Integrating Personality and Mood with Agent Emotions

Extended Abstract

Suman Ojha
Centre for Artificial Intelligence,
University of Technology Sydney
Suman.Ojha@student.uts.edu.au

Jonathan Vitale
Centre for Artificial Intelligence,
University of Technology Sydney
Jonathan.Vitale@uts.edu.au

Syed Ali Raza
Centre for Artificial Intelligence,
University of Technology Sydney
Syed.Raza@uts.edu.au

Richard Billingsley
Centre for Artificial Intelligence,
University of Technology Sydney
Richard.Billingsley@uts.edu.au

Mary-Anne Williams
Centre for Artificial Intelligence,
University of Technology Sydney
Mary-Anne.Williams@uts.edu.au

ABSTRACT

An intelligent agent should be able to show different emotional behaviours in different interaction situations to become believable and establish close relationships with human counterparts. It is widely accepted that *personality* and *mood* play an important role in modulating emotions. However, current computational accounts of emotion for intelligent agents do not effectively integrate the notions of personality and mood in the process of emotion generation. Previous attempts that have been made are mostly based on the assumptions of the researcher, rather than on empirical data and scientific validation. In this paper, we present the results of a novel supervised machine learning approach used to train a network of emotions that integrates the factors of personality and mood, which provides a high emotion intensity prediction accuracy.

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1 INTRODUCTION

Researchers have identified that emotionality is an inevitable aspect of an intelligent agent required for it to become believable while interacting with humans [2, 17] and to maintain a long term relationship [4]. If an agent is able to generate and express situation-congruent emotions, people can find the interaction more engaging and believable than interacting with a lifeless machine that shows unemotional responses through text or a monotonous voice [4].

However, emotion is not an isolated phenomenon. Literature suggests that the mechanism of emotion processing is influenced by individual-specific factors such as *personality* [5, 27, 31] and *mood* [19, 21]. It is important to model the influence of such factors in emotion generation mechanisms of artificial agents, since in practical applications, an intelligent agent should exhibit relevant emotional responses and different action tendency if it is to be employed in wide range of human-centred situations. For example, an intelligent agent intended to be employed as a personal development assistant is desirable to have an organised and systematic characteristic that conveys competence. As such, the agent might have to express disappointment or similar emotions if the person under training ignores some important scheduled activity. However, if the agent is to be deployed as an emotional support companion, then it may be preferable to forgive such a minor ignorance – hence it is desirable to have an easy going nature. Similarly, mood can also play an important role in modulating the emotional responses of the agent. For example, consider a hypothetical situation where an agent is in positive mood state (based on its recent human interaction experience). The agent might easily forgive an insult from the human interacting with it, while it may not do so if it is in negative mood state. The above examples show only a few of many situations where personality and mood can substantially influence the process of emotion generation during human-agent interaction.

In this paper, we present the results of emotion prediction accuracy demonstrated by our computational model of emotion – EEGS [22–25]. EEGS integrates the aspects of mood and personality using a machine learning technique called stochastic gradient descent [3]. In the past, there have been remarkable contributions in the field of modelling emotion (see for example [1, 6–8, 10–15, 20, 30]). However, unlike existing models of emotion processing, which normally justify the fine-tuning of personality and mood factors with the analysis of emotion literature, we suggest to train such factors by using machine learning approach. We train our model with a dataset gathered from human participants assessing personality, mood and emotion factors in a given situation and use the trained model to predict the emotion intensities.

2 EMOTION PREDICTION MECHANISM

A total of 47 unique responses were obtained from Amazon Mechanical Turk survey (*male* = 31 and *female* = 16). The data collected was reformatted to create a machine learning suitable data table with the following columns.

$$v_1 \ v_2 \ \ldots \ v_k \ O \ C \ E \ A \ N \ M \ e$$

where, v_1, v_2, $\ldots$ v_k indicate the appraisal variables [16, 26, 29], which are used to denote how the situation is evaluated by the target of interaction. O, C, E, A and N denote the five personality factors of openness, conscientiousness, extroversion, agreeableness and neuroticism respectively [9]. M denotes the mood factor. e denotes the intensity of the emotion. Because of the complex nature

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Table 1: Intensity prediction accuracy in EEGS.

Emotion	$\bar{x}$ Accuracy	$\tilde{x}$ Accuracy	σ
joy	79.2%	83.4%	0.151
distress	73.4%	76.1%	0.187
appreciation	81.1%	84.2%	0.145
reproach	77.0%	81.8%	0.199
gratitude	79.1%	82.1%	0.152
anger	76.3%	80.2%	0.190
liking	80.8%	83.7%	0.148
disliking	77.7%	82.9%	0.191
Overall	**78.1%**	**82.2%**	**0.173**

of each emotion and to allow the methodology to be applicable in any artificial agent having any number of emotions, we ran the training algorithm for each emotion type separately *i.e.* links associated with a particular emotion (say *joy*) were trained separate to other emotions types. This offered simplicity in the training process and helped in avoidance of probable learning errors. Therefore, a separate dataset was created for each emotion type. For each emotion, the set of $\{v_1 \ \ v_2 \ \ \ldots \ \ v_k \ \ O \ \ C \ \ E \ \ A \ \ N \ \ M\}$ was used as the input features. As the survey scenario had 11 core emotion inducing actions and 47 unique responses, we ended up having a dataset containing 517 (=11 x 47) rows for each emotion type.

Out of the total data rows, 70% of the rows i.e. 362 rows were used for training the network and remaining 30% selected in random order were used to test the accuracy of the trained network i.e. 155 rows in test dataset. For each emotion type, the algorithm was used for 100 epochs. Thus, one complete training session consisted of 100 * 362 = 36,200 weights update (iterations).

3 RESULTS AND CONCLUSION

Table 1 shows the overall accuracy in prediction of the intensities of various emotions in EEGS. The accuracy of each emotion represents the combined intensity prediction accuracy of that emotion over the 10 testing sessions after the completion of the corresponding training process. Since each testing data set consisted for 155 rows, the overall accuracy for each emotion shown in Table 1 represents a comparison 1,550 accuracy tests (where, $error = |target_{intensity} - predicted_{intensity}|$). It is evident from the table that the mean accuracy ($\bar{x}$) in the prediction of the intensity of various emotions ranged from 73.4% for *distress* emotion to 81.1% for *appreciation* emotion with an average mean accuracy of 78.1% for all the emotions considered. Likewise, median accuracy ($\tilde{x}$) ranged from 76.1% for *distress* emotion to 84.2% for *appreciation* emotion with an average median accuracy of 82.2% when all the emotions were considered. For each emotion, the standard deviation (σ) of the prediction accuracy for individual emotions was minimal ranging from 0.145 to 0.199 with an average of 0.173 for all the emotions together. It is a promising outcome where the accuracy in intensity prediction of all the emotions are quite close to each other even if the model was trained separately for each emotion.

Although not common, use of machine learning approaches in similar applications has been suggested by some other researchers. However, *the novelty of our work lies in the prediction of actual emotion intensity instead of mere classification of emotions.* For example,

Table 2: Classification accuracy obtained by [18].

Classification Type	Average Accuracy
Positive/ Negative	93%
4 Emotion Clusters	60.5%
12 Emotion Classes	27.9%
Individual Emotion Intensity	Not Performed

Meuleman and Scherer [18] also used ISEAR data collected from the Geneva Emotion Analyst [28] for training a model to predict emotion classes based on appraisals rated by human participants. Meuleman and Scherer [18] conducted three types of classification tasks. First, they tested the accuracy in differentiating positive and negative emotions. Second, they tested the accuracy in differentiating four emotion clusters (*happiness*, *anger*, *shame/guilt* and *distress*). Third, they tested the accuracy in differentiating the 12 emotion classes namely *sadness*, *fear*, *despair*, *anxiety*, *shame*, *guilt*, *rage*, *disgust*, *irritation*, *joy*, *pleasure*, and *pride*. The best accuracy achieved in each of the above tasks were 93%, 60.5% and 27.9% respectively. As evident from Table 2, the classification accuracy in the study of Meuleman and Scherer [18] dropped significantly as the requirement of the task specificity increased. They have not performed the 'intensity prediction test' in their study because the utilised data set lacks the continious intensity values for the emotion classes – instead a mere binary activation is available. Given the difference of their task (classification) with our task (regression of emotion intensities) it is not possible to make an exact and reliable comparison of the two sets of accuracies. However, if we assume that by regressing the elicited emotion intensities for each input interaction we can also gather a valid cue to classify such interaction in a single emotional class, we can view their classification task as closely related to our regression one even though the results are not easy to compare. The ISEAR data set used by Meuleman and Scherer [18] can not be directly utilised in the training and validation of the appraisal-emotion mapping of our model, EEGS, because (i) ISEAR data consists of the appraisals proposed by Scherer [29] that can not be seamlessly matched with the appraisal variables offered by the OCC theory [26], which forms the basis of our implementation, and (ii) the goal of current research is not only to establish a quantitative relationship between appraisal variables and emotions (which is still not fully offered by Meuleman and Scherer [18]) but also to integrate the aspects of personality and mood in the mapping process. As such, *a notable contribution of our research is a new approach that allows to establish a quantitative association between appraisal variables and emotions by 'learning' the degree by which other human factors influence this association (such as personality and mood)* – which has not yet been provided by past research.

In summary, this paper presents the results of emotion intensity prediction exhibited by our computational emotion model, EEGS [22–25]. Our work is the first of its kind which attempts to predict the actual emotion intensity based on data collected from humans and also provides a benchmark for future researchers.

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