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Emotional Appraisal : A Computational Perspective

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Abstract

Research on computational modelling of emotions has received significant attention in the last few decades. As such, several computational models of emotions have been proposed which have provided an unprecedented insight into the implications of the emotion theories emerging from cognitive psychology studies. Yet the existing computational models of emotion have distinct limitations namely:(i) *low replicability* - difficult to implement the given computational model by reading the description of the model, (ii) *domain dependence* - model only applicable in one or more predefined scenarios or domains, (iii) *low scalability and integrability* - difficult to use the system in larger or different domains and difficult to integrate the model in wide range of other intelligent systems. In this paper, we propose a completely domain-independent mathematical representation for computational modelling of emotion that provides better replicability and integrability. The implementation of our model is inspired by *appraisal theory* - an emotion theory which assumes that emotions result from the cognitive evaluation of a situation.

1. Introduction

Appraisal theory is the emotion theory in psychology that relates the process of emotion generation in humans to the cognitive aspects of brain (Lazarus, 1991; Ortony et al., 1990; Roseman, 1996; Scherer, 2001). According to the theory, generation of emotion in an individual is determined by the way the emotion inducing situation is appraised(evaluated) by the individual. This evaluation is achieved through measurement criteria called *appraisal variables*. Appraisal theory posits that whenever an emotion-inducing event occurs, an individual does an assessment of the situation based on these appraisal variables, which are then used for the generation of emotion. For example, the appraisal variable *desirability* measures whether an event is desirable or not, *praiseworthiness* determines if the action of the agent is praiseworthy or not and the variable *appealingness* determines whether the agent interacting with the system is appealing or not. We shall discuss more about the computation of appraisal variables in section 3.4.

Although, appraisal theories have been understood as being able to provide a theoretical foundation for achieving domain independence in computational modelling of emotions (Gratch et al., 2015), most existing computational emotion models based on appraisal theory have implemented rule-based domain specific designs (Aylett et al., 2005; Dias & Paiva, 2005; El-Nasr et al., 2000; Velasquez, 1997) to achieve cognitive appraisal for the generation of emotion. This is a significant problem because using domain specific pre-defined rules makes it difficult to reuse the model in other domains. We aim to resolve this issue through our research, which shall be discussed in detail in the following sections.

Moreover, most of the existing computational emotion models do not offer a clear explanation of their implementation details (Dias et al., 2014; Marsella & Gratch, 2009; Velasquez, 1997). This seriously limits the further study of their model and does not promote further experimental analysis. This might be one of the reasons the research on computational modelling of emotions is not advancing as compared to other cognitive studies. We believe that a better computational approach whose implementation details are well documented can help in the advancement of the emotion modelling research. Although some researchers have contributed a certain level of transparency regarding their implementation (Gratch & Marsella, 2004b), most existing emotion models are not replicable. In this paper, we present a detailed mathematical explanation of the computation mechanism in our computational model of emotion named EEGS – shorthand for "Ethical Emotion Generation System" (Ojha & Williams, 2016).

Similarly, most existing accounts of computational emotion models are not able to adapt if the scope of the domain changes or if the model needs to do emotional appraisal in different domain (Aylett et al., 2005; Dias & Paiva, 2005; El-Nasr et al., 2000; Velasquez, 1997). For example, if a model is designed for a particular scenario using pre-defined rules, then the model will not function properly if new events are introduced in the same scenario or new actors are incorporated (i.e. scope changes). Also, if a model designed for one scenario is to be used for a completely new scenario with different set of events and actors (i.e. domain changes), then the whole implementation of the computation mechanism needs to be changed. In other words, if the domain changes, implementation also needs to be changed. It might be difficult, even impossible in some cases, to change the existing implementation. These limitations make it difficult to integrate such emotion models in wide range of intelligent systems because they would require a separate interfacing mechanism for each system. Because of hard-coded implementations using domain-specific rules, many models can neither be used in domains other than those are designed for, nor be integrated into other systems easily.

In this paper, we aim to offer the following improvements in computational emotion modelling research through the presentation of our novel model:

- ***Replicability*** - The mechanism of computation of appraisal variables in EEGS will be accompanied by concrete mathematical formulations. This will allow the reproduction of EEGS's appraisal mechanism as computer code.
- ***Domain Independence*** - EEGS does not use pre-defined domain-specific appraisal rules thereby making the rules applicable across various domains.
- ***Scalability and Integrability*** - EEGS can function effectively even if the scope of application changes or even the domain changes without the need of changing the implementation details of the model. Also, it can be easily integrated with other systems.

The discussion in this paper will be more inclined to the mechanism of computation of appraisal variables in EEGS. The computation mechanism of EEGS will be explored in relation to the above mentioned characteristics because we believe that these are the basic properties that a computational emotion model should have in order to help in furthering the research of cognitive appraisal process

Table 1. Comparison of Computational Models

	Replicable	Domain Independent	Scalable and Integrable
FAtiMA	✓	✗	✗
EMA	✗	✓	✓
FLAME	✓	✗	✗
Cathexis	✗	✗	✗
EEGS	✓	✓	✓

of emotion. It is important to make an emotion model replicable, domain-independent, and scalable and integrable in order to allow the model to be used in general purpose cognitive systems. We anticipate that the presentation of our work will help the advancement in that direction.

2. Related Work

In the previous section, we had a brief discussion on the problems in the existing computational models of emotion and how our work can be a useful step in addressing those gaps and aiding in the advancement of computational emotion research. In this section, we compare some of the most cited computational models of emotion, which are based on appraisal theory, with our model - EEGS.

For the comparison of the models, we have considered the properties that we identified in the the Introduction section. Table 1 lists the candidate computational models of emoiton indicating whether the given model satisfies a specific property or not (✓ indicating that the model satisfies the property while ✗ indicating that the model does not satisfy the property). The computational emotion model Fearnot AffecTIve Mind Architecture (FAtiMA) proposed by Dias & Paiva (2005) is replicable to some extent since the researchers have released the implementation detail of different scenarios in their model as public repository[1]. But, FAtiMA is not domain independent since it uses pre-defined scenario-specific rules for the computation of appraisal variables. This property makes it difficult for the model to be applied in other domains and also tedious to be integrated into other intelligent systems like cognitive architectures. Another computational model of emotion based on appraisal theory – EMotion and Adaptation (EMA) (Gratch & Marsella, 2004a; Marsella & Gratch, 2009) is somewhat domain independent since it uses the concept of utility for determining the goals which in turn influence the computation of appraisal variables. This allows the model to be scalable and integrable to some extent. Yet, it might not be possible to replicate the model in order to understand its functionality because of limited technical details of the model in the published works. While Fuzzy Logic Adaptive Model of Emotions (FLAME) (El-Nasr et al., 2000) is relatively replicable compared to EMA, it computes the appraisal based on rules that rely on the implementation domain thereby limiting its scalability and integrability in other systems. Computational model Cathexis (Velasquez, 1997) does not satisfy any of the properties listed in Table 1.

In this paper, we shall present our computational model of emotion (EEGS) that can be easily implemented as a computer program (replicable). The computation mechanism in our model does

1. The source code of FAtiMA and implementation details can be obtained from the following link: `https://sourceforge.net/projects/fatima-modular/`.

not need to be changed when the interaction domain changes (domain independent) thereby making it usable in different domains and incorporated into other systems (scalable and integrable) like virtual conversational agents, software agents, social robots, and many more. This shall be discussed in more detail in section 3.

3. Proposed Computational Model

In the previous sections, we identified common limitations in the published work in computational emotion models. We identified that most of the existing computational models based on appraisal theory are not either: (i) replicable, (ii) domain-independent or (iii) scalable and integrable. This makes it difficult for computational emotion researchers to have their own implementations of the model or to extend the model for further experiments. In this section, we shall discuss how we have been able to develop a computational model of emotion that is replicable, domain-independent, and scalable and integrable. Let us start the with the understanding of the structural components of the model.

3.1 Emotion

EEGS is currently able to generate and express eight types of emotions which are the subset of emotion types in the appraisal theory of Ortony et al. (1990) commonly called *OCC theory*. Based on the available literature, emotion in EEGS is structured as:

```
(<Name>,<Valence>,<Degree>,<Threshold>,<Intensity>,<Decay Time>)
```

Where, the identifier Name represents the name of the emotion (i.e. joy, distress, etc.), Valence represents the sign of the emotions (i.e. Positive or Negative), Degree[2] represents the level of positivity or negativity of the emotion, Threshold indicates the minimum intensity required for the emotion to be triggered, Intensity represents the level of arousal of a particular emotion and Decay Time is the total time taken by the emotion to reach a state of 0.0 intensity. For example, emotion structure `("JOY", "POSITIVE", 1.0, 0.0, 0.7, 10)` indicates a "JOY" emotion having "POSITIVE" valence and degree of 1.0 with threshold of 0.0, intensity of 0.7 that can decay completely in 10 seconds. In the above representation, Valence can be "POSITIVE" or "NEGATIVE". Degree ranges from -1 to +1, -1 meaning the very negative emotion and +1 denoting very positive emotion. The range of [-1, 1] for Degree is just a design choice. It can alternatively be represented as [-10, 10] or [-100, 100] without affecting the functioning of the model. Intensity ranges from 0 to 1, where 0 is the very low intensity and 1 is very high intensity. The difference between Degree and Intensity in our notion of emotion is that Degree is the measure of positivity or negativity and Intensity shows how strongly that positivity or negativity is experienced. Decay time can be any positive value unless it is too large[3].

2. We have derived the degrees (the level of positivity or negativity) of various emotions with the help of multiple emotion data sets presented by Remington et al. (2000).
3. It is well accepted in literature that emotions are short lived. Hence a decay time of several hours may not be appropriate for an emotion.

Table 2. An example of a set of Objects in Memory

Name	Familiarity	Perception
PAUL	0.5	-0.4
JOHN	1.0	0.0
ROBERT	0.0	1.0
JESSICA	0.3	0.6
ALEX	0.1	-0.9

3.2 Object

An object can be understood as something tangible that an individual can perceive. For example, person, car, dog, etc. can be considered as objects. In EEGS, an object is structured in the form:

```
(<Name>, <Familiarity>, <Perception>)
```

Name denotes the name of the object (proper noun or common noun), Familiarity is a numerical representation showing how familiar is the model to the object in interaction and Perception denotes how positive or negative is the model towards the object. This structure of an object can be easily modified by adding more dimensions as per the requirement without affecting other components of the model. In the remaining of the paper, we will discuss the implementation of our model considering this object as a person. However, it should be noted that the model is able to perform appraisal and generate emotions for any other object. Familiarity can range from 0.0 to 1.0, where 1.0 denotes complete stranger and 0.0 denotes a very familiar person. This choice was made with an analogy that close person would not be far in distance, hence the number '0' for more familiar person. Perception can range from -1.0 to +1.0, where -1.0 denotes very negative perception and +1.0 denotes very positive perception. For example, `("PAUL", 0.5, -0.4)`, denotes a person named PAUL who is somewhat familiar to the model and model has a negative (-0.4) perception about him. We do not want to argue that our notion of person is a complete structure that can represent all the information about a person that might be relevant to the elicitation of emotions. Our notion of person/object can be improved by introducing other aspects like "Relationship" which denotes the type of relationship between the model and the person interacting with the model.

Table 2 shows an example of reduced list of persons in the memory of EEGS. The person in the first row is named "PAUL" about whom the model has a familiarity of 0.5 and perception of -0.4 towards the person. Initially, when a person is first introduced with the model, the person is considered stranger (i.e. familiarity = 1.0) and the model has a neutral perception (i.e. perception = 0.0) about the person. This design choice was made not to bias the model when a new person is introduced. The perception and familiarity about object changes in the course of interaction. This change is the result of continuous interaction of the object (person) with the model thereby affecting the goals, standards and attitudes of the system, which shall be detailed in the following sections.

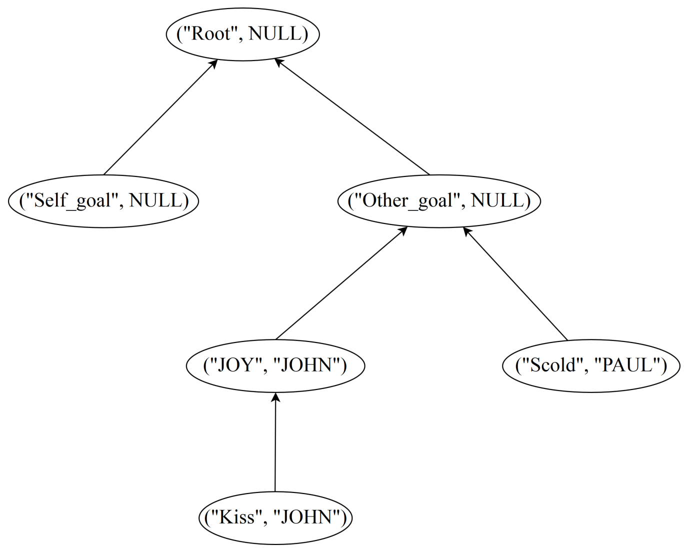

Figure 1. An example of a Goal Tree.

3.3 Goals, Standards and Attitudes

Computation of appraisal variables (variables used for the evaluation 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 as suggested by OCC theory. Although OCC theory describes the relationship of the goals, standards and attitudes to different variables, it does not provide explicit mathematical relation to compute the values of appraisal variables. In the following sections, we present a mathematical relationship of the goals, standards and attitudes to the computation of appraisal variables. Before we proceed to our mathematical formulation, we need to understand the representation of goals, standards and attitudes.

3.3.1 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.

Fig. 1 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)`

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.

Table 3. 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

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").

3.3.2 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 3.

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 as many recognised persons, as many recognised actions and many possible emotions. An individual's standards should account for all of those aspects. The list of standards in Table 3 is not exhaustive, it only shows a few representative examples for the understanding of how the standards are structured in our com-

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.

putational 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.

3.3.3 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.

3.4 Calculation of Appraisal Variables

As previously mentioned, emotions are the result of appraisal of a particular situation or event happening in an individual's surrounding. So far we have understood that whenever an event occurs, an individual does the evaluation of the situation using several appraisal variables and resulting values of the various appraisal variables cause the elicitation of various emotions. Please note that the numeric value of most appraisal variables in EEGS range from the value of -1.0 to +1.0, which is only a design choice and we believe other alternatives should be equally effective. The value of +1.0 for appraisal variable "desirability" indicates that a particular event is extremely desirable while the value of -1.0 indicates that the event is extremely undesirable. In the following sections, we shall discuss in detail how the numerical values of various appraisal variables are calculated in our computational model and also demonstrate how these computation promote the replicability, domain-independence, and scalability and integrability of our model.

3.4.1 Desirability

Desirability is the measure of how desirable a particular situation or event is. In order to evaluate the desirability of an event, it is compared to the goals of the individual (Ortony et al., 1990). If the event is likely to help in achieving goals, then the event is said to be desirable. However, if the event is likely to hinder the accomplishment of the goals, then the event is said to be undesirable. The degree of desirability or undesirability depends on the degree the event helps or hinders the achievement of the goals. An event may not be related to all the goals in the current goal tree (see section 3.3.1 for the detailed structure of goals and goal tree). Desirability of an event in EEGS is computed based on the overall effect of the event in the accomplishment of each goal in the goal tree depending on whether the event is relevant to the goal or not. Before calculating the OCC appraisal variable desirability, we compute a value called *Goal Conduciveness*[6] which calculates the degree

6. The appraisal variable Goal Conduciveness is adapted from Scherer's theory of appraisal(Scherer, 2001).

to which the event helps or hinders the achievement of a particular goal node that is related to the event. When the conduciveness of each goal is calculated, then the numerical value of desirability is computed as the average conduciveness of all the goals in the goal tree.

Suppose there are N goal nodes in the goal tree. If we denote the degree of the action[7]/emotion defined in the i^{th} goal node as $d_{g_i} \in$ [-1, 1]; the degree of the action in the recent event that is relevant to the i^{th} goal node as $d_{e_i} \in$ [-1, 1]; height of the i^{th} goal node from root node in the goal tree as h_i, then conduciveness of i^{th} goal in the goal tree is given by (1).

$$GC_i = \begin{cases} 1 - \frac{||d_{g_i}|-|d_{e_i}||}{h_i} & \text{if } sign(d_{g_i}) = sign(d_{e_i}), \\ & \text{or } d_{g_i} = d_{e_i} = 0 \\ \frac{||d_{g_i}|-|d_{e_i}||}{h_i} - 1 & \text{if } sign(d_{g_i}) \neq sign(d_{e_i}) \\ -\frac{|d_{e_i}|}{h_i} & \text{if } d_{g_i} = 0 \text{ \& } d_{e_i} \neq 0 \\ -\frac{|d_{g_i}|}{h_i} & \text{if } d_{g_i} \neq 0 \text{ \& } d_{e_i} = 0 \end{cases} \tag{1}$$

Where, GC_i is the conduciveness of the i^{th} goal in the goal tree. $sign(d_{g_i})$ represents the sign (positive or negative) of d_{g_i} and $sign(d_{e_i})$ represents the sign of d_{e_i}.

The formula in (1) gives a numeric value between -1 and 1 which indicates the degree by which the event helps in attaining the i^{th} goal in the goal tree. A positive value of GC_i indicates that the event helps in achieving the i^{th} goal while a negative value indicates that the event hinders the accomplishment of the goal. Goal conduciveness basically computes the signed deviation of the event from the goal. The reason of dividing the quantity by the height of the node from the root is the assumption that if a goal node is closer to the root, its achievement will have more effect on the desirability than a goal node which is farther from the root node. When the conduciveness of each goal in the goal tree is computed, the value of desirability is computed as the average goal conduciveness.

$$D = \frac{\sum_{i=1}^{N} GC_i}{N} \tag{2}$$

Where, D is the desirability of the event. GC_i is the conduciveness of the i^{th} goal. N is the total number of goal nodes in the goal tree.

The formula for the computation of desirability in (1) and (2) can be easily represented as a computer code which makes our approach easily replicable. Moreover, the calculation depends on the values of degree of the action/emotion in the goal node (d_{g_i}), degree of the action in the event (d_{e_i}) and height of the goal node from the root node (h_i). The signed numeric value of d_{e_i} is the input received by the cognitive appraisal component when an event occurs. This phenomenon is similar to what Lambie & Marcel (2002) consider as the first order (lower level) non-cognitive evaluation of an emotion inducing situation. The signed numeric value of d_{g_i} in a goal node can

7. In our computational model, an action like *slapping* is considered to have negative degree and an action like *appreciating* is considered to have positive degree. The numeric value of degree of an action depends on how positive or negative the action is. This input value can be considered as the result of first order non-cognitive appraisal process in line with the arguments of Lambie & Marcel (2002)

be considered as the *expected utility* of the achievement of the goal. When the application domain changes, the values of d_{g_i} and/or d_{e_i} might change. Yet, since our computation does not care about the actual parameters of the domain but relies only on the numeric representation, our computation of desirability can be applied in any domain. This helps in increasing the scalability and integrability of our model into other systems without changing the computation mechanism.

3.4.2 Praiseworthiness

While the appraisal variable desirability is calculated based on goals (as in section 3.4.1), the variable praiseworthiness is computed based on the standards of the model. An action is considered praiseworthy if it matches closely with the standards of the computational model and blameworthy (negative value of the variable praiseworthiness) if it deviates from the standard(s). Praiseworthiness compares the degree of an action performed by an agent with the approval degree of that particular action from the given source to the target in the standards of the computational model (see Table 3 for an idea on how an standard is denoted). If we denote the degree of the action in the event as $d_e \in$ [-1, 1]; the approval degree for the action in a given standard as $d_a \in$ (0, 1], then, praiseworthiness is computed using the formula in (3).

$$P = \begin{cases} \text{for } d_e < 0; & \begin{cases} -(d_e * d_a) & \text{if } pref = YES \\ d_e * d_a & \text{if } pref = NO \end{cases} \\ \text{for } d_e > 0; & \begin{cases} d_e * d_a & \text{if } pref = YES \\ -(d_e * d_a) & \text{if } pref = NO \end{cases} \\ \text{for } d_e = 0; & \begin{cases} d_a & \text{if } pref = YES \\ -d_a & \text{if } pref = NO \end{cases} \end{cases} \tag{3}$$

Where, P is the praiseworthiness of an action of a person. $pref$ is the preference of the action in the standard. $pref$ can be "YES" if the action is preferred and "NO" if the action is not preferred.

Similar to the appraisal variable desirability, the computation of praiseworthiness in our model can be easily converted to a computer code hence making it completely replicable. Likewise, as previously mentioned, the degree of an action d_e is the signed numeric representation of the lower level non-cognitive evaluation. Approval degree d_a, which comes from standards, is the numeric value that changes dynamically in the course of interaction. This allows the computation of praiseworthiness to be independent of the interaction domain thereby helping in the scalability and integrability of the emotion system.

3.4.3 Appealingness

The appraisal variable appealingness measures how appealing (likeable) is the person/object to the appraising individual. In EEGS, appealingness is determined based on the perception of the model about the person interacting with it. A person who has done nice things in the past might be appealing while a person who has done bad things might not be. Our computational model adopts similar assumption for calculating the appealingness of a person/object.

$$A = Object.Perception \tag{4}$$

Where, A is the appealingness of a person/object. $Object.Perception \in$ [-1, 1] is the numeric value of perception about the person the model has in its memory.

As previously mentioned, the model starts with a neutral perception (i.e. 0.0) about a person indicating neither appealing nor unappealing. This perception changes dynamically during interaction depending on the actions of the person (positive or negative) without the need of pre-defined rules to update the perception value. This makes the computation of appealingness replicable, domain-independent, and scalable and integrable. Currently, we have used a very simplified notion for the computation of appealingness. Further research may be able to improve the formula to include other aspects of appealingness. We are open to suggestions for improvements of our computational approach.

EEGS is able to compute seven appraisal variables namely goal conduciveness, desirability, praiseworthiness, appealingness, deservingness, familiarity and unexpectedness. This paper presents the computation of only first four appraisal variables of which desirability, praiseworthiness and appealingness are the core appraisal variables as described in OCC theory. The detailed computation of other appraisal variables is not presented in this paper because these explanations are enough to demonstrate the three previously identified properties of a computational model of emotion i.e. replicability, domain-independence, and scalability and integrability. Following section presents the detailed evaluation of the presented appraisal mechanism in our computational model of emotion – EEGS.

4. Evaluation

As previously mentioned, since this paper mainly aims to present the details of computation of appraisal variables in EEGS, we shall incline our evaluation methodology more to these variables rather than the final emotional state of the model.

4.1 Validity of Replicability

By saying replicability, we meant that the mechanism of computation of appraisal variables in EEGS can easily be converted to a program code. Since, all the formulae and parameters needed to compute the variables is presented in detail in our paper, we can assert that the appraisal mechanism in EEGS is replicable for research purposes by anyone who has some programming knowledge.

4.2 Validity of Domain-Independence

Domain-independence is a property of a computational model of emotion in which same computation mechanism can be applied to several domain without making changes to the system. In order to test the ability of EEGS to operate in domain-independent fashion, we ran it in two completely different scenarios[8]. Naive adults were requested to design scenarios of interaction between two individuals such that the action of one person is likely to induce emotional response on another

8. For more details on how scenarios were designed, please refer to our companion paper in press(Ojha et al., 2017).

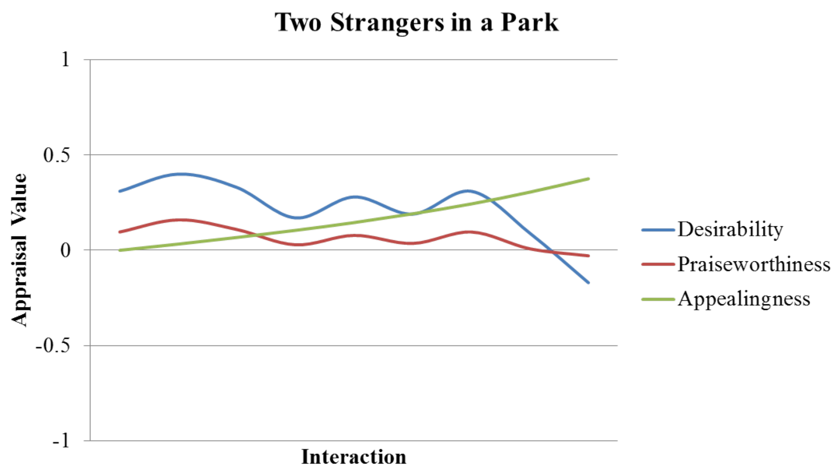

Figure 2. Appraisal Dynamics of Rosy (EEGS) in Response to the Actions of Bill.

person. The methodology used for designing the scenarios can be found in our companion paper to be published (Ojha et al., 2017). Two of the scenarios were simulated in EEGS for evaluating the claims of this paper, which are described below.

4.2.1 Scenario 1: Two Strangers in a Park

The first scenario considered for the experiment included an interaction between two strangers in a park, which reads as below.

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.

The scenario described above was simulated in EEGS where a user acted as Bill and EEGS system was treated as Rosy. Core emotion-triggering actions from Bill to Rosy were extracted and assigned a numeric score in the range [-1,+1] to denote the degree of positivity and negativity of the action performed by Bill (user) in the given context. The numeric scores for degrees of actions were obtained by conducting an anonymous online survey, which is explained in our companion paper in

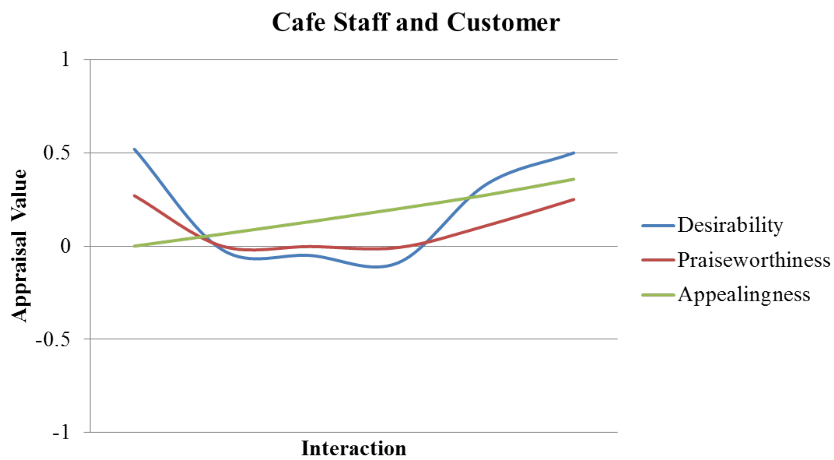

Figure 3. Appraisal Dynamics of Gopal (EEGS) in Response to the Actions of Hari.

press (Ojha et al., 2017). EEGS (Rosy) was able to appraise the actions of Bill towards herself by computing the appraisal variables based on the context. Appraisal dynamics of Rosy in response to the actions of Bill is shown in Figure 2.

4.2.2 Scenario 2: Cafe Staff and Customer

In order to validate the ability of EEGS to compute appraisal variables independent of the domain, we simulated scenario of a completely different domain from scenario 1 i.e. an interaction between cafe staff and a customer. The scenario reads as below.

Gopal is a cafe staff. It is a very busy Monday afternoon. Yet, Gopal is in neutral mood. A customer (Hari) comes to the cafe and orders food. Order takes very long to be served. Finally, the food arrives. Hari thanks Gopal for serving the food. Hari complains Gopal about the late service. Gopal apologizes for being late. While trying to eat, Hari finds out that the food served is not as per the order. Hari complains Gopal about the wrong order. Gopal sympathizes with Hari and promises to replace the food, but for Hari it is not enough. Hari asks Gopal for a refund. Gopal offers complimentary item with main order and promises to serve it quickly. Hari agrees with Gopal's offer. Order arrives quite quickly. Hari appreciates Gopal for quick service.

Above scenario was simulated in EGGS similarly as the previous one. EEGS was attributed as Gopal (cafe staff) and a user was asked to act as Hari (customer). Actions of Hari were extracted to create emotion-inducing events and appraisal dynamics of Gopal (EEGS) was recorded. Figure 3 shows the appraisal dynamics of Gopal (EEGS).

Simulating the above mentioned scenarios allowed us to test the ability of EEGS to perform emotional appraisal independent of the application domain. EEGS was able to compute appraisal variables in both the scenarios without the need of changing any parameter in the formulae. Simply adjusting the input values (i.e. actions) to the systems was enough for the system to perform cognitive appraisal of the given situation of interaction.

4.3 Validity of Scalability and Integrability

In previous section, we demonstrated how appraisal mechanism in EEGS is domain-independent and able to compute appraisal variables in any domain. Because of the same property, even if the domain of application extends i.e. new events need to be introduced in the scenario, EEGS is able to perform cognitive appraisal of the situation. This provides EEGS with the flexibility to be integrated into various cognitive systems that use emotions for decision making. Since EEGS can take a signed number between -1 and +1 as a representation of an action/event and provides an emotion with respective intensity as an output[9] any cognitive system that needs emotion in decision making can make use of EEGS.

5. Discussion

The above three validations support our claim that appraisal mechanism in EEGS allows our model to be replicable, domain-independent as well as scalable and integrable. Moreover, we conducted an experiment to examine the precision of emotion generation mechanism in EEGS which is to appear in our companion paper (Ojha et al., 2017). Results indicated that our appraisal mechanism is around 70% accurate in generating emotions as a human would in the similar situation. As per our knowledge, we are the first in the filed to make a direct comparison of the emotions generated by a computational model of emotion with data collected from humans. Achieving an accuracy in the range of 70% is a significant achievement in computational emotion modelling research. The appraisal mechanism presented in this paper can be very useful not only for computational emotion modelling researchers but also for cognitive systems researchers who study the effect of emotion on cognition or use emotion in decision systems.

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References

Aylett, R. S., Louchart, S., Dias, J., Paiva, A., & Vala, M. (2005). Fearnot! - an experiment in emergent narrative. *International Workshop on Intelligent Virtual Agents* (pp. 305–316). Springer.

Dias, J., Mascarenhas, S., & Paiva, A. (2014). Fatima modular: Towards an agent architecture with a generic appraisal framework. In *Emotion modeling*, 44–56. Springer.

9. After the computation of all appraisal variables, these variables are mapped into emotion intensities and an emotion convergence mechanism is applied to reach to a final emotional state.

Dias, J., & Paiva, A. (2005). Feeling and reasoning: A computational model for emotional characters. In *Progress in artificial intelligence*, 127–140. Springer.

El-Nasr, M. S., Yen, J., & Ioerger, T. R. (2000). Flame - fuzzy logic adaptive model of emotions. *Autonomous Agents and Multi-agent systems*, *3*, 219–257.

Gratch, J., Cheng, L., & Marsella, S. (2015). The appraisal equivalence hypothesis: Verifying the domain-independence of a computational model of emotion dynamics. *International Conference on Affective Computing and Intelligent Interaction (ACII)* (pp. 105–111). IEEE.

Gratch, J., & Marsella, S. (2004a). A domain-independent framework for modeling emotion. *Cognitive Systems Research*, *5*, 269–306.

Gratch, J., & Marsella, S. (2004b). *Technical details of a domain-independent framework for modeling emotion*. Technical report, DTIC Document.

Lambie, J. A., & Marcel, A. J. (2002). Consciousness and the varieties of emotion experience: a theoretical framework. *Psychological review*, *109*, 219.

Lazarus, R. (1991). Emotion and adaptation.

Marsella, S. C., & Gratch, J. (2009). Ema: A process model of appraisal dynamics. *Cognitive Systems Research*, *10*, 70–90.

Ojha, S., Vitale, J., & Williams, M.-A. (2017). A domain-independent approach of cognitive appraisal augmented by higher cognitive layer of ethical reasoning. *Annual Meeting of the Cognitive Science Society*.

Ojha, S., & Williams, M.-A. (2016). Ethically-guided emotional responses for social robots: Should i be angry? *International Conference on Social Robotics* (pp. 233–242). Springer.

Ortony, A., Clore, G. L., & Collins, A. (1990). *The cognitive structure of emotions*. Cambridge University Press.

Remington, N. A., Fabrigar, L. R., & Visser, P. S. (2000). Reexamining the circumplex model of affect. *Journal of personality and social psychology*, *79*, 286.

Roseman, I. J. (1996). Appraisal determinants of emotions: Constructing a more accurate and comprehensive theory. *Cognition & Emotion*, *10*, 241–278.

Scherer, K. R. (2001). Appraisal considered as a process of multilevel sequential checking. *Appraisal processes in emotion: Theory, methods, research*, *92*, 120.

Velasquez, J. D. (1997). Modeling emotions and other motivations in synthetic agents. *AAAI/IAAI* (pp. 10–15).