Recognizing Reader's Affect Using EEG Data

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Abstract

Emotions or affect is known to play vital roles in rational and intelligent behavior such as cognition and decision making. Detecting or recognizing affect can be done by analyzing physiological data or a combination of various physiological data. One such example of a physiological data is the brain's electrical activity which is measured using an Electroencephalogram (EEG). EEG-based affect recognition has been done while a person is solving math problems, listening to music, watching movies, or watching music videos. This research proposes an EEG-based affect recognition model on an unexplored application domain, which is while a person is reading short stories.

Keywords: affective computing, affect recognition, EEG, digital signal processing, machine learning

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Chapter 1

Research Description

This chapter introduces the research undertaken in the field of Affective Computing. It is divided into four sections which discuss the research problem, the research objectives, the scope and limitations, as well as the significance of the study.

1.1 Overview of the Current State of Technology

Although emotion theorists still do not have a clear definition as to what emotions are (Kleinginna Jr. & Kleinginna, 1981), many studies suggest that *emotions* or *affect* play vital roles in rational and intelligent behavior such as cognition and decision making (Bechara, Damasio, & Damasio, 2000; Schwarz, 2000). Emotions interplay with rational thinking in ways that are imperceptible but important for intelligent functioning. Humans already observe emotional intelligence (EI), which is a subset of social intelligence that involves the ability to monitor one's own and others' feelings and emotions, to discriminate among them and to use this information to guide one's thinking and actions (Salovey & Mayer, 1990). Ciarrochi et al. (2000) present a critical evaluation of the importance of EI versus the intelligence quotient (IQ). They conclude that while a number of people claim that EI is more important than IQ, there is little scientific evidence to support said claim. However, using the Multi-factor Emotional Intelligence Scale (MEIS), they were able to justify some of the claims of EI like being an important determinant of success in relationships and careers. Note that the same stimulus creates different emotions in different individuals, and the same individual may express different emotions in response to the same stimulus, at different times.

With regard to affective computing (which relates to, arises from, or influences emotions), it is simply imbuing a computer the capability to have emotional intelligence. Imagine a computer that is aware of a person's psychological well-being, that is his mental or emotional state. Theoretically, its responses would adjust accordingly depending on your current mental state. Thus, affective interactions with computers can easily and immediately give direct feedback as opposed to human interactions (Picard, 1997). However, before computers can give feedback, it has to detect a person's psychological state first. This is where emotion recognition comes in.

Humans usually perceive emotions by facial or vocal expressions. However, there are other physiological cues such as knowing that a person is nervous because their hand is clammy when held (relating to skin conductance); or determining that a person is excited when you feel their pulse (relating to heart rate). Hence, people naturally read many physiological signals of emotions (Picard, 2000). Translating this to computers, emotion recognition involves physiological pattern recognition. This proves to be a challenge because, again, there is no clear definition for what emotions are, and there is still the issue whether there are distinct physiological patterns that are associated with each emotion (Cacioppo & Tassinary, 1990). Regardless of the difficulty, there have already been various studies in emotion detection and recognition for various domains and motivations. Such detection is possible through analysis of facial and/or vocal expressions (Zeng et al., 2006; Zeng, Pantic, Roisman, & Huang, 2007), a combination of physiological data (e.g., heart rate, skin conductance, muscle tension) (Picard, Vyzas, & Healey, 2001), or even something as unusual as mouse-click behavior (Azcarraga & Suarez, 2012).

Electroencephalography (EEG) is the recording of the brain's electrical activity and represents a way to look at the brain functions in real time (Rossetti & Laureys, 2015). The brain's electrical activity or brainwaves is another example of physiological data. EEG is a noninvasive procedure and can be recorded digitally with commercial portable devices such as Emotiv EPOC/EPOC+[1], Muse[2], or iBrain[3]. In the field of medicine, EEG evaluation has played critical roles in accurate patient diagnosis, seizure detection, evaluation of patients with consciousness disorders, and even sleeping disorders. Whereas in the field of affective computing, EEG serves as a standalone or an additional modality for affect detection and recognition while doing an activity. Azcarraga and Suarez (2012) used EEG coupled with mouse-click behavior to predict academic emotions (confidence, excitement, frustration, and interest) of students while solving varying

[1]Emotiv, `https://emotiv.com/`
[2]InteraXon, `http://www.choosemuse.com/`
[3]Neurovigil, `http://www.neurovigil.com/`

difficulty levels of math equations. Yazdani et al. (2012) made use of EEG and various physiological data to classify the valance, arousal, and preference of the participants on music videos. Nie et al. (2011) attempted to find the relationship of EEG and human emotions while watching movies. Lastly, Lin et al. (2010) applied machine learning algorithms to categorize EEG dynamics according to emotional states while listening to music.

Reading literary texts or fiction is not simply an activity but rather an experience that is never the same from one reading to the next (Tompkins, 1980). It is a pleasurable activity when the reader's imagination is engaged in an active and creative way (Iser, 1972). Reading non-fiction differs from reading fiction. Usually, when one reads non-fiction such as memoirs or news articles, the goal is to be informed. Whereas when one reads fiction such as novels, short stories, or poems, the goal is to be entertained and moved (experience a variety of emotions) (Mar, Oatley, Djikic, & Mullin, 2011).

Reader-response criticism (a school of literary theory that focuses on the *reader*, the *reading process*, and *response*, rather than the literary text itself) is said to have started with I.A. Richard's discussion of emotional response (Tompkins, 1980). Emotions arising from reading the literary text are called *narrative emotions* (Mar et al., 2011). There have been empirical works that have established the relation between reading and emotions or emotional response in areas of culture, media, and arts. Cupchik et al. (1998) showed how different literary texts elicit different emotional responses (emotions of identification vs. remembered emotions). Miall and Kuiken (1994) tested how stylistic variations in the literary text affects the response of people in terms of reading time, strikingness, and affect. However, there is no current work that has studied brainwave patterns and their association to affect while a person is reading literary fiction.

1.2 Research Objectives

1.2.1 General Objective

To build an affect model that maps the EEG signals collected from readers (while they are reading stories) to specific emotions.

1.2.2 Specific Objectives

1. To review the approaches, methodologies, and experiments of existing affect detection or recognition studies that use EEG data;
2. To identify different emotions that can be elicited from the readers as they read the stories;
3. To determine which elements of a story affect the reader's emotional state;
4. To build a corpus of EEG signals;
5. To implement machine learning algorithms for classifying the emotion based on the EEG signals; and
6. To define evaluation metrics for assessing the performance of the model.

1.3 Scope and Limitations of the Research

The research will focus on EEG data as its modality for emotion detection and recognition. A review of existing affect detection or recognition studies that use EEG data is needed to determine what the approaches and techniques are in tackling this area of research. It includes the review of how the data are collected and prepared, how tests and experiments are conducted, what machine learning algorithms and features are used to train their models. Aside from emotion detection of recognition studies, a review of researches establishing the association of affect and EEG is also needed.

To associate the brainwave patterns to specific emotions, the research must identify these specific emotions first. This will entail a review of different emotion models and determine which of them is appropriate for reader affect. The basis for *appropriateness* is dependent on the goal of the research and its participants. The academic emotion model is an example of a model that is not aligned to the goal of the research. Ekman's model of six basic emotions (happiness, sadness, fear, anger, disgust, and surprise) may not be enough for the participants to fully articulate their emotional state.

The study will attempt to determine which element of the story triggered the reader to evoke that emotion. The story elements are limited to character traits and behavior, the reader's empathy to the character, the story plot or casual chain of story events, and lexical choices and sentence structure.

For the computer to be able to associate patterns of brainwaves to specific affect, a data corpus of EEG signals must be built. The participants will be people of ages between 18 and 25 of diverse demographics. Participants will read pre-selected short stories recommended by the resource person while an EEG sensor is attached to them. The chosen literary fiction is short stories because a short story can be read in a single sitting. The pre-selected short stories are as follows: *The Veldt* by Ray Bradbury, *Man from the South* by Roald Dahl, and *The Fisherman and the Jinni* from *One Thousand and One Nights* (refer to Appendix A for the complete list of short stories and their justification). Similar to the experiments of Miall and Kuiken (1994), these short stories have been segmented, which were checked and approved by the resource person as well. The set-up of Miall and Kuiken (1994) and the studies mentioned in Section 2.2.1 will be used as basis for the data collection methodology. Since this proposed study involves the participation of human subjects, informed consent forms will given to them following the ethical research guidelines of DLSU (refer to Appendix B for a sample of the informed consent form). The rationale behind the 18 to 25 age group is that the short stories have appeared in must-read lists for *high school and college students*. Having said that, a younger age group may have difficulty in understanding the material itself, thus, may lead to negative emotions such as confusion and frustration. Furthermore, based on Hannon and Daneman (2009) and Phillips et al. (2002), younger and older adults more or less have similar reading comprehension abilities as well as understanding and decoding emotions from written passages. The young adult age group of 18-25 is already accessible within DLSU and the assumption is that they are the ones who have the time to spare (please take note that a single session per participant may last at least 2 hours) to be a participant of this study as opposed to an older age group. The maximum age of 25 is only tentative and may change depending if there is someone willing to participate in the experiment (refer to Section 2.3.1 for more information on these two studies).

Weka (Hall et al., 2009), Rapidminer (Hofmann & Klinkenberg, 2013), and Cloudbrain[4] are being considered to perform the data analytics. All three are open source tools for data science tasks. Cloudbrain, however, is tailored for wearable data. This study will identify classification techniques best suited for the data.

The usual metrics for machine learning tasks, which are precision, recall, accuracy, and f-measure, will be used to evaluate the performance of the affect model.

[4]Cloudbrain, `http://getcloudbrain.com/`

1.4 Significance of the Research

Affective computing is a field that does not use new technologies, but rather it is a combination of various existing technologies and computer science concepts like wearable computing, digital signal processing, computer vision, pattern recognition, machine learning, and human-computer interaction (HCI). This study can contribute to the feasibility and application of these technologies and concepts on an unexplored application domain. Furthermore, this study provides a basis of the brainwave activity of people's emotions while they are reading, compared to their self-reported emotions. The methodology on data collection, data preparation, pre-processing, and classification will also be useful to future studies relating to EEG.

The results of this study can provide more understanding of emotions, which can be further utilized in affect-related systems such as intelligent tutoring systems (ITS) or embodied conversational agents (ECA). Other possible applications for the results of this study are in multimedia indexing, retrieval, and recommendation. Aside from the field of computer science, the contributions of this work may be informative to affective science and psychology as well. Various iterations of experiments can be done depending on research objectives such as in-depth comparative studies (per demographic profile, e.g. per age group, per gender) of affective states while reading. Emotion detection can also be an indicator for behavior prediction, most especially when monitoring certain emotional states that could lead to potentially harmful or dangerous behaviors. From a business perspective standpoint, the contributions of this work may also be of use to product and market analysis. Given a narrative, product description, commercial script, or something of the same nature, the findings of this research will give insights to the public's or audience's response to the narrative.

Chapter 2

Review of Related Literature

This chapter discusses the features, capabilities, and limitations of existing research, algorithms, or software that are related or similar to the proposed research. This chapter is divided into three sections. The first section describes emotion recognition in general. The second section discusses the relation of brainwaves and emotions as well as existing affect recognition studies using brainwaves. The last section tackles studies on affective reader-response.

2.1 Emotions and Computing

The field of Affective Computing was pioneered by Picard when she presented her ideas on the feasibility of affect-aware computers and possible implications and applications in 1995 (which eventually was published into a book in 1997). *Affective computing*, defined as computing that relates to, arises from, or influences emotions, is an aggregation of already existing technologies and computer science concepts such as wearable computing, digital signal processing, computer vision, pattern recognition, machine learning, and human-computer interaction. However, before Picard presented her ideas and theoretical applications on the field, she first justified as to why emotions should be imbued to computers (Picard, 1997).

2.1.1 Importance of Emotions

Kleinginna Jr. and Kleinginna (1981) compiled a categorized list of emotion definitions. This list is comprised of 92 definitions and 9 skeptical statements from various emotion theorists and sources of emotion literature. Despite the plethora of definitions, the relevance of emotions in a person's day-to-day activities has been proven by various studies. Examples of these studies are that of Bechara et al. (2000) and Schwarz (2000), which show the role of emotions in intelligent behavior.

In the field of neurology, Bechara et al. (2000) posit that the decision-making process is consciously or unconsciously influenced by marker signals arising from bioregulatory processes. These bioregulatory processes include those that are expressed in emotions. Decision-making is subserved in the orbitofrontal cortex of the brain as well as other cortical and subcortical areas. They have shown that lesions in the ventromedial (VM) prefontal cortex, a region of the brain which is involved in emotional response, seriously impairs the efficiency of decision making. The same goes for substance abusers and people with psychiatric disorders.

In social psychology, Schwarz (2000) points out the interplay of emotions, cognition, and decision making. He identifies scenarios and studies showing the role of emotions in various stages of decision-making. Before actually making a decision, a person's emotional state serves as a bias towards one of the options. Similarly, after a decision is made, there is an emotional reaction (e.g. regret, disappointment). Aside from the emotions elicited before and after making a decision, anticipated affect and memories of past affect also come into play. Anticipated affect simply means that a person is motivated to choose a certain option because he wants to avoid, for example, disappointment (anticipated affect). The same goes for memories of past affect, wherein instead of anticipating a certain emotion, the person already knows that a particular emotion is a likely outcome due to having already experienced it before.

A body of intelligence terminologies concerning affect was coined by Salovey and Mayer (1990). They define *emotional intelligence* (EI) as the subset of social intelligence that involves the ability to monitor one's own and others' feelings and emotions, to discriminate among them, and to use this information to guide one's thinking and actions. Ciarrochi et al. (2000) present a critical evaluation of the importance of EI versus the intelligence quotient (IQ). They conclude that while a number of people claim that EI is more important than IQ, there is little scientific evidence to support said claim. However, using the Multi-factor Emotional Intelligence Scale (MEIS), they were able to justify some of the claims of EI like being an important determinant of success in relationships and careers.

2.1.2 Emotion Models

A challenge for affect recognition is determining the appropriate emotion model to be used. The reason for this problem goes back to the unclear definition of emotions. With reference to the numerous research done in emotion theory, it has resulted to two general kinds of emotion models: the categorical models and the dimensional models.

Categorical models are those that define a number of discrete basic emotions. Ekman (1972) is an example of this model. He defines six basic emotions: happiness, sadness, fear, anger, disgust, and surprise. In contrast, dimensional models describe the components of emotions and are often represented as a two- or three-dimensional space where the emotions are presented as points in the coordinate space of these dimensions. The arousal-valence scale by Russell (1980) is an example of this model. The dimension *valence* provides information about the degree of pleasantness of the content and ranges from pleasant (positive) to unpleasant (negative), while the dimension of *arousal* represents the inner activation and ranges from energized to calm.

2.1.3 Emotion Recognition

Humans usually read and express emotions through face and voice. However, there are other physiological cues such as feeling clammy hands (relating to skin conductance) to mean that a person is nervous or having a fast heart rate to mean that a person is excited. Hence, people naturally read many physiological signals of emotions (Picard, 2000). Translating this to computers, emotion recognition involves pattern recognition of physiological cues. This proves to be a challenge because there is still the issue of whether there are distinct physiological patterns that are associated with each emotion (Cacioppo & Tassinary, 1990). A fast heart rate may imply that a person is either nervous or excited. So there must be other indicators that differentiate the two.

For an affect recognition system to be accurate, it needs to combine multiple kinds of physiological signals from the user as well as information about the user's context, situation, goals, and preferences (Picard, 1997). Picard (2000) attempted to classify a single person's physiological patterns of over a period of several weeks into eight distinct emotions. They used Clynes and Menuhin's set of emotions for their classification. The emotion set was chosen not because it is the best for HCI but rather because it has an already existing method for eliciting emotions (via *Sentograph*, also developed by Clynes and Menuhin). This set includes *no emotion (neutral)*, *anger*, *hate*, *grief*, *platonic love*, *romantic love*, *joy*, *reverence* with high/low arousal and positive/negative valence taken into consideration. Results show an 81% recognition accuracy on all eight classes of emotions.

Picard (2003) wrote a paper addressing most of the concerns and challenges in affective computing. One of the issues she points out was that her previous experiment (Picard, 2000) was forced to eight choices only. However, naturally we know that each emotion has its own varying degrees of intensity, thus, it is not only limited to eight. Picard gives an analogy to treat emotions like the weather. To quantify the weather, there are various sensors that measure temperature, pressure, humidity, etc. With emotions, it is building the sensors for the equivalents of temperature, pressure, etc. Like weather, the prediction may not be perfectly reliable, however, at least having a little foresight is useful.

Another issue Picard has addressed is with gathering *good* affect data. The first concern here are the sensors. Sensors are typically expensive, invasive, and/or obtrusive. There can be difficulty in gathering accurate physiological data due to technical factors such as the location where the sensors are applied, how much gel is used for the electrode. However, there are now advances in wearable technology that seamlessly integrates these sensors to what humans usually wear, i.e. the smart watch. Apart from the sensors, another challenge she present regarding affect data is the ground truth to compare the classifications to. An outsider cannot objectively say that the subject is feeling this certain emotion. Only the subject can know what emotional state he is in. If the outsider explicitly asks what the subject is feeling, that may also compromise the ground truth depending on how comfortable the subject is with expressing his feelings, how aware he is to his feelings, or if the subject becomes irritated with the constant asking of how he feels. Thus, Picard set the following factors on obtaining good affect data as show in Table 2.1. Underlined are the best conditions for gathering genuine affect data. The problem with it is that it is opportunistic and quite impossible to obtain as it breaches some privacy and ethical issues (Picard, 2000).

2.2 Emotions and Brainwaves

Electroencephalography (EEG) is the recording of the brain's electrical activity and represents a way to look at the brain functions in real time (Rossetti & Laureys, 2015). The brain's electrical activity or brainwaves is another example of physiological data.

Table 2.1: Five factors on obtaining *good* affect data.

Subject-elicited vs. event-elicited	Does subject purposefully elicit emotion or is it elicited by a stimulus or situation outside the subject's efforts?
Lab setting vs. real-world	Is subject in a lab or in a special room that is not their usual environment?
Expression vs. feeling	Is the emphasis on external expression or on internal feeling?
Open-recording vs. hidden-recording	Does subject know that anything is being recorded?
Emotion-purpose vs. other-purpose	Does subject know that the experiment is about emotion?

2.2.1 EEG-based Affect Recognition

Azcarraga and Suarez (2012) made use of EEG data coupled with mouse-click behavior to classify the academic emotions of the subjects. They have limited the academic emotions to *confidence*, *excitement*, *frustration*, and *interest* with the intensity taken into consideration. They used an Emotiv EPOC sensor, which has 14 channels, to record the EEG data and took note of the number of mouse clicks, each click's duration, and mouse movement. They first established the baseline EEG recording *resting state* by allowing the participant to relax for 3 minutes. The subjects were tasked to solve four algebra equations of varying levels of difficulty for a period of 15 minutes. A self-assessment window will pop up every 2 minutes and the participant will tag each academic emotion with intensity from 1 to 100 using their own developed observation module.

They have identified 17 features from the prepared data sets (14 EEG channels and 3 mouse behavior information) and used Multi-Layered Perceptron (MLP) and Support Vector Machines (SVM), with 10-fold cross validation, as classification algorithms for their success in general approximation. Their metrics for assessing performance are precision, accuracy, and F-measure. Issues encountered in data preparation are with cleaning the data and balancing the data set. They had to manually synchronize the EEG recordings to the self-assessments. In addition, noise artifacts in the EEG which are not concerned with affective states were removed (i.e. blinking, hand movements), only 16 out of 25 data from the students were found useful given the conditions they set for balancing the data set. Six different datasets were prepared based on the percentage of feature outliers. A feature is considered an outlier if exceeds 1 standard deviation away from the mean of that particular feature of that particular subject. Their results show that as the number of outlier features increases, prediction accuracy also

Table 2.2: Summary of MLP accuracy results of Azcarraga and Suarez (2012).

Dataset	**Brainwaves**	**Mouse**	**Brainwaves + Mouse**
0	54.66	32.26	61.04
10	63.74	38.9	69.8
25	75.27	45.11	78.58
33	74.92	45.46	80.69
50	83.65	43.85	88.56
60	88.33	48.79	92.27

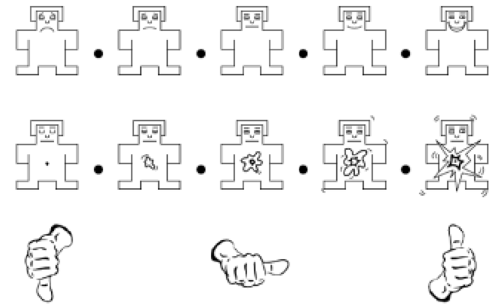
increases. The combination of brainwave and mouse behavior data yields better results than brainwave or mouse behavior alone. Note, however, that brainwave data performed better than mouse behavior data. On all cases of their experiments, MLP algorithm performed better than SVM. Table 2.2 shows a summary of their prediction accuracy results.

Yazdani et al. (2012) combined EEG signals and various physiological signals in order to classify the emotional state of a person while they are watching music videos. Based on the valence-arousal scale proposed by Russell (1980), they classify the EEG and physiological signals into high/low arousal and positive/negative valence. They also added an additional like/dislike classification to see the preferences of their participants. They recorded the EEG and physiological signals using a BioSemi ActiveTwo system[1]. The EEG recording is composed of 32 channels and the accompanying physiological signals are the following: Galvanic Skin Response (GSR), respiration, skin temperature, blood volume pulse by plethysmograph, EMGs of of zygomaticus major and trapezius muscles (2 channels each), and a 4-channel electrooculogram (EOG). Figure 2.1a shows participant with the EEG and physiological sensors attached to him.

Their experiment started with having the participant relax for a period of two minutes, a fixation cross was displayed on the screen. This recording served as their baseline recording. 20 music video clips were presented at random in separate runs. Each run consists of a five-second baseline recording (display of the fixation cross), two-minute display of the music video, and the participant's self-assessment for his arousal, valence, and preference. Figure 2.1b shows the symbols that they used for the self-assessment, which was based on Morris's Self-Assessment Manikins (SAM). Preprocessing includes filtering, downsampling, and artifact removal to ensure artifact-free signals for all channels. They introduced a novel approach for feature extraction, which is using the relative wavelet energies (RWE) of each channel and the RWE of symmetrical channel pairs as extracted features. SVM classifier with radial basis function kernels and 20-fold cross val-

[1] BioSemi, `http://biosemi.com/`

(a) A participant with the EEG and physiological sensors attached to him.



(b) Images used for self-assessment of (from top to bottom) arousal, valence, and preference.

Figure 2.1: Experimental set-up of Yazdani et al. (2012)

Table 2.3: Summary of accuracy results of Yazdani et al. (2012).

	Arousal	**Valence**	**Preference**
EEG Data	69.58%	73.66%	70.25%
Physiological Data	55.7%	54%	66.6%

idation was used in the classification. Table 2.3 shows the averaged accuracy of their results. Despite having the accuracy of the EEG data higher than the physiological data, their performance results are incomparable because they used different window lengths.

An additional experiment that they explored was the feasibility of having a general-purpose affect recognition system. To test this, they trained a classifier on the physiological data of the participants and employed a leave-one-participant-out cross validation. They conclude that the accuracy varies among the participants, which indicates that classification is participant-dependent. Further investigation needs to be done to build a general classifier for all participants.

Nie et al. (2011) used EEG signals to classify *positive* and *negative* emotions while watching movie clips. Their rationale for only choosing two classes is because emotions come in mixed forms, hence, if the subject could not properly distinguish his emotions, he could at least identify whether it is a positive or a negative emotion. They used a 62-channel electrode cap to record the EEG with a 32-bit level at a sampling rate of 1000Hz.

Their experimental protocol is as follows. For each session, one movie clip is played. Five seconds to indicate the start of the session followed by a four-minute showing of the movie clip. After which, 45 seconds of self-assessment and then

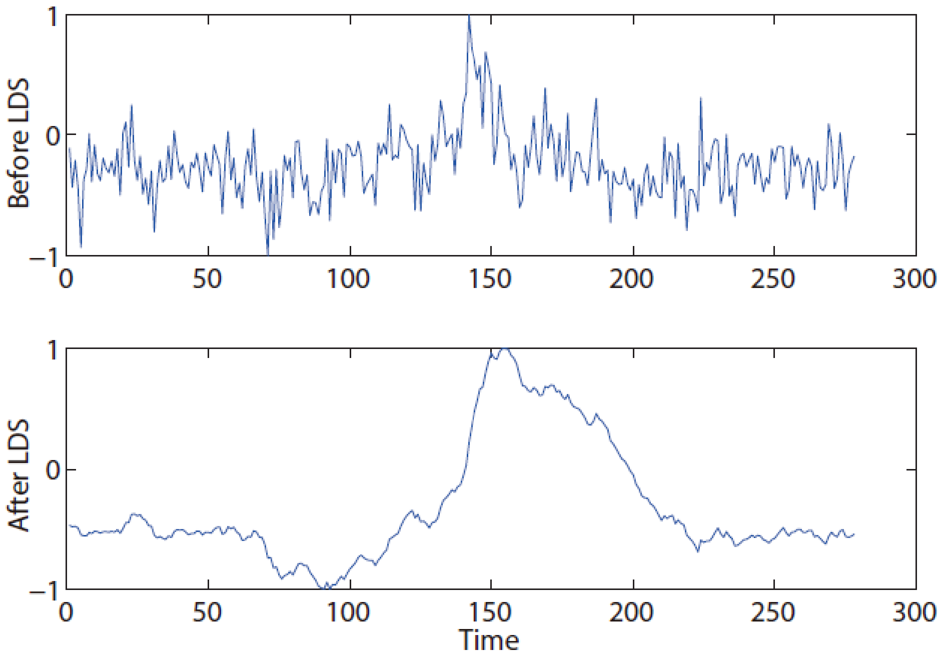


Figure 2.2: Comparison of features before and after LDS.

a 15-second rest before proceeding to the next session. They did not indicate whether they have a baseline recording of the participants before the experiment. For self-assessment, they used the SAM by Bradley and Lang (1994).

Data preparation and cleaning includes the removal of the artifacts not related to the emotional states and extracting the five frequency bands. To further remove noise, they smoothed the features by applying a linear dynamic system approach for each band. Figure 2.2 shows the difference of before and after using the LDS approach. For feature selection, they calculated the correlation coefficients between features and labels for each channel and band on the training set. They ranked them and obtained the top 50 and top 100 features. This is done in order to find subject-independent features. For classification, they used SVM with linear kernel to train the data for each band. This was done with a 7:3 ratio of training and testing data. Lastly, they employed another SVM for all of them. This was validated with a 10-fold cross validation. Table 2.4 shows the summary of prediction accuracy results of their classification.

Lin et al. (2010) applied machine learning algorithms in order to associate EEG patterns to self-reported emotional states while listening to music. The goal of their research was to identify emotion-specific EEG features as well as explore the efficiency of two classifiers, MLP and SVM. They used a 32-channel EEG module by Neuroscan, Inc. to record the EEG signals. Their emotion model is based

Table 2.4: Summary of accuracy results of Nie et al. (2011).

Subject	Delta	Theta	Alpha	Beta	Gamma	ALL
1	68.23	66.21	92.38	82.83	100	99.63
2	57.58	87.09	86.30	72.86	73.65	81.95
3	91.30	77.74	84.06	85.82	91.20	87.16
4	38.80	74.28	65.63	100	88.47	91.13
5	45.81	74.19	90.48	77.42	62.26	82.90
6	71.24	84.65	94.35	82.71	89.82	82.39
Average	62.16	77.36	85.53	83.61	84.23	87.53

on the four emotional states following the 2D arousal valence-arousal scale by Russell (1980): *joy* (positive valence, high arousal), *anger* (negative valence, high arousal), *sadness* (negative valence, low arousal), and *pleasure* (positive valence, low arousal). These emotional states were recorded with the use of FEELTRACE by Cowie et al. (2000).

From the recorded data, they have identified four feature sets. First is the individual spectral power from the 30 scalp electrodes (30 channels, namely Fp1, Fp2, F7, F3, Fz, F4, F8, FT7, FC3, FCz, FC4, FT8, T7, C3, Cz, C4, T8, TP7, CP3, CPz, CP4, TP8, P7, P3, Pz, P4, P8, O1, Oz, and O2). The first feature set was named PSD30 for *power spectrum density for all 30 channels*. The next two feature sets involve the symmetric electrode pairs, namely Fp1-Fp2, F7-F8, F3-F4, FT7-FT8, FC3-FC4, T7-T8, P7-P8, C3-C4, TP7-TP8, CP3-CP4, P3-P4, and O1-O2. Asymmetry indexes were calculated in two ways. DASM12 (*differential asymmetry of 12 electrode pairs*) was computed by power subtraction (i.e. power of C3 - power of C4) whereas RASM12 (*rational asymmetry of 12 electrode pairs*) was computed by power division (i.e. power of C3 / power of C4). The last feature set is the PSD24 which is the *power spectrum density of 24 channels*. The PSD24 is a subset of PSD30 wherein the channels along the midline were not included (Fz, FCz, Cz, CPz, Pz, and Oz).

MLP and SVM classifiers were trained and evaluated with a 10-fold cross validation. Table 2.5 and Table 2.6 shows the results of their classification. DASM12 gave the best performance results among the frequency bands and general classifier of the frequency bands for SVM and MLP, with SVM having a marginally higher result. Since DASM12 gave the best results, they applied an F-score index with a leave-N-feature-out scheme to rank the features across all frequency bands. They obtained the top 30 subject-independent features and applied SVM, obtaining a result of approximately 74% accuracy.

Following Picard's five factors on obtaining good affect data, it is observed that

Table 2.5: Summary of MLP accuracy results of Lin et al. (2010).

Feature Type	EEG Frequency Band					
	Delta	Theta	Alpha	Beta	Gamma	All
DASM12	**63.93**	**63.67**	**64.07**	55.71	53.24	**81.52**
RASM12	48.54	50.69	55.40	48.21	44.82	65.33
PSD24	49.20	52.10	57.79	53.20	54.46	75.66
PSD30	52.12	55.61	61.89	**57.92**	**58.04**	79.54

Table 2.6: Summary of SVM accuracy results of Lin et al. (2010).

Feature Type	EEG Frequency Band					
	Delta	Theta	Alpha	Beta	Gamma	All
DASM12	**69.91**	**68.27**	**66.94**	**58.83**	57.35	**82.29**
RASM12	50.91	51.39	56.95	50.29	47.61	65.81
PSD24	51.02	53.27	54.61	55.42	56.80	69.54
PSD30	53.38	55.61	56.64	58.71	**59.54**	71.15

Azcarraga and Suarez's, Yazdani et al.'s, Nie et al.'s, and Lin et al.'s experimental set-up is *event-elicited*, conducted in a *lab setting*, concerned with *feeling*, is *open-recorded*, and is *emotion-purpose*. Table 2.7 shows a summary of EEG-based affect recognition studies while doing an activity.

Table 2.7: Summary of EEG-based affect recognition studies.

Reference	**EEG Recording**	**Emotion Model**	**Self-Assessment Scheme**	**Classification Algorithm**	**Features**	**Results**
Azcarraga, J., & Suarez, M. T. (2012). Predicting Academic Emotions Based on Brainwaves, Mouse Behaviour and Personality Profile.	14-channel Emotiv EPOC sensor	Confidence, interest, excitement, frustration	Own observation tool	MLP (10-fold cross validation)	Power spectrum density of 14 channels	54-88%
Yazdani, A., Lee, J.-S., Vesin, J.-M., & Ebrahimi, T. (2012). Affect Recognition Based on Physiological Changes During the Watching of Music Videos.	32-channel EEG electrodes recorded via Biosemi ActiveTwo system at 512Hz sampling rate	Arousal, valence, like/dislike	Morris's SAM for arousal and valence; thumbs up and down symbols for like/dislike	SVM with radial basis function kernel (20-fold cross validation)	Relative wavelet energies of each electrode together with RWE of symmetrical electrode pairs	69.58% (valence), 73.66% (arousal), 70.25% (like/dislike)
Nie, D., Wang, X.-W., Shi, L.-C., & Lu, B.-L. (2011). EEG-based emotion recognition during watching movies.	62-channel electrode cap recorded with 32-bit level at 1000Hz sampling rate	Positive, negative	Bradley's SAM	Linear SVM (7 [testing]:3 [training] ratio)	Top 100 and top 50 subject independent features obtained through the reduction of the original features by correlation coefficients	89.22% (Top 100), 84.94% (Top 50)
Lin, Y.-P., Wang, C.-H., Jung, T.-P., Wu, T.-L., Jeng, S.-K., Duann, J.-R., & Chen, J.-H. (2010). EEG-based emotion recognition in music listening.	32-channel module by Neuroscan, Inc. at 500Hz sampling rate	Joy, anger, sadness, pleasure	FEELTRACE	MLP, SVM with radial basis function kernel (10-fold cross validation)	Power spectrum density of 30 channels, differential asymmetry of 12 electrode pairs, rational asymmetry of 12 electrode pairs, power spectrum density of 24 channels	65-81% (MLP), 65-82% (SVM)

2.3 Emotions and Reading Fiction

The act of reading literary fiction is part of a broader aspect of human growth and development based on understanding one's own experiences and the social world (Freire & Slover, 1983). Mar et al. (2009) and Kidd and Castano (2013) proves that reading improves a person's empathy and *theory of mind*, defined as the ability to impute mental states (i.e. beliefs, intents, desires, pretending, knowledge) to the self and others and to understand that others have their own beliefs, desires, intentions, and perspectives that are different from one's own (Doherty, 2008). Vezzali et al. (2015) proves this when they showed how reading Harry Potter improves attitudes (reduces prejudices) towards out-group individuals, e.g. immigrants, homosexuals, refugees.

Reader-response criticism is a school of literary theory that focuses on the *reader*, the *reading process*, and *response*, rather than the literary text itself. It is said to have started with I.A. Richard's discussion of emotional response (Tompkins, 1980). Emotions are central to the experience of reading literary narrative fiction. A person's affect and mood influences and is being influenced before, during, and after the actual reading. Mar et al. (2011) cites current empirical studies on emotions and narrative fiction at each stage of reading. The research being done will focus on the emotions evoked during reading, which are called *narrative emotions*. Note that these are emotions concerning with entering the narrative world. This is different from the *aesthetic emotions*, which are evoked when looking at a piece of fiction from a distance, evaluating its craft, style, etc.

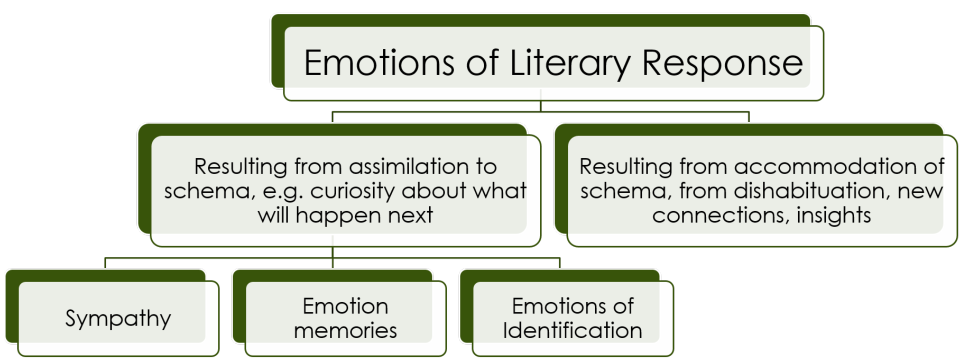


Figure 2.3: Oatley's taxonomy of emotions.

Figure 2.3 presents Oatley's taxonomy of emotions in literary response. *Sympathy* is when the reader is a witness to the scene but unable to affect the action in any way. *Emotion memories* is when the text makes the reader remember a past feeling, thus, emotion memories are not only recalled but also relived. *Emotions of identification* is when the reader takes on the characteristics and goals of the character. This taxonomy is further extended by Mar et al. (2011). They included *emotions of empathy*, which is closely related to emotions of sympathy and identification. Here, the reader does not identify with the character but rather empathizes with it. Emotion memories are split into relived emotions and remembered emotions. *Relived emotions* come from a recollection of past personal experiences whereas *remembered emotions* is a recalled emotion that does not fall under past personal experiences.

Miall and Kuiken (1994) observes how foregrounding, or stylistic variation in the text, influences the affect of the reader. *Foregrounding* refers to a range of stylistic variations that occur in literature at a phonetic level (alliteration, rhyme), grammatical level (inversion, ellipsis), or the semantic level (metaphor, irony). They have noted that readers are more likely to report the phrases that struck them or caught their eye when presented with the original text as opposed to one written in neutral terms. Hence, this means that foregrounding strikes interest. Their experiment consists of three literary stories, each short enough for an hour-long, single reading session. Each story contains a variety of foregrounded features and they were divided roughly into equal segments using phrase and sentence divisions while still retaining meaningful units as far as possible (approximately 77-86 segments per story). Their test subjects include both those with high and low literary competencies. For each participant, there were two readings. In the first reading, story segments are presented one at a time, with reference to the previous segment, and the current segment is highlighted. By the second reading, story segments are presented again one at a time, with reference to the two previous and succeeding segments. Then the participants are asked to rate the current segment based on strikingness (1 to 5 scale) and affect (no feeling to strong feeling). Their findings show that despite the test subjects having different interests and literary competencies, the affect of the reader to the story is independent. It may imply that only those with higher literary competencies draw more meaning on the text. Another finding they discovered is that the more foregrounded the segment, the more emotions it may elicit from the segment. In relation to the research project, this set-up seems like an appropriate methodology to adopt in the data gathering phase.

Cupchik et al. (1998) conducted a similar experiment but instead of focusing on what aspects of the texts elicited the emotional response, it is concerned with what type of emotional response the reader evoked. Their selected short stories were divided into four equal segments. Two of the stories have unifying emotional themes, while the other two were descriptively dense. The participants were instructed to either be a spectator and feel sympathy for the main character or to imagine oneself as the main character. After reading each segment, they were to rate the experience on 11-point scales measuring pleasure, intensity, and tension. Aside from rating, they were asked if they experienced *fresh emotions* (emotions of sympathy, identification, or empathy) or *emotional memories* (relived or remembered emotions).

2.3.1 Age-Related Changes in Emotion Understanding and Reading Comprehension

Hannon and Daneman (2009) (this was the study I mentioned) conducted an experiment to show the age-related changes in reading comprehension between young adults (people of ages 18-25) and older adults (people of ages 64-87) based on four components: text memory (tested memory for information explicitly presented in the paragraph), text inferencing (tested inferences about information that was implied in the paragraph), knowledge integration (required participants to access prior knowledge and integrate that knowledge with text information), and knowledge access (tested access to prior knowledge). Their results shows that those four components are susceptible to decline with aging. However, they also conclude that overall reading comprehension ability remained the same regardless of the age of their participants. With regards to understanding and decoding emotions from written passages, Phillips et al. (2002) reveals that there is no difference between young adults (people of ages 20-40) and older adults (people of ages 60-80). In summary, younger and older adults more or less have similar reading comprehension abilities as well as understanding and decoding emotions from written passages.

Chapter 3

Research Methodology

This chapter lists and discusses the phases and activities that will be performed to accomplish the research project. The phases occur in a sequential manner unless otherwise stated. The phases may also be revisited when new limitations are discovered.

3.1 Research Activities

3.1.1 Concept Formulation and Review of Related Literature

This phase is concerned with the formulation of the thesis, particularly the identification of the research problem and its objectives, as well as defining its scope and limitations. A review of related literature on emotions, brainwaves, and reading fiction is done to understand how these concepts correlate with each other. The methodologies and approaches presented in some of these studies will be considered to see if they are applicable to this research. The tools that will be used are also learned in this phase as well as canvassing and procuring the needed equipment. This phase is important because this will build the background knowledge needed before proceeding to the next phases.

3.1.2 Development of Data Collector Tool

In this phase, the tool to be used for data collection will be developed. Prior to the development, the pre-selected short stories will be split into segments while still retaining meaning and coherence per segment (see Appendix C for a sample of the short story segments to be used). The data collector tool will be based on the system used by Azcarraga and Suarez (2013). The software tool output of this phase is relevant to the next phase.

3.1.3 Data Collection and Corpus Building

The data for training and evaluation of the affect model are collected in this phase. At least 30 participants will read the segmented short stories while an EEG sensor is attached to them. Their EEG recordings and self-assessments are gathered via the data collector tool described in the previous section. This phase may take up most of the duration of the research because each session per participant per story may last up to two (2) hours. Data preparation and pre-processing are also involved here. This phase may need to be repeated in case a larger corpus is required.

3.1.4 Training and Evaluation

This phase is involved with the application of the to-be-determined supervised and unsupervised machine learning techniques as well as feature extraction and selection. Experiments include various combinations of machine learning techniques and feature sets applied to the data sets. The results of each model will be evaluated according to the metrics set in Section 1.3. This phase will also occur more than once as more data are added and new machine learning algorithms are discovered.

3.1.5 Documentation

The documentation phase is necessary all throughout the duration of the research. Taking down notes on the observations and findings during the other research activities and review of related literature, writing related technical documents, and the research paper itself fall under this phase.

3.2 Calendar of Activities

Table 3.1 shows the Gantt chart of the activities. Each asterisk represents approximately one week worth of activity.

Table 3.1: Timetable of activities.

Activities (2016)	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Concept Formulation and Review of Related Literature	$\star\star\star\star$	$\star\star\star\star$	$\star\star\star\star$	$\star\star\_\_$								
Development of Data Collector Tool			$\_\_\star\star$	$\star\star\_\_$	$\star\star\_\_$							
Data Collection and Corpus Building					$\_\_\star\star$	$\star\star\star\star$	$\star\star\_\_$		$\_\star\star\star$	$\star\star\star\star$		
Training and Evaluation							$\star\star\star\star$	$\star\star\star\_$	$\_\star\star\star$	$\star\star\star\star$	$\star\star\_\_$	
Documentation	$\_\_\star\star$	$\star\star\star\star$	$\star\star\star\star$	$\star\star\_\_$	$\star\star\star\star$	$\star\star\star\star$	$\star\star\star\star$	$\star\star\star\_$	$\_\star\star\star$	$\star\star\star\star$	$\star\star\star\star$	$\star\_\_\_$

Appendix A

Selection of Reading Materials for the Participants

The short story is considered the most viable form of narrative for this research since it will entail a brief period of reading time (more or less than an hour). This delimitation is set in response to the perceived short attention span of teenage students (13-16 years). Nonetheless, the proposed selections are deemed some of the best in the world and have appeared in must-read lists for high school students. Another criterion is that these selections are deemed to contain prominent levels of emotional resonance (e.g. surprise, confusion, horror, pathos, shock, amusement) due to the clever use of narrative devices by the authors (e.g. suspense, atmosphere, mood, intrusion of the fantastic, characterization).

The proposed selections are:

- ***The Lovely House* by Shirley Jackson** tells of a young girl Margaret who spends one summer vacation with her friend in the latter's ancestral house. It is a ghostly tale concocted in the Gothic tradition. Shirley Jackson (American author, 1916-1965) is known for the *subversive impact* of her work, for her disquieting portrayal of history and society.

- ***The Veldt* by Ray Bradbury** is a story of a family who lives in an automated house with machines and gadgets that do all the work for them. This house has a nursery room that is able to create virtual realities in response to the telepathic wishes of the children. The finale of this science fiction masterpiece is quite disturbing. Ray Bradbury (American author, 1920-2012) is one of the foremost science fiction writers of the 20th century, known for his compelling visions of a dystopic world.

- ***Gangrene* by F. Sionil Jose** is a moving story about a brief reunion between a father and his son in an army hospital in Sierra Madre. The father is a brain surgeon of the Philippine Army, while the son is with the insurgents. The boy lies dying in the hospital room after he has been captured and tortured. Francisco Sionil Jose is National Artist for Literature. His stories, vividly realistic and socially relevant, are canonical representations of Philippine traditions.

- ***Man from the South* by Roald Dahl** is set in a Jamaican hotel, where a chance encounter takes place between a South American man and a boy. It is a story about a strange bet. Roald Dahl (British author, 1916-1990) wrote such children's classics as *Charlie and the Chocolate Factory* and *James and the Giant Peach.* He is famous for his macabre short fiction, tinged with dark humor, irony, and surprise ending.

- ***The Fisherman and the Jinni* from *One Thousand and One Nights*** is a tale-within-a-tale, filled with magic and sorcery. It begins with an unfortunate meeting between a fisherman and a jinni, and ends with a marvelous tale of a prince and his enchanted kingdom. *One Thousand and One Nights* (ca. 850 AD) is deemed the first novel in the annals of world literature. Composed of several tales of wonder and framed within other narratives, this significant work, originally of Indian, Persian and Arabic origins, is a classic of all times. Its juicy tales are satires of human follies and foibles.

Appendix B

Informed Consent Form

A. Purpose and Background of the Study

You are being asked to volunteer for a research study. This study aims to associate brainwave patterns to specific emotions while reading literary fiction. The researcher in charge is Kristine Ma. Dominique Kalaw supervised by Prof. Ethel Ong. It will involve at least 30 participants.

B. Participation and Withdrawal

Your participation in this study is completely voluntary. If at any point in time you wish to withdraw during or after the experiment, you may do so without penalty or consequence of any kind. Any data collected, should you withdraw, will be disposed properly.

C. Procedure

Each session will last approximately 2 hours per story. If you agree to participate in this research, the following will happen:

1. An EEG sensor will be attached to the participant.
2. The participant will be asked to relax for a period of two minutes in order to obtain the baseline recording.
3. Each story is done in two readings. The first reading will be concerned with annotating the basic emotions. The second for adjusting the intensity of the basic emotion.
4. The segments will be read one at a time. So before proceeding to the next segment, the participant will annotate the current segment using the provided tool.

D. Potential Risks and Discomfort

Emotiv EEG sensors are commercial products marketed worldwide. They are typically used for modern computer games, instead of a gamepad, keyboard, or joystick. These sensors are safe to use since they just read brainwave signals and then send these signals to a computer thru a USB connection. They are not connected to any electrical outlet while attached to the head of the user.

These sensors do not emit any radiation nor any magnetic signals that will harm the user.

These sensor devices have been used in a number of University research laboratories in the US and Japan.

If you find the EEG sensor uncomfortable to use, or if you decide to stop the session for any other reason, the experiment will be halted immediately.

E. Potential Social and Personal Benefits

Since the study will analyze and detect your emotions while you are reading based on your brainwave signals, the results of the study would provide useful baseline data for future affect-aware systems.

F. Confidentiality

Any information that is obtained in connection with this study and that can be identified to be those of your child/ward will remain confidential and will be disclosed only with your permission or as required by law.

Apart from this possible usage, such data will only be viewed/used for experimental purposes. At any time during or after the experiment, you may request to review have your recorded data be destroyed.

G. Identification of Researcher

If you have any questions or concerns about the research, please email or contact:

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Appendix C

Sample Segments of Selected Short Stories

The Veldt by Ray Bradbury

Segment #1

"George, I wish you'd look at the nursery."

"What's wrong with it?"

"I don't know."

"Well, then."

"I just want you to look at it, is all, or call a psychologist in to look at it."

"What would a psychologist want with a nursery?"

"You know very well what he'd want." His wife paused in the middle of the kitchen and watched the stove busy humming to itself, making supper for four.

"It's just that the nursery is different now than it was."

"All right, let's have a look."

Segment #2

They walked down the hall of their soundproofed, Happy-life Home, which had cost them thirty thousand dollars installed, this house which clothed and fed and rocked them to sleep and played and sang and was good to them. Their approach sensitized a switch somewhere and the nursery light flicked on when they came within ten feet of it. Similarly, behind them, in the halls, lights went on and off as they left them behind, with a soft automaticity.

Segment #3

"Well," said George Hadley.

They stood on the thatched floor of the nursery. It was forty feet across by forty feet long and thirty feet high; it had cost half again as much as the rest of the house. "But nothing's too good for our children," George had said.

Segment #4

The nursery was silent. It was empty as a jungle glade at hot high noon. The walls were blank and two dimensional. Now, as George and Lydia Hadley stood in the center of the room, the walls began to purr and recede into crystalline distance, it seemed, and presently an African veldt appeared, in three dimensions, on all sides, in colors reproduced to the final pebble and bit of straw. The ceiling above them became a deep sky with a hot yellow sun.

Segment #5

George Hadley felt the perspiration start on his brow.

"Let's get out of this sun," he said. "This is a little too real. But I don't see anything wrong."

"Wait a moment, you'll see," said his wife.

Man from the South by Roald Dahl

Segment #1

It was getting on towards six o'clock so I thought I'd buy myself a beer and go out and sit in a deckchair by the swimming pool and have a little evening sun.

I went to the bar and got the beer and carried it outside and wandered down the garden towards the pool.

Segment #2

It was a fine garden with lawns and beds of azaleas and tall coconut palms, and the wind was blowing strongly through the tops of the palm trees, making the leaves hiss and crackle as though they were on fire. I could see the clusters of big brown nuts hanging down underneath the leaves.

Segment #3

There were plenty of deck-chairs around the swimming pool and there were white tables and huge brightly coloured umbrellas and sunburned men and women sitting around in bathing suits. In the pool itself there were three or four girls and about a dozen boys, all splashing about and making a lot of noise and throwing a large rubber ball at one another.

Segment #4

I stood watching them. The girls were English girls from the hotel. The boys I didn't know about, but they sounded American, and I thought they were probably naval cadets who'd come ashore from the U.S. naval training vessel which had arrived in harbour that morning.

Segment #5

I went over and sat down under a yellow umbrella where there were four empty seats, and I poured my beer and settled back comfortably with a cigarette.

It was very pleasant sitting there in the sunshine with beer and cigarette. It was pleasant to sit and watch the bathers splashing about in the green water.

The Fisherman and the Jinni from *One Thousand and One Nights*

Segment #1

It is said, oh wise and happy King, that a very poor fisherman who swore by Almighty God that he would only cast his net three times each day, went down to the sea late one afternoon as usual, waited until he saw the moon shining above him, and then threw his net very carefully into the water.

Segment #2

He sat there for a time, and then, when he pulled on his net and felt that it had grown heavy, he sang to himself:

"Glide over to me, my magnificent fish

And slither into my waiting net

So that someone asleep on his soft silken bed

Will awaken and buy you with his silver bread."

Segment #3

He opened his net and there, to his horror, found a dead donkey. "A donkey?" he cried out. "My wretched luck. You send me a donkey when you know that my family and I are starved out of our brains?" He managed to free it from his net with one hand while pinching his nose with the other to block out the horrible smell.

Segment #4

He cast his net carefully into the sea again, waited for it to sink, tugged on it and to his amazement felt that the net was even heavier than the first time. It was so heavy he had to climb back on to the shore, drive a stake into the ground, and tie the rope of the net to the stake. Then he hauled with all his might until he managed to pull the net up out of the sea.

Segment #5

But instead of an abundance of fish jumping and playing in the net he found a broken, rusty wooden chest filled with sand. He shouted in a loud voice, “A chest? Is this how you compensate my work? My labour? Or are you telling me that the key to my good fortune lies inside this coffin?”

He kicked the chest as hard as he could, but then managed to recover his patience, and washed out his net once again.

Appendix D

Resource Persons

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