Incorporating Emotional Information in Decision Systems

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Abstract – The media equation [22] states that users react to systems as they would to another person, while continuously emitting social signals. Today's users expect systems to be empathetic and understand these social signals. Decision systems are a specific sub-branch, facing the need to incorporate affective information, to facilitate users to maximize their cognitive resources. To this end, we attempt to incorporate affective information in the form of physiology to learn users' decision behavior. In a controlled experiment, we record participants' decisions and measure physiological signals elicited from subjects. To predict the binary decision to buy or sell, three algorithms, multi-layer perceptron, radial basis function, and decision trees, are compared, and they yield recognition rates of 76%, 73% and 77.2% respectively. Taking these results, we propose that a decision tree with feature-level fusion, factors in affective information in this controlled context best. These results however have to be extrapolated to decision contexts that elicit emotions more strongly.

Keywords—Multimodal Systems, Emotion, User Behavior

1 Introduction

During decision-making, people are found to be lingering between two bounds: the influence of a myriad of emotions, which could be adverse for rational thinking; and the lack of emotions of any kind and adhering strictly to rational thinking and behavior [7]. While emotions (or their absence) at the crucial point of decision making have been found to contain valuable information about the decision's nature [8], a diverse amount of work establishes that emotions can be induced and regulated by means of continuous training in the arts, like music [6]. In general, the consequences of decisions made by taking into view all the cognitive resources available to the brain, are more likely to be accepted, and less likely to be regretted than those made without incorporating sufficient information as one has been trained to.

In the field of economics, however, emotions have proven to be hazardous, leading to expensive actions, which have been regretted later. Physiological evidence for these emotions has been measured in specific contexts, such as auctions [1]. A lot of work has been done in affective computing to understand and classify the emotions that a subject is likely to be experiencing, in an attempt to build empathetic user systems [22]. The application of machine learning algorithms, like support vector machines, enabled the classification of emotions into one of 8 classes, and many more [20]. The implications of these findings are far-reaching, especially for building systems capable of identifying and classifying emotional intelligence.

Under the premise that emotions are a key factor in decision-making, we aim to build a decision prediction system that incorporates affective information revealed by participants and hence, leads to better decisions. To this end, we focus on (1) economic aspects, like the risk and the stakes associated with the decision, (2) affective information through physiology, and (3) individual characteristics, like emotion regulation strategy, risk aversion and expertise levels of subjects. We record participants' decisions by means of an experiment to investigate a decision bias in a controlled environment. Based on the above three layers, we present the results of three classification algorithms, Multi-Layer Perceptron, Radial Basis Function, and CART Decision Tree, to predict the decision a subject is likely to make, applying the methodologies suggested in [15] for decision systems. The overall goal is to be able to employ the classification results in building decision systems to aid humans to deal with affect in a desirable way, especially in cognitively demanding situations.

The paper is structured as follows. Section II discusses related work, followed by an experimental and analysis methodology in Section III, the results in Section IV, and conclusions drawn from this approach towards decision prediction in Section V.

2 Related Work

Utility functions factoring in emotions like regret and pride have been proposed in recent literature to understand why traditional financial models failed [9]. While these functions are the foundational steps to factor in emotions in a financial context, further empirical work needs to be done to delineate finer aspects, such as the information processed before decision making, the emotional content, and individual behavioral characteristics. We present an overview of emotions in finance, decision support systems, emotion recognition, decisions and emotions, and behavioral characteristics.

2.1 Emotional Finance

The concept of incorporating emotions in financial decision making has received much focus in recent literature, especially due to the tendency of investors to fall into "traps", or behavioral fallacies, such as the irrational belief that stocks will revert to their mean, or the belief that losing stocks will outperform winners in future [24]. Such beliefs have been attributed to cognitive biases [10, 26], personality traits such as loss aversion or risk aversion [29], and heuristics employed in making good judgments [12]. Another explanation is due to emotional factors, since they are driven by the core tendency of not acknowledging visceral emotions such as fear of regret, or the fear of failure [17]. In this context, one of the existing methodologies is to employ an objective measurement of subjects' physiology, as a proxy for their emotional arousal [4]. Of these, previous literature agrees that SCR (Skin Conductance Response) is the most useful, since it is easy to elicit, is reliable, and it has been studied thoroughly by psycho physiologists, in normal individuals of various ages and cultures [7]. Secondly, cardiovascular activation after negative emotions has been found to last longer than after positive emotions [5]. While the use of an affective parameter could be a simplification in interpreting emotional states, it suggests as being a tangible way of understanding an excited state of the person, and hence serving as an indicator for anomalies in the experience of emotions. Our first research question is as follows: By means of an affective parameter as a proxy for emotions, is it possible to predict participants' behavior?

2.2 Emotion Recognition & Multimodal Fusion

The combination of two physiological modalities to build multimodal systems has been extensively employed in building affective and speech extraction [25] systems. Literature reveals that by applying multimodal fusion of physiological information, it is possible to achieve higher classification rates in emotion recognition, as early as [16]. Several approaches exist, for fusing data: early fusion, late fusion, feature-level fusion, and decision-level fusion, among many others [25]. The right approach for fusion thus depends on the type of application being built. Feature-level fusion has been regarded suitable for building systems with different modalities, without building a separate classifier for each modality, but taking into account the heterogeneous nature of each feature, as long as they are temporally synchronized. Hence, our second research question is as follows: By incorporating multimodal information, do we obtain additional validity of the correctness of our classification algorithm, and also improve predictions about user behavior?

2.3 Behavioral Characteristics

While incorporating affective information in building decision systems, one of the factors to be considered is if subjects inherently refrained from revealing emotional information. Emotion regulation [14] has been a long-standing theory in the study of emotions. Emotion regulation is defined as the ability to increase or decrease emotions in accordance with situational demand [13]. Effective regulators and reappraisers of emotions address their emotional state, and cognitively reappraise them by factoring in their emotions, or altering their emotional state in their decisions. On the other hand, suppressors do not adopt a similar strategy, but ignore, or even allow the negative impact of emotions to persist, thus leading to major physiological and psychological impacts. Hence, along with measuring subjects' intermittent emotions, we

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propose that an affective system incorporating such stable behavioral characteristics, can improve learning participants' behavior, and hence provide a higher degree of decision support.

2.4 Decision Support Systems

A variety of statistical methods and heuristics from AI literature have been applied to decision-making scenarios such as business failure prediction [27] and debt risk assessment [28]. Based on several such as (1) normality (2) linearity in relationship between variables, (3) multicollinearity, (4) multimodality (5) size and (6) dynamic versus static nature of the application; a variety of algorithms are available for use in decision support systems, and a complete survey can be found in [15]. According to this work, Neural Networks, Decision Tree (C4.5), Logistic Regressions are algorithms, are applied depending on continuity of sample size, density of regions, lack of multimodality, respectively, and necessitates a thorough understanding of the type of data. Due to the multimodality, neural networks and decision trees are most suitable candidates of comparison in this context. We work towards building business decision-making systems, which could incorporate affective information while decision making, to avoid traps created in the mind, which lead to regrettable and expensive decisions. This leads us to our final research question: In a multimodal context, which learning algorithm (between decision trees and neural networks) is most suited in terms of classification accuracy for predicting user behavior in a complete information context, while incorporating affective information?

To summarize, in a decision context with complete information, we explore (1) whether incorporating multimodal fusion improves predictions about participants' behavior, (2) incorporating behavioral characteristics with multimodal fusion improves predictions about participants' behavior (3) which learning algorithm is most suited for predicting buy/sell behavior in a simple decision task, while incorporating affective information? In order to answer these questions, we detail an experiment design in the next section.

3 Methodology

In order to build a decision system incorporating affective information, we simulate a decision environment in the lab, wherein emotional information is measured non-invasively. There are several benefits of a controlled lab experiment to elicit affective information. Field environments typically involve variable noise levels in the signal (such as bodily movement, temperature changes, etc.), which influences the level of skin conductance and heart rate, and hence makes it difficult to measure. Secondly, during continuous social interchange, multitasking and interruption of tasks are inevitable, which could lead to non-specific emotions not relevant to the current decision. In a field setting, emotions could occur in short periods of time, making their measurement even harder. Finally, in these situations, obtaining good training data becomes a non-trivial problem. A controlled experiment enables to correlate the information provided to a user to his decision more directly. Moreover, by means of event-related markers, emotions elicited specifically to this information are measured in a temporally synchronous manner. By means of repeated trials, we simulate a situation in which subjects make repeated decisions, providing a suitable context to learn subjects' behavior. The experiment design is detailed below.

3.1 Experiment Task

The experiment is designed to examine subjects' decisions when holding/selling a winning/losing stock. Two types of information are provided to the subject: the probability of price increase, and the stakes associated with the stock, with two levels for each variable (0.45 or 0.55 for probability, and €2 or €10 for stakes). Similar to the experimental design of [29], each subject is initially endowed a stock worth €100, and information about the stock's value after one trading round (whether it gained/lost). Subjects' task is to now decide whether to hold/sell this stock based on the information presented to them. After their decision, the participant is shown how the stock performed in the next trading round. If the participant held/sold the stock, their final profit would be the loss/gain after two/one rounds of trading. In this context, we define the strategy of the rational risk-neutral homo-economic subject, that the subject is expected to always sell in the 0.45 probability case, and always hold in the 0.55 probability case irrespective of stakes and gain/loss in the stock. By this design, we attempt to magnify into the individual decision to hold/sell the stock, by providing complete information and a minimal path-dependent scenario. The experiment was implemented on z-tree [11] and conducted with 100 participants.

3.2 Affective Considerations

In order to obtain the affective information revealed by a subject, we employ both subjective and objective measures. Subjects reported their happiness and regret levels at the end of each trial, on a standardized 7-point Likert scale. For an objective measurement, during the entire experiment, the participants' skin conductivity using Ag/AgCl electrodes (silver/silver chloride) was observed. The electrodes were attached on the thenar and hypothenar eminences of the palm of the non-dominant hand by use of standard SCR electrode paste [4]. Heart rate was measured using the ECG electrodes provided by Bioplux systems [21], and both modalities were recorded simultaneously by connecting to two channels on the Bioplux system. Physiological data for each subject was transferred via Bluetooth, and stored on each corresponding subject's machine.

3.3 Multimodal Measures

Multimodal physiological systems incorporate several modalities of information about the subject at the same time. In this experiment, we measure two modalities, namely, the SCR and the Heart Rate Variability of a person as a proxy for their emotion at a particular point in time. It has been shown that multimodal systems are able to gain from the complementarity of information in their unimodal parts [19] especially in the domains of speech extraction and emotion recognition from facial recognition. Figure 1 illustrates the complete methodology employed in this study. We start with a decision context, wherein subjects' decision, their behavioral data is acquired using questionnaires, and their emotional data could be acquired using both subjective and objective methods. The experimental data is next classified as three layers: economic, behavioral and physiological parameters.

Due to the intricate interplay between emotions and decisions, it is vital to consider the direct and possible interaction effects between the three sets of variables. In an offline processing step, we identify direct, as well as indirect effects of economic indicators on decisions. From the questionnaires, participants' characteristics, such as emotion regulation strategy, etc. are computed. As part of physiological preprocessing, signals were band-pass filtered and artifact corrected, before feature extraction. By use of suitable signal processing tools, various features (such as high frequency, low frequency power for heart rate and tonic and phasic activity features for skin conductance) were extracted offline. The two modalities yielded up to 23 different sets of physiological features. While this is the complete data set representing emotional information, it is possible that some of the features are highly correlated, or are not explaining any variance in data. In order to decrease the complexity of the data, we reduce the number of features by means of PCA (Principal Component Analysis).

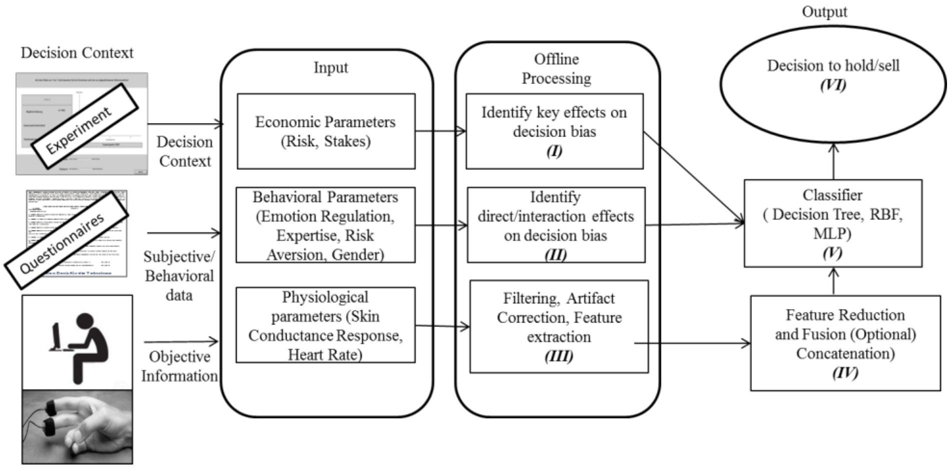

Fig. 1. Methodology illustrating steps in including affective information

This reduced feature set is then fed into a classifier, to predict the final binary decision (to hold/sell). We present the results of three classification algorithms, namely, decision trees, radial basis function, and multi-layer perceptron.

4 Results

Of the 100 participants, 67 participants reported good or expert level of knowledge in economics and stock experiments, while 33 participants reported basic knowledge. By comparing the participants' score on the emotion regulation questionnaire [14], 57 of them used reappraisal as an emotion regulation strategy, while 58 were classified as suppressors (in addition, 32 participants applied both these strategies, and 17 of them used neither). The classification was carried out by dividing subjects into those scoring higher and those scoring lower than the arithmetic mean on the respective questions for reappraisal (6 items) and suppression (4 items). We herewith present the results for the two research questions, whether incorporating affective information could predict behavior in decision support system, and a comparison of three learning algorithms.

4.1 Economic Behavior

A preliminary analysis revealed that the amount of risk and the amount of stakes significantly impacts the decision to hold/sell the stock, in tune with [18]. Further, behavioral parameters such as expertise, gender [3], and emotion regulation were strongly correlated to whether the participant sold in the high/low stakes situation. We investigate by means of learning algorithms whether there is a systematic influence of the amount of arousal on behavior.

4.2 Decision Prediction – An attempt, and a comparison of algorithms

The properties of a good feature set according to [21] should be: (1) related to the classification problem, (2) not strongly interdependent, (3) able to be interpreted easily, (4) extracted robustly (5) and calculated rapidly. We utilize the heart rate variability, decrease in heart rate, and the skin conductance features correlated with decisions. All physiological data was normalized to each person's baseline measure in the initial cool down period of 5 minutes, such that the classifier is expected to perform in a person-independent manner. In order to represent the information content of the features resulting physiology, we apply a Factor Analysis method to build a reduced parameter, using the PCA algorithm. The inherent advantage of this method is that it is easy to implement, and accounts for interrelations between signals [25]. A reduced joint feature space is thus obtained, which can be passed through a single classifier and hence improve the overall time performance.

We split the data into two parts; the classifier was trained on the first part and the second part of the samples was used for testing. A 3-fold cross validation was applied for all algorithms. In case of decision-trees, the C&RT algorithm was employed, such that the trees were post-pruned to avoid over fitting. Table 1 depicts the classification results of three algorithms, Radial Basis Function (RBF), Decision Tree, and Multilayer perceptron (MLP). Decision trees performed better than RBF, even when considering only economic variables and without information fusion. MLP's classified

76% of samples correctly, with all three layers, and information fusion, and adding interaction terms did not improve the classification rate. As can be observed, decision trees factoring in interaction terms and information fusion performed the best (predicting up to 77.2% of the samples in the test set).

Table 1. Classification results

Classification Algorithm	Classification Methodology		Accuracy (*Average % of samples classified correctly)*	
	Independent Variables	**Information Fusion Employed**	**Training (50%)**	**Testing (50%)**
Radial Basis Function	E + B + P	No, only SCR	73.7%	71.1%
Radial Basis Function	E + B + P	Yes	73.5%	83.3%
Multi-layer Perceptron	E + B + P	No, only SCR	73.2%	73.9%
Multi-layer Perceptron	E + B + P	Yes	72.2%	76.0%
Decision Tree	E + B + P	No, only SCR	N.A.	74.3%
Decision Tree	E + B + P	Yes	N.A.	74.8%
Radial Basis Function	E + B + P + I	No, only SCR	74.6%	71.4%
Radial Basis Function	E + B + P + I	Yes	72.7%	73.0%
Multi-layer Perceptron	E + B + P + I	No, only SCR	74.80%	72.20%
Multi-layer Perceptron	E + B + P + I	Yes	80.50%	75.10%
Decision Tree	E + B + P + I	No, only SCR	N.A.	74.40%
Decision Tree	E + B + P + I	Yes	N.A.	77.2%

Results reported in increasing order of testing accuracy. Wherever missing, it can be assumed that employing that combination was not a significant improvement.
E = Economic, B = Behavioral, P = Physiological, I = Interaction Terms, N.A. = Not applicable
N=6000 Decisions to buy or sell a stock

(E) consisted of the economic information shown to the subject, namely the stakes, and the probability of increase. B consisted of behavioral attributes, such as gender, expertise level, risk aversion level, and the type of emotion regulation strategy employed. (P) comprised of heart rate and skin conductance features, and (I) consisted of significant interaction terms within these subsets for instance, the interaction between reappraiser and SCR features. Multi-Layer Perceptron & Radial Basis functions did not perform better with the inclusion of interaction terms (a drop by around 1%), whereas decision trees classified 3% better in both with and without information fusion, when the interaction terms are included. This improved performance of a decision tree enables the usage of affective information in a decision support system, and predict user behavior in real time, while factoring in possible moderating or interaction effects at the same time. Further, systems could learn which decisions deviate from the user's expected decisions, and seek confirmation in a non-invasive manner, before the subject makes a possibly deviant decision. A point worth noting is that most of the improvement from 50% (up to 73%) is explained by the economic variables (E), physiological and behavioral attributes add only a marginal value under all three algorithms. However, it is worth noting that the contribution by physiology and behavioral terms is positive, and might be significantly more in a real-world situation, where subjects are less influenced by economic factors, but more likely to be influenced by emotions (such as real-life trading decisions, or contexts of electoral voting). Table 2 summarizes the variable importance of the factors adding up to the 77.2% classification accuracy obtained for the last row (Decision Tree method E+B+P+I) in Table 1.

Table 2. Variable Importance

Independent Variable Importance

Independent Variable	**Importance**	**Normalized Importance**
Int: (Reappraiser) x (is_high_probability)	.116	100.0%
Dummy: is_high_probability	.113	96.9%
Dummy: is_high_valuation	.035	30.1%
Int : (Reappraiser) x (SCR_Factor)	.009	7.3%
Int : (Male) x (SCR_Factor)	.005	4.6%
Dummy: is_suppressor	.005	4.3%
Dummy: is_expert	.005	3.9%
Dummy: is_reappraiser	.004	3.2%
SCR_Factor	.003	2.7%
ECG_Factor	.003	2.6%
Int: (Male) x (SCR_Factor) x (is_reappraiser)	.003	2.5%
Factor_3_mixed	.003	2.3%
Dummy: is_risk_averse	.002	1.9%
Dummy: is_gain	.002	1.4%
Dummy: is_male	.001	1.3%

Int : Interaction terms
Dummy: dichotomous variables used
Growing Method: Decision Tree
Dependent Variable: Binary Decision to Hold/Sell

5 Conclusion

Decision support systems are a specific sub-branch of information systems, facing the need to incorporate affective information, to facilitate users to maximize their cognitive resources. This study moves towards building empathetic decision support systems. To this end, we attempt to incorporate affective information in the form of physiology to learn users' decision behavior. In a controlled experiment, we record participants' decisions and measure physiological signals elicited by subjects. To predict the binary decision to buy or sell, three algorithms, multi-layer perceptron, radial basis function, and decision trees, are compared, and they yield classification rates of 76%, 73% and 77.2% respectively. Taking these results, we propose within the scope of our analysis that a decision tree with feature-level fusion, factors in affective information in order to understand user behavior. Whether emotions impact decisions positively or negatively is highly context & person dependent, but they do add valuable information to the decision to be made, as illustrated in the methodology in this paper.

In order to avoid over-fitting, decision trees were suitably optimized by means of post-pruning. Applying optimization lets us obtain a good estimate of performance; however there could be a bias towards experiment conditions. The choice of the physiological features might suffer from limitations as well, for instance, SCR response rate needs to be taken into consideration depending on the time scale of the decision to be taken. Further work needs to carry out an evaluation of such a user system, taking into account quality of service (such as interaction performance and influencing factors), and quality of experience metrics to evaluate affective information in a decision context. The proposed methodology could be applied in incorporating affect in decision systems – such as risk management information systems, used by bankers, private investment systems, credit assessment systems, etc. While a majority of these analyses are performed offline in this study, the onset of real-time algorithms has enabled real-time detection of change in user state, and arousal state. The onset of unobtrusive measurements (such as mouse pressure [23]) makes the shift towards a real-time system more achievable. Further work incorporating affective measures from other modalities has to be carried out. Additionally, another important factor to consider is the expertise level of subjects, which have shown to play a vital role in their decision-making process, and how they exhibit emotions in complex situations.

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