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Implementing the Dynamic Role of Mood and Personality in Emotion Processing of Cognitive Agents

Suman Ojha SUMAN.OJHA@STUDENT.UTS.EDU.AU
Jonathan Vitale JONATHAN.VITALE@UTS.EDU.AU
Syed Ali Raza SYED.A.RAZA@STUDENT.UTS.EDU.AU
Richard Billingsley RICHARD.BILLINGSLEY@UTS.EDU.AU
Mary-Anne Williams MARY-ANNE.WILLIAMS@UTS.EDU.AU
The Magic Lab, Centre for Artificial Intelligence, University of Technology Sydney, Sydney, Australia

Abstract

An ability to generate and express emotions constitutes an integral part of an artificial intelligent system be it cognitive architecture, virtual conversational agent or social robot. It is important to have an emotional component in those systems to enable the system to exhibit emotionally intelligent behaviour. This is in part achievable by integrating computational models of emotion into such cognitive systems. However, it is challenging to develop a computational model of emotion that embraces a wide range of cognitive aspects related to the process of emotion generation. As evident from the literature, *mood* and *personality* are the two aspects that are inseparable from the mechanism of emotion generation. In other words, mood and personality of an individual play a crucial role in determining the emotional state of an individual to a large extent. Thus, an emotion model that incorporates the notion of mood and personality is necessary to achieve a desirable level of emotional intelligence in cognitive systems. In this paper, we demonstrate how this integration has been achieved in our emotion model – EEGS. We also present how an artificial agent can show variation in emotion dynamics because of the influence of such factors, thus validating our theory.

1. Introduction

It is well accepted that the goal of artificial intelligence can not be achieved without considering the aspects of emotion (Minsky, 1986, 2007). Moreover, computational mechanism for the generation of emotion is inevitable to achieve a believable and socially acceptable behaviours by artificially intelligent agents like cognitive architectures, software agents or even robots (Ball & Breese, 2000; Hollinger et al., 2006; Hudlicka, 2005). However, empowering such cognitive systems with *emotional intelligence*[1] (Salovey & Mayer, 1990) requires consideration of wide range of aspects that participate in the process of emotion generation in humans. One important aspect that affects emotional processing is the *mood* of an individual (Morris, 1992). For example, an individual in bad

1. Although the term ‘emotional intelligence’ is commonly defined in vague sense, our discussion in this paper refers to the term as a general ability to intelligently generate an appropriate emotion by performing a cognitive evaluation of the event occurring in its surrounding.

mood has lower tendency of experiencing positive emotions. Another important property that impacts the phenomenon of emotion elicitation is the *personality* of the individual (Zelenski, 2007). As an illustration, an extrovert person has higher tendency of experiencing positive emotions compared to an introvert (Watson & Clark, 1997).

Most existing computational models of emotion do not consider both of these aspects together (El-Nasr et al., 2000; Gratch & Marsella, 2004). Although there are a few models that use both the mood and personality in modelling emotion (Gebhard, 2005; Kshirsagar, 2002; Soleimani & Kobti, 2016; Velásquez & Maes, 1997), these models have two distinct limitations. First, they model the effect of mood and personality on emotion independently irrespective of the interplay between mood and personality, and, second, they only explain how mood and personality affect the excitation threshold of various emotions without addressing the mechanism of how the mapping of *appraisal variables*[2] to the emotions is affected by mood and personality. Literature suggests that studies examining the effects of mood and personality on emotion without considering the mutual effects of these aspects have shown inconsistent and implausible results (Rusting, 1998). As such, we have integrated the mutual interplay of mood and personality in emotion processing of our computational model – EEGS (Ojha & Williams, 2016, 2017) which shall be later discussed in detail. In this paper, we will also demonstrate how our approach helps in explaining the mechanism by which mood and personality affect the mapping of appraisal variables to various emotions, which is often unclear in existing computational emotion modelling literature.

In short, this paper will investigate two questions:

i *How can the aspects of personality and mood play a dynamic role in mapping cognitive appraisals into emotions*?

ii *Can a difference in personality traits and mood cause variation in emotion dynamics of an artificial agent*?

The answers to the questions will provide new insights on the role of mood and personality in the process of emotion the implications of which will promote the advancement in the design and development of human-centred robotic technologies in the future.

2. Background

Appraisal theory of emotion (Ortony et al., 1990; Scherer, 2001) is a commonly used emotion theory in computational modelling of emotion. According to this theory, there might be different variations in the way an event/situation is assessed by an individual and hence result in different emotions felt by different individuals in response to the same event. Appraisal theory posits that an event is assessed based on a set of variables called appraisal variables. The evaluation of these variables is then mapped into the emotions of the individual. These emotions might in turn lead to various action tendencies. Figure 1 shows the mechanism of how an event triggers the appraisal of the situation and how the computed appraisals are mapped into the emotional state.

2. According to appraisal theories of emotion (Ortony et al., 1990; Scherer, 2001), emotion in individuals result from the evaluation of the situation using a set of criteria called appraisal variables.

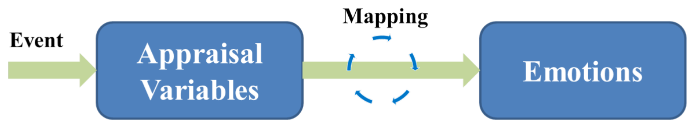

Figure 1. An Event triggering the Appraisal mechanism thereby leading to the generation of various Emotions.

Previously, we mentioned that different individuals appraise the same situation differently and hence reach to a different emotional state. But the core question is what causes this difference in emotion processing? Literature suggests that mood and personality are two important players that take part in the process of generation of emotion (Morris, 1992; Zelenski, 2007). Research on the nature of mood in relation to emotion seems sparse except some work suggesting that mood represents a longer duration (Salovey & Mayer, 1990) accumulated effect of series of emotional experiences (Morris, 1992; Parkinson, 1996). Several computational emotion models have adopted this viewpoint in modelling mood (El-Nasr et al., 2000; Gratch & Marsella, 2004; Velásquez & Maes, 1997). Unlike mood, there has been extensive research on studying the nature of personality. A large number of personality researchers have come up with five basic factors of personality thereby calling the model as Five-Factor Model (FFM) (McCrae & John, 1992). FFM model of personality considers five dimensions to determine the personality of a person namely *openness, conscientiousness, extraversion, agreeableness*, and *neuroticism* and which are explained below.

- *Openness* - It includes characteristics such as eagerness to learn new things or try something risky instead of following the regular trend or routine (McCrae & John, 1992).
- *Conscientiousness* - It is the characteristic that makes a person organised, reliable and systematic (McCrae & John, 1992).
- *Extraversion* - It refers to the characteristic in which a person is more outgoing and talkative and has more tendency of experiencing positive emotionality (Watson & Clark, 1997). Contrastingly, the individuals who score low on extraversion scale are quiet, reserved and shy (John, 1989).
- *Agreeableness* - It covers the range of characteristics that makes a person friendly (Digman & Takemoto-Chock, 1981), compassionate, approachable and forgiving, sympathetic, kind and trusting (McCrae & John, 1992).
- *Neuroticism* - It refers to the higher tendency of experiencing negative emotions like distress (McCrae & John, 1992). Highly neurotic people are also found to experience chronic negative effects (Watson & Clark, 1984).

While the factors extraversion and neuroticism seem to have direct relation to emotion processing mechanism, it is not explicit how other factors might contribute to the process of emotion. Yet some general inferences can be drawn from these ideas. For example, agreeableness can be linked to the tendency of being less angry if someone opposes your opinion. Likewise, conscientiousness can be linked to be more frustrated in case of failure and openness can be linked to the ability of remaining calm if something undesired or unexpected happens. These inferences can be useful in the computational models using personality factors to influence emotion.

This section discussed the theoretical relation of mood and personality with emotion and how these concepts can be applied in computational model. Although there have been computational implementations using mood and personality to determine emotion, these models do not either explain how mood and personality interact in the process (El-Nasr et al., 2000; Gratch & Marsella, 2004; Velásquez & Maes, 1997) or do not account for the dynamic role played by mood and personality in the process of mapping of appraisal variable to emotions (Gebhard, 2005; Kshirsagar, 2002; Soleimani & Kobti, 2016). In the following section, we shall discuss how existing computational models of emotion have implemented the notion of mood and/or personality in the mechanism of emotion generation and highlight the limitations of the models.

3. Related Work

So far, we have gained some understanding of the relationship between mood, personality and emotion. In this section, we shall review some existing work on computational modelling of emotion. First, we will present the discussion of the models that implement the effect of mood and/or personality on emotion without considering the mutual effect of these characteristics. Then our discussion will follow the review of models that include the interaction of both the mood and personality factors but do not explicitly explain how these factors help in the process of mapping appraisal variables to emotions, which is a crucial aspect of a computational emotion model based on appraisal theory.

Fuzzy Logic Adaptive Model of Emotions (FLAME) (El-Nasr et al., 2000) is a computational model of emotion that incorporates the notion of mood in the process of emotion generation but fails to account for another important aspect i.e. personality. In FLAME, mood is used as a modulating factor for emotion that can either be positive or negative and "depends on the relative intensity of positive and negative emotions" (El-Nasr et al., 2000, p.16). Since FLAME only considers the role of mood in the generation of emotion without accounting for the interplay of personality with mood and emotion, it fails to model the interaction between mood and personality. EMotion and Adaptation (EMA) (Gratch & Marsella, 2004) is a domain-independent computational model of emotion. Like FLAME, EMA also only models the effect of mood on emotion. In EMA, mood is computed as an aggregation of emotion instances passed through a sigmoid function. This mood is then used to alter the intensities of the emotion instances in the next appraisal round. EMA does not model the impact of personality factors in the emotion generation mechanism. Moreover, Cathexis by Velasquez (Velásquez & Maes, 1997) models both mood and personality individually but does not explain how mood and personality might interact to alter the emotional state.

Now, we shall review some computational models that model the mutual interaction of mood and personality but do not describe how mood and/or personality play a dynamic role in the mapping of appraisal variables into emotion intensities. A Layered Model of Affect (ALMA) (Gebhard, 2005) is one such example. ALMA is a computational model of emotion initially aimed to be implemented in embodied conversational characters. ALMA models both the mood and personality where mood is also determined by personality factors. However, it fails to establish dynamic mapping of appraisals into emotion intensities influenced by the factors of mood and personality. Similarly, the multi-layer personality model of Kshirsagar (Kshirsagar, 2002) implements a layered approach where personality interacts to influence the mood of the model. Yet, the model does not provide a clear explanation of how mood and personality take part in the process of mapping from appraisal to emotions.

In summary, it can be stated that existing computational models of emotion do not effectively capture the notions of mood and personality for the dynamic mapping of appraisals into emotions. In this paper, we will present our computational model that operationalises a mutual interaction between personality, mood and emotion thereby enabling a dynamic mapping of appraisals into emotion intensities.

4. Emotion Model

Figure 2 shows four basic stages in the process of emotion generation in the proposed model[3]– (1) *Emotion Elicitation*, (2) *Cognitive Appraisal*, (3) *Affect Generation*, (4) *Affect Regulation*. *Emotion elicitation* can be defined as an early process of attending to the stimulus event and recognising that the event can have either positive or negative impact on the individual. This kind of mechanism is usually considered as a first-order phenomenological response without the involvement of conscious cognitive component (Lambie & Marcel, 2002). This mechanism can be related to the concept of *relevance detection* in the appraisal theory of Scherer (2001). When an event is determined significant enough to trigger emotional reaction, a second-order (higher level) (Scherer, 2001; Lambie & Marcel, 2002) *Cognitive Appraisal* is performed. This is where the concepts of various appraisal theories come into play. The variables proposed by the appraisal theories (called appraisal variables) are evaluated to analyse how the event may affect the individual or any other agent or object in the environment of the appraising individual. The appraisal variables are associated with various emotions. For example, the appraisal variable *desirability* is related to the emotion *joy* because if an event is desirable then it may induce joy and the degree of joy is determined by the degree of desirability of the event. This kind of mapping leads to the process of *Affect Generation*. According to appraisal theories, an event can lead to the generation of more than one emotions at the same time – but with different intensities (Ortony et al., 1990; Scherer, 2001). Such a situation is handled by the mechanism called *Affect Regulation* (Gross & Thompson, 2007). This process can be understood as a ‘post emotion-generation’ coping response as described in the theory of Lazarus (1991).

3. It should be noted that there can be several components involved in the completion of an emotional episode as identified by Moors (2009), namely *somatic*, *cognitive*, *feeling*, *motivational* and *motor*. However, at the heart of appraisal theories lies the *cognitive* aspect of emotional episode which results in the activation of *feeling*, *somatic*, *motivational* and/or *motor* components. As such, the discussion in this paper is mainly focused on the operationalisation of *somatic*, *cognitive* and *feeling* components as reflected by the *emotion elicitation*, *cognitive appraisal* and *affect generation* modules in Figure 2.

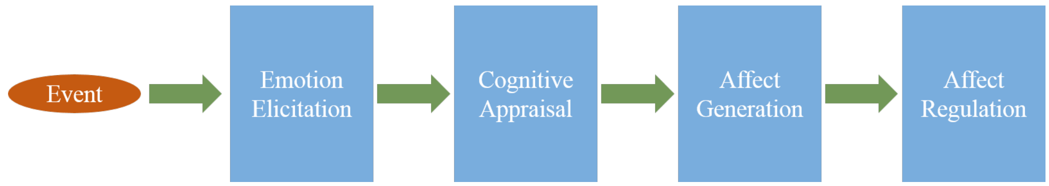

Figure 2. Process flow in the proposed computational model of emotion.

4.1 Cognitive Appraisal Process

Cognitive appraisal theory states that emotions result from the subjective evaluation of the stimulus event by the appraising individual (Scherer, 2001; Lazarus, 1991). OCC Theory (Ortony et al., 1990) is one of the most prominent theory of emotion that has inspired a large number of computer scientists for the development of computational emotion models. Since our implementation has been inspired by the postulates of OCC theory of emotion, the emotions of EEGS are governed by *goals*, *standards* and *attitudes*.

4.1.1 Goals, Standards and Attitudes

Appraisal of a situation is affected by goals, standards and attitudes of an individual (Ortony et al., 1990). Hence, we need to understand the link between appraisal variables and goals, standards and attitudes before we can operationalise such a mechanism in autonomous agents.

Goals

Goals represent a set of states that an individual wants to achieve. In EEGS, goals are represented in a hierarchy where a goal that helps in accomplishing another goal lies in the lower level of the hierarchy. We have represented the goals of the system as a tree structure in line with the proposal of the OCC theory. Each node of the tree is a goal node and a node may be linked to one or more lower level (child) nodes.

Figure 3 shows an example of a goal tree in our computational model. Each goal in the goal tree is in the form `(<Action/Emotion>, <Person>)`, where Action/Emotion denotes the action to be done or emotional state to be attributed to a particular Person[4]. For example, goal node, `("JOY", "JOHN")` aims to bring "JOHN" in state of "JOY". The root node `("Root", NULL)` has two children nodes `("Self_goal", NULL)` and `("Other_goal", NULL)`, which denote the goals intended for self and for others respectively. Children of Self_goal node are the goals that are aimed for the benefit of oneself while the children of Other_goal node are aimed for the benefit of others. "NULL" Person for these goal nodes indicates that there is no specific target person- they just divide the goals into two categories. Lower level goals are useful for the accomplishment of the higher level goals. For example, the goal `("Kiss", "JOHN")` helps in the accomplishment of the goal `("JOY", "JOHN")`.

4. Our computational model currently is intended to interact with humans only, hence the goals can either be an action performed to a person or an emotional state that the model wants to see in a person. But, it should be noted that this notion of goals can be extended beyond this scope without changing the computational mechanism of our model.

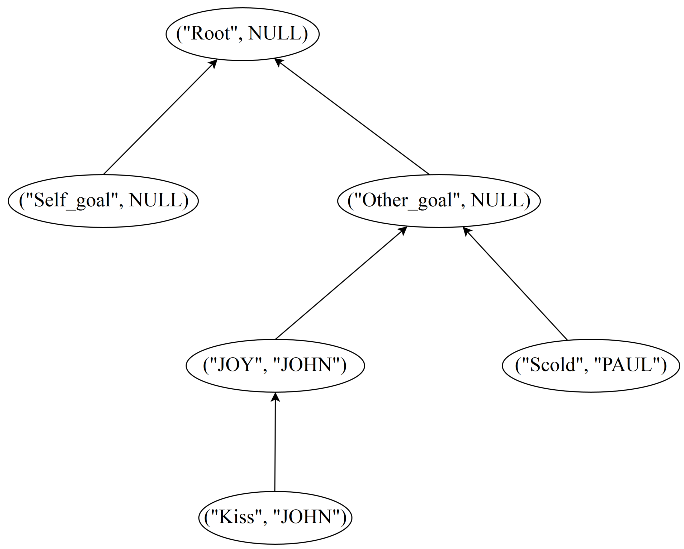

Figure 3. An example of a Goal Tree. Adapted from Ojha & Williams (2017).

Standards

Standards maintain a collection of norms and values of an individual shaped by the social context or learned concepts. In EEGS, we structure standards[5] in the form:

`(<Action/Emotion>, <Source>, <Target>, <Approval>)`

which stores a belief that an Action/Emotion performed/expressed by the Source upon the Target has certain level of Approval as per the standard. Approval is further broken down into the structure `(<Preference>, <Approval Degree>)`, where Preference indicates if the action from source to target is preferred or not and Approval Degree indicates the degree of that preference. For example, `("Slap", "PAUL", "NEIL", ("NO", 0.8))` means "PAUL is NOt supposed to Slap NEIL and the degree of this preference is 0.8". Approval Degree denotes how strong belief an individual has on the standard. Its value can range from 0 (exclusive) to 1 (inclusive). An Approval Degree of 1 indicates very strong belief on the standard and a value close to 0 indicates very weak belief of the standard. An example of reduced list of standards is shown in Table 1.

Since standards contain a set of beliefs, the notion of standard should be dynamic as beliefs of a person might change in the course of life experience. For example, let us consider the example we presented in the previous paragraph. The standard `("Slap", "PAUL", "NEIL", ("NO", 0.8))` might be changed if NEIL does some severely bad action.

It should be noted that an individual (and hence our model) can have many recognised persons and actions as well as different possible emotions. An individual's standards should account for all of those aspects. The list of standards in Table 1 is not exhaustive, it only shows a few representative

5. We have opted for this representation of standards because of insufficient evidence in the literature on how an standard should be represented as a data structure. We are open to further discussion for the improvement of this notation.

Table 1. An example of a set of Standards

Action/Emotion	Source	Target	Preference	Approval Degree
Slap	PAUL	NEIL	NO	0.8
Scold	SELF	ROBERT	YES	0.5
JOY	SELF	JASMINE	YES	0.9
DISTRESS	SELF	NEIL	NO	0.4

examples for the understanding of how the standards are structured in our computational model. Moreover, when our computational model is run for the first time, it starts with empty standards. It keeps on building and updating the standards as it interacts with various persons. This makes our model completely independent of the implementation domain and can build on its own as per the environmental context.

Attitudes

Attitudes defined in OCC theory (Ortony et al., 1990)can be considered as perception of an individual regarding persons or objects. But unlike the standards, attitudes in EEGS have a slightly different structure. An attitude is structured as `(<Person/Object>, <Perception>)`, where Person/Object refers to the person or object about whom the attitude is and Perception is the perception about the Person/Object. For example, `("JOHN",0.8)` means "the model has positive perception about JOHN and the degree of the positivity is 0.8". As denoted earlier in the discussion about the structure of an object, Perception about an object/person in our model can range from -1 to +1, where -1 indicates an extremely negative perception and +1 indicates extremely positive perception.

However, it should be noted that the process of cognitive appraisal forms only a part of the complete emotional episode (as indicated in Figure 2). When the situation is assessed and appraisals are computed, the resulting appraisal variables should be mapped to the corresponding emotion intensities. In the following sections, we explain the process by which the interaction among emotion, mood and personality have been operationalised for such a mapping in the proposed computational model of emotion.

5. Emotion, Mood and Personality in Action

Emotion can be considered as an instantaneous valanced reaction to an event (Ortony et al., 1990). In other words, emotion is a short lived experience in which an individual realises some degree of positivity or negativity in reaction to an event in its surrounding. Mood is rather longer lived (Salovey & Mayer, 1990) cumulative effect of continuous (Parkinson, 1996) and prolonged emotional episodes. While there is general consensus that emotion and mood are rather short lived compared to personality, there is some debate on whether personality is a stable characteristic of a person or not (Dweck, 2008). Yet, several researchers believe that personality of a person is something that does not change with time and remains the same throughout life after adulthood (Costa & McCrae, 1988; Rusting, 1998). In our computational model, we adopt the assumption that personality does not change with time in line with the findings of Costa and McCrae(Costa & McCrae, 1988). Hence, emotion and mood do not affect the personality as shown in Figure 4.

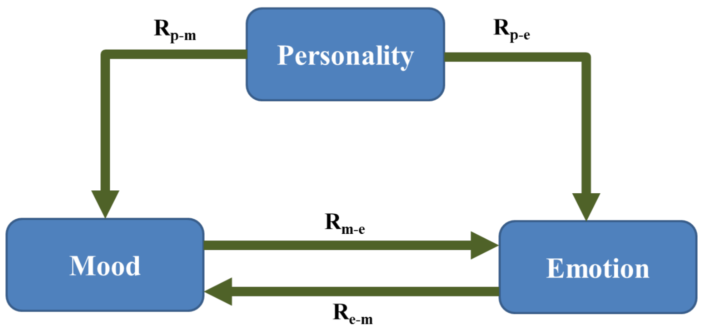

Figure 4. Interaction between Emotion, Mood and Personality.

Figure 4, shows an interaction between emotion, mood and personality in our computational model. Our implementation has been inspired by the work of Rusting (1998), except we consider an additional relationship where emotional state also alters the mood of the model in accordance with the findings of Parkinson (1996) and Beedie et al. (2005). In Figure 4, rectangular boxes represent the emotional state, mood state and personality of the model. We explicitly do not use the term "state" for personality because we assume that personality of our model is not variable characteristic, in line with the arguments of Costa & McCrae (1988) and Rusting (1998). Arrows indicate the effect of one characteristic onto another. In our model, personality affects the mood state and emotional state; mood state affects emotional state; and emotional state affects mood state. Let us call the arrow from personality to mood as *personality-mood* relation (R_{p-m}), the arrow from personality to emotion as *personality-emotion* relation (R_{p-e}), the arrow from mood to emotion as *mood-emotion* relation (R_{m-e}) and the arrow from emotion to mood as *emotion-mood* relation (R_{e-m}). We can see that personality affects emotion through two different paths - one direct and another through mood. Thus, we call our model to have *dual-effect* of personality on emotion. Also, when the model initialises, it is in neutral emotional state and hence emotional state will have no effect on mood state at this stage. In the first stage, only the event in the surrounding along with the personality and initial (neutral) mood will cause an emotional state to be triggered. Only after this, in second stage, subsequent emotional states will then alter the mood state. Hence, we call our model to be have *dual-stage* interaction between emotion, mood and personality. Combining these two properties, our model implements a *dual-effect-dual-stage* interaction between emotion, mood and personality. As previously mentioned, it is important to have this kind of dual-effect interaction of personality with emotion because psychology studies suggest that the effect of personality on emotion is not independent of mood (Rusting, 1998). Hence, it is crucial to consider the mutual interaction of personality and mood, which is achievable in our dual-effect-dual-stage interaction of personality, mood and emotion.

6. Appraisal-Emotion Network

As previously mentioned, according to appraisal theories (Ortony et al., 1990; Scherer, 2001), appraisal variables are the criteria used for the evaluation of the event occurring in an individual's surrounding. When an event is encountered, an assessment of these variables is performed and the resulting measures of these variables are used in the generation of various emotions. The mapping of appraisal variables into emotional states constitutes an important aspect of a computational model of emotion as this might be affected by the mood (Morris, 1992) and personality (Zelenski, 2007) of the model. Moreover, according to OCC theory (Ortony et al., 1990), one appraisal variable may affect the generation/intensity of more than one emotion and an emotion may be affected by more than one appraisal variable. Also, the relationship between an appraisal variable and an emotion has a weight indicating the degree by which the emotion is affected by the given appraisal variable (Ortony et al., 1990). We present this relationship as an appraisal-emotion network in Figure 5.

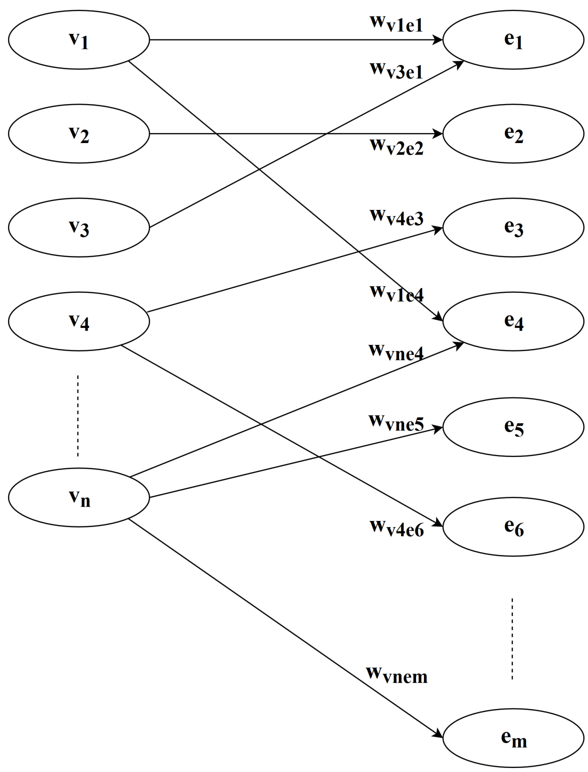

Figure 5. Weighted Appraisal-Emotion Network.

In the previous sections, we discussed that existing computational models of emotion (El-Nasr et al., 2000; Gebhard, 2005; Gratch & Marsella, 2004; Soleimani & Kobti, 2016; Velásquez & Maes, 1997) do not explicitly describe how the appraisal variables are mapped into emotion intensities. Instead of learning the association dynamically based on the mood and personality factors, these models opt for uder-defined thresholds for emotion intensities. We argue that such an approach of operationalising the mapping of appraisals into emotions is not plausible. As such, in this section, we will present an explanation of how appraisal variables can be linked to emotions and how mood and personality can affect the process of mapping the appraisal variables into various emotions.

In Figure 5, the set of appraisal variables $\mathbf{V} = \{v_1, \ldots, v_n\}$ and the set of emotions $\mathbf{E} = \{e_1, \ldots, e_m\}$ are linked to each other by a weighted network. We have used n appraisal variables and m emotions in our explanation in order to allow the flexibility of adjusting a model as per the application need. Our model currently computes seven appraisal variables for the generation of eight different types of emotions[6] which have been adopted from OCC theory (Ortony et al., 1990). However, the framework we have presented here can be applied to any number of appraisal variables and emotions and also in different domains. As evident from Figure 5, some appraisal variables can affect more than one emotion and an emotion can be affected by more than one appraisal variable. For example, appraisal variable v_1 affects more than one emotions namely e_1 and e_4. Likewise, emotion e_1 is affected by appraisal variables v_1 as well as v_3.

7. Modelling of the Relationship between Emotion, Mood and Personality

The weight of the link between an appraisal variable $v_i \;: i \in [1, n]$ to an emotion $e_j \;: j \in [1, m]$ is denoted by $w_{v_i e_j}$. For example, the weight of association of the appraisal variable v_1 to the emotion e_4 is denoted by $w_{v_1 e_4}$. This weight is affected by the mood and personality of the model as previously mentioned. If we denote the personality dimensions of the model by $\mathbf{P}_d \in \{O, C, E, A, N\}$[7] and mood state by $\mathbf{M}_s$, then the weight of the link between an appraisal variable and an emotion ($w_{v_i e_j}$) is a function of $\mathbf{P}_d$ and $\mathbf{M}_s$ as shown in equation 1.

$$\begin{aligned} w_{v_i e_j} &= \mathcal{W}(\mathbf{P}_d, \mathbf{M}_s) : \; i \in [1, n] \;\&\; j \in [1, m] \\ &= |f_{O_{ij}} * O + f_{C_{ij}} * C + f_{E_{ij}} * E + f_{A_{ij}} * A + \\ &\quad f_{Nij} * N + f_{M_{ij}} * M_s| \end{aligned} \tag{1}$$

In equation 1, the factors f_{ij} are the scaling factors for a particular personality dimension or mood state. This multiplication factor specifies the degree by which a personality dimension or mood state affects the weight of the link between i^{th} appraisal variable and j^{th} emotion. In our model, these multiplication factors have been learned by using a supervised machine learning algorithm called stochastic gradient descent (Bottou, 2010). Detail description of how the training data was collected and how the weights were determined is out of the scope of this paper. This paper mainly focuses on explaining the possibility of learning such a weighted relationship between appraisal variables and emotion intensities using machine learning approaches.

6. Six of the appraisal variables used in our model are adopted from OCC theory (Ortony et al., 1990) and one is adopted from the appraisal theory of Scherer (Scherer, 2001). Likewise, the emotions currently considered in our model are Joy, Distress, Appreciation, Reproach, Gratitude, Anger, Liking and Disliking (Ortony et al., 1990).
7. O, C, E, A and N denote the personality dimensions of Openness, Conscientiousness, Extraversion, Agreeableness and Neuroticism respectively, as described in Five Factor Model of personality (McCrae & John, 1992).

The weights associated with each appraisal-emotion pair, contributes in determining the degree by which the appraisal variable affects the intensity of the emotion. This implies that the effect of an appraisal variable on an emotion is the function of the quantitative value of the appraisal variable (v_i) and the weight of the association of the appraisal variable ($w_{v_i e_j}$) with the emotion (e_j).

$$\begin{aligned} \hat{i}_{e_{j_i}} &= \mathcal{I}_e(v_i, w_{v_i e_j}) : \; i \in [1, n] \;\&\; j \in [1, m] \\ &= v_i * w_{v_i e_j} \end{aligned} \tag{2}$$

$\hat{i}_{e_{j_i}}$ denotes the contribution of the i^{th} appraisal variable to the intensity of j^{th} emotion. If there are k appraisal variables related to an emotion, then, the final intensity of each emotion is determined by the cumulative effect of all the appraisal variables linked to the emotion, as shown in Figure 5.

$$\hat{i}_{e_j} = \sum_{i=1}^{k} \hat{i}_{e_{j_i}}, \forall\, j \in [1, m] \tag{3}$$

This process results in a set of emotions $\mathbf{E} = \{e_1, \ldots, e_m\}$ with respective intensities **I**=$\{\hat{i}_{e_1}, \ldots, \hat{i}_{e_m}\}$. Hence, the appraisal-emotion network presented in Figure 5 helps in the computation of the intensities of various emotions of the model. The equations 1, 2 and 3 support the relations R_{p-e} and R_{m-e} as shown in Figure 4 because these show how the mood and personality take part in the computation of the emotion intensities. Following sections shall explain how the relations R_{p-m} and R_{e-m} are captured in our model.

As previously mentioned, since personality factors do not change with time, the substantial effect of personality factors on mood (R_{p-m}) only occurs at the initialisation of the model i.e. initial mood state of our model is determined by the personality factors, which is functionally represented in equation 4

$$\begin{aligned} \mathbf{M}_s^{initial} &= \mathcal{M}^{initial}(\mathbf{P_d}) \\ &= \mathcal{M}^{initial}(O, C, E, A, N) \end{aligned} \tag{4}$$

In order to model the effect of emotion on mood i.e. the relation R_{e-m}, we provide the cumulative effect of newly computed emotion intensities that finally alter the mood of the model to a new mood state ($\mathbf{M}'_s$). This can be represented as shown in equation 5.

$$\begin{aligned} \mathbf{M}'_s &= \mathcal{M}(\mathbf{E}) \\ &= \mathbf{M}_s + \delta \end{aligned} \tag{5}$$

Equation 5 suggests that the new mood of the model is affected by current emotional state ($\mathbf{E}$) of the model. The factor δ denotes the aggregate value of various emotion intensities. The equation 5 represents the relation R_{e-m} because it shows the effect of emotion on mood. Now, this new mood state ($\mathbf{M}'_s$) will affect the process of emotion generation when next subsequent event occurs in the surrounding of the system. Suppose a new event triggers the appraisal component of the model which results in the computation of various appraisal variables, as described in the Background section. In the next emotional processing stage, both the mood and personality along with the values of appraisal variables determine the emotional state to be generated.

All the four relations R_{p-m}, R_{p-e}, R_{m-e} and R_{e-m} presented in Figure 4 are explained by the equations (1 – 5). Hence, this supports the claims of this paper that our computational model: (i) *explains how the mood and personality work together to impact the emotion processing mechanism* and (ii) *also adopts an approach in which mood and personality play a dynamic role in the process of mapping the cognitive appraisal to emotional state*.

8. Evaluation

In the previous section, we presented how the dynamic interaction of personality and mood with emotions can be computationally realised by offering functional level description of these processes in our emotion model – EEGS. In this section, we shall discuss how the difference of the personality and mood factors can cause a significant change in the emotion processing mechanism.

In order to examine the effect of personality factors on emotions, we simulated two scenarios. The first scenario was "Two Strangers in a Park" and the second scenario was "Husband and Wife" (see Appendix for the full description of the scenarios). In the first scenario, Rosy was simulated as the model and Bill as the interacting agent while in the second scenario, David was simulated as the model and Anna as the interacting agent. We wanted to investigate the variation in emotional response of EEGS for factors of *extraversion* and *neuroticism* because these factors are most widely studied in relation to positive and negative emotionality respectively. In order to test the effect of the personality factor *extraversion*, we set all other personality factors to be constant and changed the factor of extraversion from -1.0 to +1.0 (where -1.0 indicated very introverted person and +1.0 indicated very extroverted person). Figure 6 shows the variation in *joy* emotion dynamics of EEGS for the first scenario i.e. Two Strangers in a Park when the personality factor of *extraversion* for EEGS is changed. It is evident from the figure that the intensity of *joy* is the highest when the level of extraversion is set to be 1 and the intensity levels gradually decline as the value for extraversion is switched towards -1 (indicating introverted personality). Additionally, the slope of the curve is more steep for the case where there is high degree of extraversion suggesting that extroverts are more likely to be happy compared to introverts (Revelle & Scherer, 2009).

Similar phenomenon is also obtained for the scenario of interaction between husband and wife (Scenario 2). Figure 7 shows how the difference in the personality factor of *extraversion* causes difference in the level of *joy* intensity experienced by EEGS in Scenario 2. These findings suggest that the learned weights for the personality factors allow the model to operationalise the influence of various factors in an effective and plausible manner.

In addition to personality factors, we also wanted to investigate the emotion dynamics of EEGS by altering the initial mood. For this experiment, personality factors were not considered because they are likely to affect the mood state thereby obscuring the true interaction between mood and emotions. Figure 8 shows how an initial positive mood increases the tendency of EEGS to experience positive emotions (*joy* and *gratitude*) and decreases the tendency to experience negative emotions (*distress* and *anger*). While the emotions of *joy* and *gratitude* reach a saturation intensity of 1.0 in the course of interaction, the emotions of *distress* and *anger* remain below the threshold intensity i.e. 0.0. Interestingly, even with a negative action of 'decline invitation', the positive

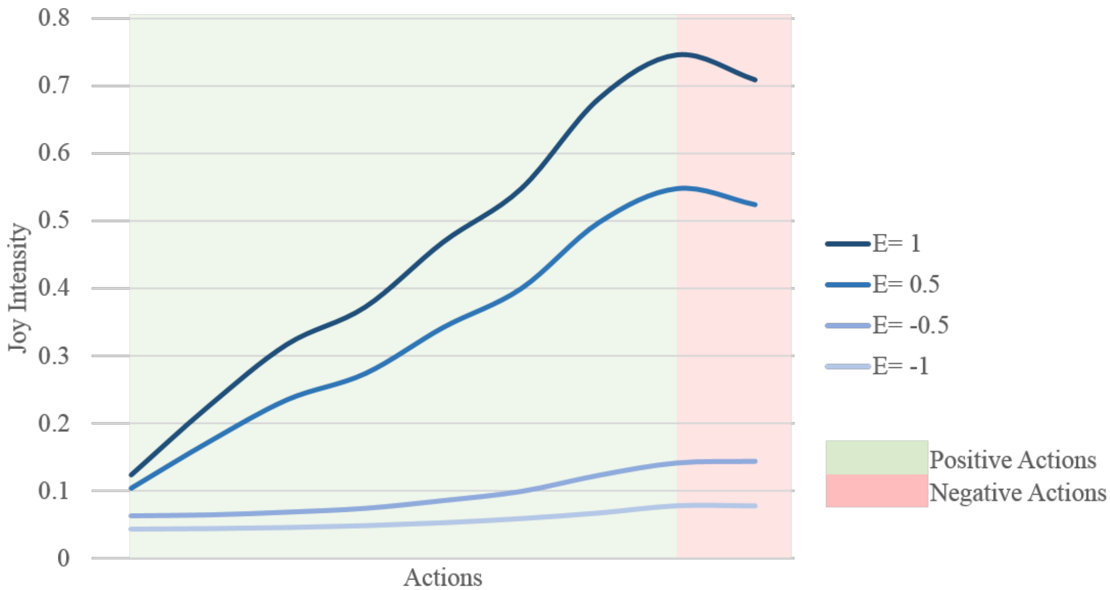

Figure 6. Difference in intensity of *joy* emotion in Scenario 1 (Two Strangers in a Park) when the personality factor of *extraversion*(E) is altered.

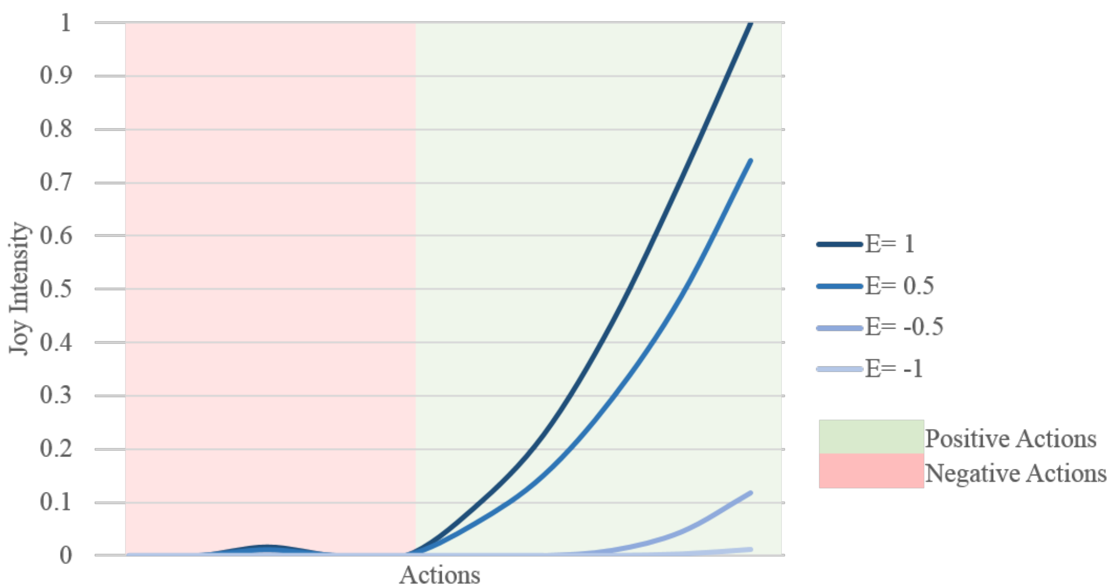

Figure 7. Difference in intensity of *joy* emotion in Scenario 2 (Husband and Wife) when the personality factor of *extraversion*(E) is altered.

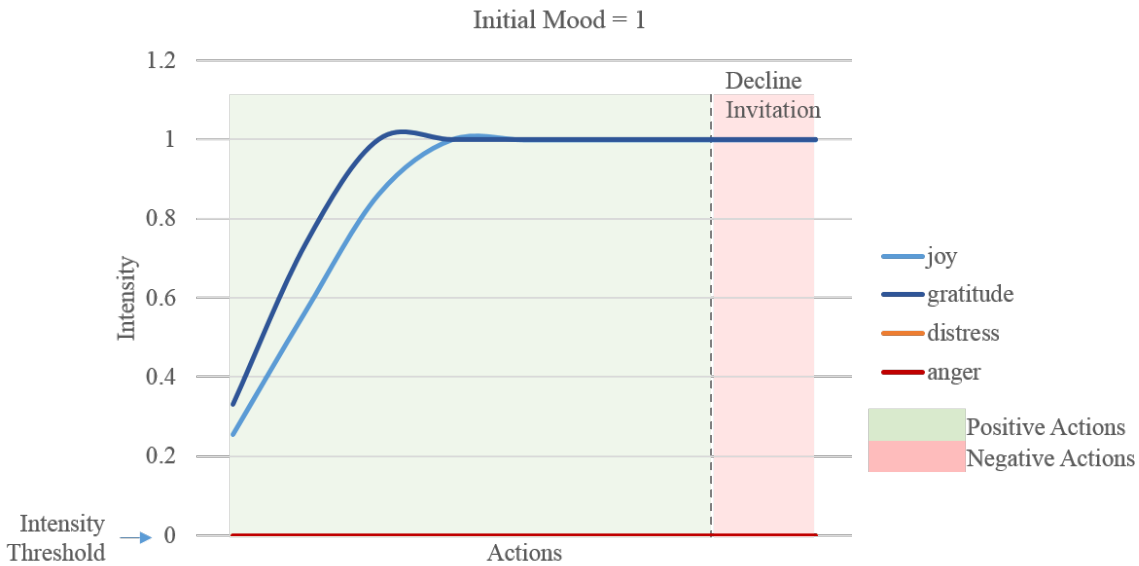

Figure 8. Emotion dynamics of EEGS when initial mood is very positive in Scenario 1 (Two Strangers in a Park).

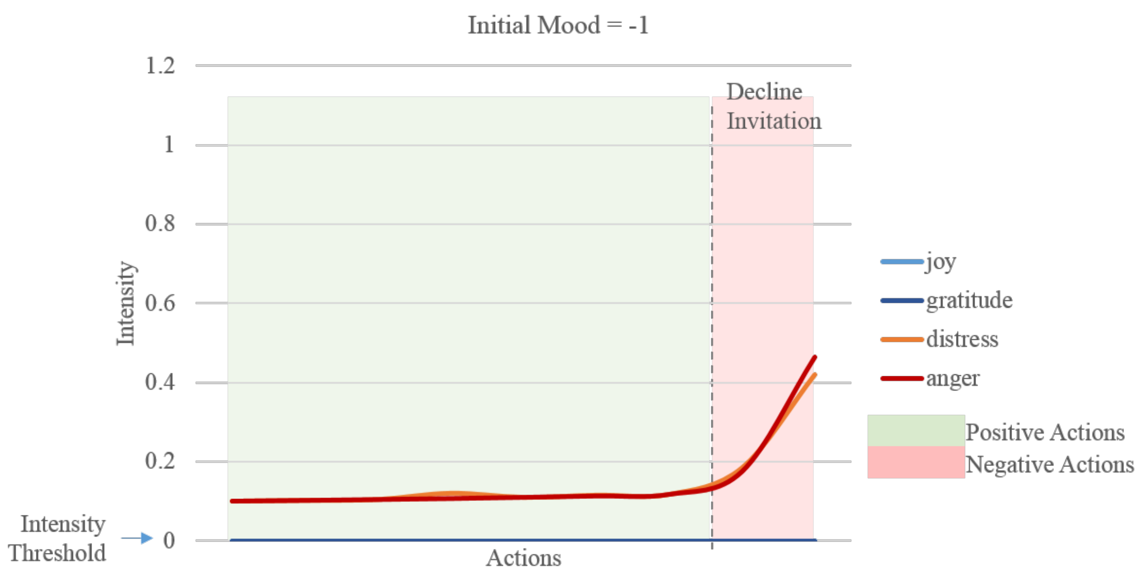

Figure 9. Emotion dynamics of EEGS when initial mood is very negative in Scenario 1 (Two Strangers in a Park).

emotions do not drop significantly because of cumulative bias caused by positive initial mood and positive emotional experience in the course of interaction.

However, an opposite phenomenon is observed if the initial mood is set to be very negative i.e -1. Figure 9 shows how the initial mood of -1 prevents the emotions of *joy* and *gratitude* from rising above the threshold level for same scenario and same set of actions. Additionally, as opposed to Figure 8, the emotions of *distress* and *anger* remain active throughout the interaction and begin to rise sharply after the 'decline invitation' action. These findings support the fact that EEGS is capable of effectively integrating the aspects of personality and mood in the determination of its emotion dynamics.

9. Conclusion and Implications

According to psychology literature, mood and personality are two important factors that influence the process of emotion generation. This is a reason why people with particular personality traits tend to show pre-disposition to particular emotional tendencies and a person in a particular mood tend to show resistance to the non-congruent emotions. As such, an intelligent agent should account for these phenomena to be able to demonstrate a plausible emotional interaction with the human counterparts. In this paper, we presented our computational model of emotion that operationalises an interaction between emotion, mood and personality. We also demonstrated how our weighted appraisal-emotion network can be learned based on the factors of personality and mood thereby allowing these aspects to dynamically influence the process of mapping appraisals into emotion intensities. Experimental results show that the learned network is able to efficiently operationalise the effect of personality and mood in emotion generation process. Such a characteristic of an agent can have numerous implications. One application is in the development of customised agents for people of particular preferences and/or needs. For example, an intelligent agent intended to be employed as a personal development assistant is desirable to have an organised and systematic characteristic. As such the agent might have to express disappointment or similar emotions if the person under training ignores some routine activity. However, if the agent is to be deployed as an emotional support companion, then it is preferred to forgive such a minor ignorance – hence it is desirable to have an easy going nature.

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Appendix

Scenario 1: Two Strangers in a Park

It is 1 PM of the last day of the year and New Year is about to come. Rosy is sitting on a bench in a park, while Bill sits on the same bench of Rosy. Bill and Rosy do not know each other. Rosy is an easy-going girl and she is currently in a neutral emotional state. Bill greets Rosy by saying "Hi" and also wishes Happy New Year. Rosy smiles and wishes him back the same. Bill also smiles with Rosy. Bill offers some chocolates he was eating to Rosy. Rose accepts the offer and eats a chocolate. Bill starts conversation with Rosy. While talking, the conversation goes on the plans for New Year's Eve. Bill shows interest by asking Rosy about are her plans for New Year's Eve. Rosy answers that she will have a party at home with a lot of friends. Bill appreciates about Rosy's plan for the eve. Rosy asks to Bill if he would like to join her in the party. Bill declines the offer saying he has already a plan with his girlfriend. Rosy thinks Bill is just making up an excuse to not hang out with her and starts to ignore Bill. Bill reciprocates by ignoring Rosy. They part their ways shortly.

Scenario 2: Husband and Wife

David and Anna are husband and wife. Today is Anna's birthday. David has not yet wished her birthday. He comes back home from work in the evening. David doesn't yet know that today is Anna's birthday. David is in neutral mood while Anna is a bit upset. David says hello to Anna. Anna ignores David. David tries to start a conversation. Anna ignores David. Anna complains David about forgetting her birthday. David realises that he forgot the birthday. Anna comments about David's bad memory. Anna scolds David. David wants to make up for his error. He says he will cook a special dinner for Anna. Anna smiles with David. David prepares the dinner and then they both start to eat. Anna appreciates David for cooking dinner. Anna forgives David. Anna hugs David. Anna kisses David.