intelligent automobile systems [6] and game industry [7].

However, almost all of automated affective recognition methods didn't take into account, in their interpretation of everyday human affective behavior, the context in which the emotional reaction occurred [1]. For instance, a computer can detect a “raw” crying visage, but it can't assert the emotion behind because this could be the expression of sadness or the expression of a totally opposite emotion like joy, depending on the emotional situation that the person in tears is facing.

In this work, we aim to respond to the question of how can we fit up machines with the capacity to recognize the probable emotion of a person and its intensity given an everyday life emotional situation? We propose to respond to this question by developing an *Emotional Machine* using a theoretical and empirical approach. The first section gives an overview of existing and recent psychological research that attempted to characterize emotional situations. It also discusses the properties of some emotional models that have been used in computer science research. The second section, details the theoretical and empirical procedures used. The third section, describes the method employed to enable the machine to accurately predict the emotion of an individual facing any everyday life situation, afterward it describes the implementation and presents the results obtained. The final section gives a brief summary of the work and discusses its possible future application.

II. CHARACTERIZATION OF AN EMOTIONAL SITUATION

Among psychological theories of emotion that had a considerable impact in computing field dealing with affection, appraisal theories are certainly some of the most pertinent (e.g., [8]). Many computational models of emotion, based on these theories, were used in researches on software agents in order to simulate or model the emotional process (e.g., [9]). The majority of them were built on the appraisal theory of Ortony et al. [10], also known as the OCC model. This model was widely used, chiefly because it was clearly and suitably conceived so as to be easily applied in the Artificial Intelligence (AI) field. Therefore, it has been used in several AI's application fields dealing with

affective recognition. For instance, many intelligent tutoring systems researches used it to capture or predict the learner emotion in a computer teaching environment (e.g., [4], [11]).

TABLE I. OCC'S PAIRS OF EMOTION

Groups of emotion	Positive Emotion	Negative Emotion
Fortunes of Others	Happy for	Pity
	Gloating	Resentment
Prospect Based	Hope	Fear
	Satisfaction	Fears confirmed
	Relief	Disappointment
Well-Being	Joy	Distress
Attribution	Pride	Shame
	Admiration	Reproach
Well-Being/ Attribution	Gratification	Remorse
	Gratitude	Anger
Attraction	Love	Hate

In fact, OCC theory proposes three types of emotions derived from three kinds of concerns: goals, standards and tastes [10]. Hence, an emotional situation could be categorized according to three main types: (1) an event having consequences on one's goal; (2) an agent's action that matches or deviates from the standards, where an agent could be a human or an institution; (3) an object (idea or concept) that suits or not one's tastes. Events are in turn differentiated into three types: those affecting the fortune of others, those influencing one's plans and prospects, and those acting on one's well-being. The classes of emotion are differentiated into six groups, which are in turn differentiated into eleven distinct pairs of opposite emotions, that is, twenty two emotions (see Table I). In fact, the largest part of research in machine recognition of human affect didn't cover a wide range of emotions, and were confined to the six basic emotions [12], whereas basic emotion doesn't embrace all of our affective experiences in every day life situations. Even for computer models based on OCC's work, the number of emotions was often limited to a few among the twenty two and emotions were specific to the context of use.

The aim of the present work is to recognize a person's emotion, among these twenty two emotions, given any situation. For this purpose, we rely on OCC's appraisal-intensity variables to characterize and formalize an emotional situation so that the machine could "understand" it (Table II).

These variables influence both the emotional outcome and its intensity. They are divided into three categories: the global variables, the central variables, and the local variables. The global variables are common for all situations. The central and local variables are specific to the type of events (consequences for others, plans and prospect, well-being), to agents actions, and to objects.

OCC model defines, in an informal way, a link between these appraisal-intensity variables and each of the twenty two emotions. This gave rise to computational models, simulating humans' emotion-eliciting process, built on rule-

based approach (e.g., [9]). This kind of implementation makes the model more rigid as it doesn't take into account the multitude of possible emotional states for different situations.

TABLE II. USED APPRAISAL-INTENSITY VARIABLES OF OCC MODEL

Variables		Indicates the degree to which
Global	Sense of Reality	emotion-inducing situation is real or not.
	Unexpectedness	situation is surprising or not.
Central	Desirability	an event is desirable or undesirable
	Praiseworthiness	an agent's action is or isn't praiseworthy
	Appealingness	an object or a concept is attractive
Local	Desire- for-other	an event is desirable for the other person
	Liking	the other person is attractive.
	Deservingness	the other person deserves what happened
	Likelihood	belief that an anticipated event will occur
	Effort	resources were expended in obtaining or avoiding an anticipated event
	Realization	an anticipated event actually occurs
	Strength of Cognitive Unit	one identifies himself with the person or the institution who is the agent of the emotion-eliciting event
	Expect-Dev	an agent's action deviates from expected norms
	Familiarity	an object is familiar.

In this research, we are not using OCC model to reproduce and simulate humans' emotional process within a machine, but we rather use it to equip machines with the ability to evaluate and recognize a person's emotion as part of a human computer interaction. Therefore, we propose a computational model, based on the appraisal-intensity variables, that doesn't control the way emotions are triggered but rather learn when each one is generated through machine learning algorithms. This implementation will enable machines to be more flexible and to learn new patterns of emotional responses extracted from an available knowledge on emotional situations. In the following section we detail how computers are equipped with this knowledge.

III. AN EMPIRICAL KNOWLEDGE ACQUISITION PROCEDURE

Humans need to "live" several situations in order to recognize efficiently a probable emotional state of an individual facing a particular situation. This kind of reasoning, where induction is made from the lived experience, is well suited to a supervised machine learning approach. Indeed, given several cases of a phenomena (i.e., emotional situation) described by a set of explanatory variables (i.e., appraisal variables) and their corresponding target variables or classes (i.e., emotion and intensity), machine learning enable to predict for new and unknown cases of the phenomena their corresponding classes. Hence, in order to implement a machine learning approach to recognize emotion, we designed and conducted an empirical study. First, varied potential emotion-eliciting situations were collected. Then, we represented each situation, within a computer, through a vector of values of explanatory variables, i.e., appraisal-intensity variables. Finally, we collected emotional reactions to situations from different

persons so as to get a dataset that allow a machine learning algorithm to run.

A. A Web-Based Recording of Situations

In accordance with the twenty two OCC’s emotions, a collection of situations was completed. Some attempts, in psychological work, were also made to assemble everyday life situations according to six emotions (e.g. [13]). Drawing on the approach established in these works, we sent a link of web-based anonymous questionnaire to the University of Montreal’s staff and students. The questionnaire was formulated in French language. Fifty people were asked to suggest, for both extreme intensity and moderate intensity of each emotion among the twenty two, a relative situation that would elicit this feeling according to them. For example, as a suggestion of a situation generating a feeling of extreme joy, an individual proposed: “find a job after spending several months looking for one”. After treatment, we ended up with 250 detailed situations almost equally distributed on emotions and intensities, extracted from 1002 ones initially received and containing several recurring situations.

B. Digital Transformations of Situations

Once situations were acquired, we had to translate their meaning from words to a vector of digits values where each value is relative to an appraisal variable of the OCC model (Table II). Actually, global variables (e.g., unexpectedness) take Boolean values, whereas local and central variables (e.g., desirability) could be high (e.g., desirable) or low (e.g., undesirable) with either moderate or extreme intensity values. An extreme high value corresponds to “1” and a moderate high value corresponds to “0.5”. Similarly, extreme and moderate low values are “-1” and “-0.5”, respectively.

A translation of a particular situation was done by identifying how most people would appraise it. For example, most people may assess the situation “After months without work and after having filed several applications, you finally succeed to get a job” as an unexpected and real event influencing plans and prospects, that is very desirable, for which several efforts were made to obtain, and that was fully realized. This semi formal translation could be formalized, according to appraisal variables, as follows: the situation type is labeled as an event affecting plans; *unexpectedness* and *sense of reality* variables take both a “true” value; *desirability*, *effort* and *realization* variables are all assigned with an extreme high value, i.e., “1”.

Therefore, to digitally translate each of the 250 situations, we designed a web-based form through which 35 persons were asked to report, for some situations, their opinion about how the majority of people would appraise them. In fact, they had to digitally describe situations by assigning values to appraisal variables. We recorded 700 digital descriptions, where each situation was described at least twice. Then, for

each particular situation we assigned a definitive description where each variable took the majority value among the relative descriptions made for the situation. We ended up with 250 definitive descriptions, digitally characterizing each emotional situation. The information about emotional responses to these situations was then needed to establish a consistent knowledge allowing the machine to make good predictions.

C. Collecting Emotional Reactions

Supervised machine learning algorithms need a training set, an experience or a preexisting knowledge, in order to efficiently perform for new prediction. A training set, in our case, might contain information about situations and their corresponding emotional reactions and intensities (classes). However, emotional reactions are not the same for everyone. They vary from one individual to another depending on cultural values, gender, age, personality, etc [13]. For this purpose, we asked the 35 persons who described the situations to also report what they would feel if they were facing these situations. Moreover, they were also asked to enter socio-demographic information like age, gender and religion as an indicator among others of a person’s cultural norms [13]. In addition, they had to fill out a personality questionnaire: the Revised Eysenck Personality Questionnaire (EPQR-A) [14]. This questionnaire measures four personality traits, mainly extraversion, psychoticism, neuroticism and “lie scale” through only 24 questions which makes it extremely convenient.

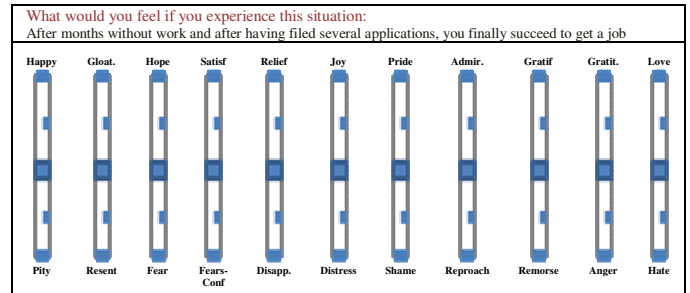


Figure 1. Emotion-Intensity Scales

Emotional reactions to situations and their intensities were captured through eleven scales (Fig. 1). Each scale corresponds to an OCC’s emotion pair and contains five intensity degrees: two for each emotion (moderate and extreme), and a neutrality level. People were able to express the non experience of an emotion and were allowed to report only one emotion and its intensity, as this work didn’t took into account the co-occurrence aspect. Thus, at the end of this procedure, the training set contained 700 examples comprising personal information and emotional reactions to 250 different situations. This dataset constituted an initial knowledge permitting to develop an application for recognizing users’ emotions.

IV. AN ONLINE EMOTIONAL MACHINE: THEORETICAL AND PRACTICAL ASPECTS

As the aim of this work is to endow machines with the ability to predict user's possible emotional response and its intensity for a given emotion-eliciting situation, we developed an online web-based *Emotional Machine* that interacts with users capturing their personal information and their reactions to some situations then predicting their emotion for a new one. Our approach is based chiefly on two supervised machine learning algorithms: the k -Nearest Neighbors (k NN) and the Artificial Neural Network algorithms (ANN). Actually, the k NN algorithm used is a refined version called the Distance-Weighted Nearest Neighbor [15]. The ANN implemented is an online version which allow to learn and to update the network gradually as new examples are entered which make it convenient for an online application. Moreover, it can perform a multi-classification task (emotion + intensity) through a simple modification of the error function. This variant of ANN is a multilayered perceptron with one hidden layer built on the on-line stochastic gradient descent for the optimization of the network parameters [16].

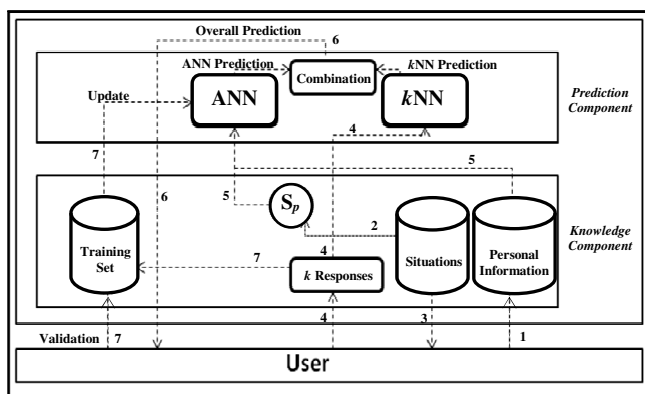


Figure 2. Architecture of the Online Emotional Machine.

The machine architecture is sketched in Fig. 2. It is based on two main components. A *Knowledge Component* which contains all the data and information needed to recognize an emotion and a *Prediction Component* composed of the k NN and ANN algorithms. The numbered and dashed arrows in Fig. 2 correspond to information flows within and between the components, where numbers indicate a chronological order of steps. In what follows, a description of each step:

- 1: First, the user has to enter its socio-demographic information and to fill out the personality questionnaire EPQR-A. These personal information are needed as emotional reactions differ from an individual to another, and are, thus, stored in a database.
- 2: In the second step, the machine picks up one situation among the 250 ones already gathered. For this situation, denoted by S_p , the application will try to predict the emotional reaction of the user.

- 3: In the third step, a subset of the most similar situations to S_p , among the 250 one's, is generated. In fact, the idea is to have a specific knowledge about the user's emotional responses when he is facing what could resemble to the situation to predict. This idea corresponds to the k NN algorithm principle. Therefore, to find the most similar situations, a standard Euclidean distance is calculated between the digital description vector of S_p and the description of each remaining situation available. Then, the k closest situations are chosen and displayed to the user (Fig. 1), who reports what he believes he would feel. The k parameter was set to 5 after testing the performance of the classification on a validation subset.
- 4: Fourth step: user responses to displayed situations are dumped to the k NN component which according to the distances, combines these responses and produces as outcome an initial prediction about user emotion and its intensity for S_p .
- 5: In the fifth step, the ANN component receives the personal information and the description vector of S_p as input and delivers as output its prediction on how people who have much in common with the actual user would react to the situation S_p .
- 6: In the sixth step, an overall prediction is established, based on two kinds of information. The first is specific to the user, acquired in step 4, based on his behavior in front of similar situations to the situation to predict. The second, acquired in step 5, corresponds to a more general level and builds on a pre-existing knowledge about people reactions to the situation. These two types of information are then combined by giving more weight to the k NN prediction (i.e., 0.66) as it is more specific, and less to the ANN's one (i.e., 0.33). The final prediction of the emotion and its intensity, along with the situation S_p , are then displayed to the user.
- 7: In the final stage, the user validates the prediction by reporting his real emotion for S_p . This information, along with the previous emotional reported reactions, is added to the training set and an online update of the ANN model according to these data is realized.

This web-based *Emotional Machine* was tested online by 203 participants among the University of Montreal's staff and students. A total of 3544 reactions to situations were reported including 634 for which a prediction was made. Prediction results are summarized in Table III.

TABLE III. ACCURACY OF COMBINED ANN AND k NN ALGORITHMS

	Emotion			Intensity
	23 classes	9 classes	3 classes	
Percentage of Correct Predictions	64.83%	72.24%	86.90%	79.83%

Indeed, the machine had to guess user emotional state among 23 possible states (OCC's emotion + the "no emotion" state). In 411 times the guessed emotion was exactly the same as that reported by the user. In other words, the *Emotional Machine* can recognize the correct emotion of the user, among the 23 possible ones, for any everyday life situation with accuracy of 64.83%.

On the other hand, this percentage may not fully reflect our machine's performance, because users may confuse similar emotions and thus report a different emotion to what they really feel, even though each one was explained by a set of synonyms. For this reason, we tried to calculate a performance percentage for less grained classes, by grouping similar emotions into 9 states or classes, according to OCC's categorization of emotions. Actually, the "Attribution" group (see Table I) and the compound group "Well-Being/Attribution" were merged, as well as the "Well-Being" and "Prospect-based" groups. The rate of correct classification increased significantly to reach a value of 72.24%. We have also tried to measure the ability of the online machine to recognize positive, negative and "no emotion" user's responses regarding a situation. The prediction was correct in 86.9% of times. In addition, the correct prediction of intensity of emotions as moderate or extreme has attained a high of 79.83%. These prediction rates are indicators of the ability of our *Emotional Machine* to "assimilate" the meaning of any type of situation, independently from the domain, and the capacity to induce instantly the probable emotion of an individual and its intensity. This may make our approach attractive and useful. It can be easily implemented in a multitude of domains dealing with online user's emotion recognition.

V. CONCLUSION

In this work, we have been able to achieve three goals. First, we used the OCC theoretical model of emotion and we formalized its cognitive variables in order to describe, in a computerized form, any everyday-life emotional situation. Second, we have been able to construct a consistent dataset including 250 detailed situations and 3544 cases of reported reactions to these situations. This dataset could be used in machine learning research as it contains several examples and multiple target variables or classes (i.e., emotion and intensity). It could provide also a framework for psychologists to study the correlations that may exist between different variables (e.g., socio-demographic and intensity). Moreover, it could be a subject of a linguistic study, dealing with the way to extract affective information from text. The third achievement is the development of an online machine learning tool, the *Emotional Machine*, for the prediction of users' emotion and intensity given any situation, based on refined versions of Artificial Neural Network and k Nearest Neighbors algorithms. It was trained on real reported data and was able to learn continuously as new information was entered. It also gave prediction with good level of accuracy. Furthermore, it is domain-

independent and can be used therefore in various applications supporting human-machine interfaces. For example, it can be used in intelligent tutoring systems to provide companion agents with information about a possible reaction in a particular situation. It can also be integrated into intelligent agents and robots to simulate the emotional behavior as a response to any environment stimulus. It might be combined with works in emotion recognition from facial expressions or speech intonations by providing a prior knowledge about the user's probable emotional state for different contexts.

REFERENCES

- [1] Z. Zeng, M. Pantic, G. I. Roisman and T. S. Huang, "A Survey of Affect Recognition Methods: Audio, Visual, and Spontaneous Expressions," *IEEE Tran. Pattern Analysis and Machine Intelligence*, vol. 31, Jan. 2009, pp. 39-58, doi:10.1109/TPAMI.2008.52
- [2] R.W. Picard, *Affective Computing*. Cambridge: MIT Press, 1997.
- [3] A. Kapoor, W. Bursleson, and R.W. Picard, "Automatic prediction of frustration," *International Journal of Human-Computer Studies*, vol. 65, Aug. 2007, pp. 724-736, doi:10.1016/j.ijhcs.2007.02.03.
- [4] M. Ochs and C. Frasson, "Emotionally Intelligent Tutoring Systems," *Proc. International Florida Artificial Intelligence Research Society Conference (FLAIRS 04)*, May 2004, pp. 251-256.
- [5] C. M. Lee and S. S. Narayanan, "Toward detecting emotions in spoken dialogs," *IEEE Tran. Speech and Audio Processing*, vol. 13, Mar. 2005, pp. 293-303, doi:10.1109/TSA.2004.838534.
- [6] Ji. Qiang, P. Lan and C. Looney, "A probabilistic framework for modeling and real-time monitoring human fatigue," *IEEE Trans. Systems, Man and Cybernetics, Part A: Systems and Humans*, vol. 36, Sep. 2006, pp. 862-875, doi: 10.1109/TSMCA.2005.855922.
- [7] S. Slater, R. Moreton, K. Buckley and A. Bridges, "A Review of Agent Emotion Architectures," *Eludamos Journal for Computer Game Culture*, vol.2, 2008, pp. 203-214.
- [8] K. R. Scherer, "Vocal affect expression: A review and a model for future research," *Psychological Bulletin*, vol. 99, Jan. 1986, pp. 143-165, doi:10.1037/0033-2909.99.2.143.
- [9] J. Bates, A. B. Loyall and W. S. Reilly, "An Architecture for Action, Emotion, and Social Behavior," *European Workshop on Modeling and Autonomous Agents in a Multi-Agent World (MAAMAW 92)*, Jul. 1992, pp. 55-68.
- [10] A. Ortony, G. L. Clore and A. Collins, *The cognitive structure of emotions*. New York:Cambridge University Press, 1988.
- [11] C. Conati and H. Maclaren, "Empirically building and evaluating a probabilistic model of user affect," *User Modeling and User-Adapted Interaction*, vol. 19, Aug. 2009, pp. 267-303.
- [12] P. Ekman, *Emotion in the human face*. New York: Cambridge University Press, 1982.
- [13] K. R. Scherer, T. Wranik, J. Sangsue, V. Atran and U. Scherer, "Emotions in everyday life: Probability of occurrence, risk factors, appraisal, and reaction patterns," *Social Science Information*, vol. 43, Dec. 2004, pp. 499-570, doi:10.1177/0539018404047701.
- [14] L. J. Francis, L. B. Brown, and R. Philipchalk, "The development of an abbreviated form of the Revised Eysenck Personality Questionnaire (EPQR-A): Its use among students in England, Canada, the U.S.A. and Australia," *Personality and Individual Differences*, vol. 13, Apr. 1992, pp. 443-449, doi:10.1016/0191-8869(92)90073-X.
- [15] T. Mitchell, *Machine Learning*. New York : McGraw Hill, 1997.
- [16] Y. Le Cun, B. Boser, J. S. Denker, D. Henderson, R. E. Howard, W. Hubbard, and L. D. Jackel, "Backpropagation applied to handwritten zip code recognition," *Neural Computation*, vol. 1, Winter 1989, pp. 541-551, doi:10.1162/neco.1989.1.4.541.