Multitasking in Divided Attention

Bachelor thesis
by
Bhanu Pratap Singh Bankoti
Chandra Shekhar Gupta

Under the supervision of
Dr. Oishila Bandyopadhyay

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Declaration

We hereby declare that the work being presented in this thesis entitled, "Multitasking in Divided Attention", submitted to Indian Institute of Information Technology, Kalyani in partial fulfillment for the award of the degree of Bachelor of Technology in Computer Science and Engineering during the period from Jan, 2019 to May, 2019 under the supervision of Dr. Oishila Bandyopadhyay, Department of Computer Science and Engineering, Indian Institute of Information Technology, Kalyani, West Bengal 741235, India, does not contain any classified information.

Bhanu Pratap Singh Bankoti (39/CSE/15014/69)

Chandra Shekhar Gupta (39/CSE/15015/70)

Department: Computer Science & Engineering

Institute: Indian Institute of Information Technology, Kalyani

This is to certify that the above statement made by the candidate is correct to the best of my knowledge.

Signed:

Date:

Certificate

This is to certify that the thesis entitled "Multitasking in Divided Attention" being submitted by Bhanu Pratap Singh Bankoti (39/CSE/15014/69) and Chandra Shekhar Gupta (39/CSE/15015/70), an undergraduate student in the Department of Computer Science and Engineering, Indian Institute of Information Technology, Kalyani, West Bengal, India, for the award of Bachelor of Technology in Computer Science and Engineering is an original research work carried by them under my supervision and guidance. The thesis has fulfilled all the requirements as per the regulations of Indian Institute of Information Technology, Kalyani and in my opinion, has reached the standards needed for submission. The work, techniques and the results presented have not been submitted to any other University or Institute for the award of any other degree or diploma.

Dr. Oishila Bandyopadhyay
Assistant Professor
Department of Computer Science and Engineering
Indian Institute of Information Technology, Kalyani

Date:

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Bhanu Pratap Singh Bankoti (39/CSE/15014/69)

Chandra Shekhar Gupta (39/CSE/15015/70)

Indian Institute of Information Technology, Kalyani

Date:

Abstract

Assessment of cognitive functionality is an important aspect of care for people. Unfortunately, few tools exist to measure divided attention, the ability to allocate attention to different aspects of tasks. An accurate determination of divided attention would allow inference of generalized cognitive decline, as well as providing a quantifiable indicator of an important component of driving skill. Divided attention in vision is fundamentally about the dependence versus the independence of visual processing across stimuli. We propose a new method for determining relative divided attention ability through unobtrusive monitoring of computer use. Specifically, we measure performance on a multi-task cognitive computer exercise as part of our test for Divided Attention. This metric indicates whether the user has the ability to pay attention to all the tasks at once, or is primarily attending to one task at a time (sacrificing optimal performance). The monitoring of divided attention in a home environment is a key component of both the early detection of cognitive problems and for assessing the efficacy of learning patterns.

Keywords: Divided Attention, Optimal Performance, unobtrusive monitoring, cognitive computing.

Contents

Chapter 1

Introduction

1.1 Background

Attention, in psychology is the concentration of awareness on some phenomenon to the exclusion of other stimuli. Attention is best described as the sustained focus of cognitive resources on information while filtering or ignoring extraneous information. It is a very basic function that often is a precursor to all other neurological/cognitive functions. It is awareness of the here and now in a focal and perceptive way. Although human experience is determined by the way people direct their attention, it is evident that they do not have complete control over such direction. There are, for example, times when an individual has difficulty concentrating attention on a task, a conversation, or a set of events. At other times an individual's attention is captured by an unexpected event rather than voluntarily directed toward it.

1.1.1 Types of attention

Focused attention: The ability to respond discretely to specific visual, auditory or tactile stimuli.
Sustained attention (vigilance and concentration): The ability to maintain a consistent behavioral response during continuous and repetitive activity.
Selective attention: The ability to maintain a behavioral or cognitive set in the face of distracting or competing stimuli. Therefore, it incorporates the notion of "freedom from distractibility".
Alternating attention: The ability of mental flexibility that allows individual's to shift their focus of attention and move between tasks having different cognitive requirements.
Divided attention: This is the highest level of attention and it refers to the

ability to respond simultaneously to multiple tasks or multiple task demands [12].

1.1.2 Determinants of attention

- Objective features (inherent to external object)
  - Motivation
  - Intensity
  - Size
  - Change
  - Color
  - Clarity
  - Repetition
- Subjective features (inherent to individuals):
  - Interest
  - Motives
  - Mental set
  - Emotional state
  - Habit

1.2 Divided Attention

Divided attention could be defined as our brain's ability to attend to two different stimuli at the same time, and respond to the multiple demands of your surroundings [5]. Divided attention is a type of simultaneous attention that allows us to process different information sources and successfully carry out multiple tasks at a time. This cognitive skills is very important, as it allows us to be more efficient in our day-to-day lives. Our ability to attend to multiple stimuli and do various tasks at a time does have its limits. When you divide your attention, the efficiency with which you do these actions is decreased, and you will almost certainly perform poorly. Interference is the term used to describe when a person has a hard time attending to two stimuli at a time. We see interference when the brain is only able to process a certain amount of information. However, cognitive training can help improve divided attention, and as a consequence, the ability to do more than one activity at a time [12].

Examples of divided attention

- Divided attention is an important factor in the academic setting. Being able to understand what the teacher is saying while reading the board and taking notes are tasks that are essential to successful learning. This may be one of the reasons why people with attention disorders (like ADHD) perform poorly in school [8].

- A truck driver is driving on the highway and starts overtaking someone. As they are passing, they see a sign for their exit. If the driver isn't able to safely pass the other car and pay attention to traffic signs, they may lose important information, or even cause danger to themselves and others. Divided attention is very important to driving safely and successfully [1] [4].

- When you are eating and talking at the same time, or even when you are watching TV and talking on the phone, you are using divided attention.

Like most cognitive abilities, divided attention typically increases during childhood, plateaus in the years following puberty, and then gradually decreases with continued aging. The decline in this cognitive skill is one of the primary facets of decreased driving ability in the elderly [2].

The loss of divided attention skill is also highly associated with other age-related risks [3], including falls and the onset of Mild Cognitive Impairment (MCI) [7], often a precursor to Alzheimer's Disease. Screening tests for MCI are coarse at best; by the time someone does poorly enough to be considered impaired, his or her family have often been worried for months or years. This is especially problematic, considering that current pharmacological agents for Alzheimer's treatment can only slow the symptoms of the disease, not bring back what has been lost.

Chapter 2

Attention Assessment

2.1 Current methods of assessment

Given the importance of divided attention ability, some way to measure it, with finer resolution than simply being able to declare someone cognitively impaired or unsafe, would be invaluable for both early detection of problems and for monitoring progress on cognitive interventions.

Assessing divided attention may be helpful in professional areas, where divided attention is key (drivers, athletes, etc.). It can also help in academic fields (if a student needs extra time taking notes or completing certain tasks), or clinical areas (maybe a patient needs more time to collect the proper information). In all of these areas, a cognitive assessment [6], may directly help the user understand their day-to-day lives in a more in-depth context.

Our approach to monitoring cognitive skills like divided attention consists of embedding algorithms to measure aspects of cognitive performance into self reinforcing (i.e., enjoyable) adaptive computer games that are played in the home. This frequent monitoring allows us to trend both absolute performance and variability in performance with unobtrusive measures. This technique also lends itself to diagnosis and management of other neurological difficulties, such as children with autism [10].

2.2 Attention Test

Usually an attention test requires to detect something in a lot of stimuli. For example, searching 4 dots in lines of groups of 3 or 5 dots, or detecting a 4 between numbers (0-9) sequentially displayed on a computer screen. In such tests you just have to focus on one task or thing and try not to be distracted by another (distractor) task. These attention tests are set up to investigate concentration (see my page on Attention problems for an explanation of different types). Unfortunately, attention tests rarely resemble daily life activities and it is therefore questionable how accurately they really measure your concentration skills in daily life. One thing is certain though, most such tests require quite a lot of focus. Probably much more than daily life activities.

2.3 Test for Divided Attention

It is the attention tests developed to measure divided attention by doing more than two things at once. There are not many tests around that assess this aspect of attention. Here, we attempt to formalize a method for analyzing one game which is designed to challenge player's ability to attend to multiple dimensions of stimuli simultaneously.

We have created a game consisting of 3 tasks in which a user has to simultaneously response to all 3 tasks in a sequential order. This game runs for around 12 minutes.

Chapter 3

Work Done

We have introduced visual search and multitask paradigm to study the divided attention. Initial consideration of divided attention is limited to a consideration of simple stimuli and tasks and focuses on divided attention across space.

3.1 Proposed algorithm

We will show divided attention effects, performance will depend on the number of task-relevant stimuli. A contrasting extreme to serial processes would be those that proceed simultaneously (i.e., in parallel) for multiple stimuli and are unaffected by the number of to-be-processed stimuli. For some situations, a set of completely independent parallel process is expected to suffer no divided attention effects. Besides serial versus parallel processing, there are other types of dependencies that can lead to divided attention effects [9]. Effects of divided attention are behavioral consequences (such as impaired performance) of manipulating the number of relevant stimuli. We offer an analysis, asking what aspect of processing is the source of the divided attention effects. In this test we are given a randomly generated stimuli which keeps on changing and we have to respond for the target stimuli. The purpose is to introduce the paradigms, recognize some of their strengths and weaknesses, and understand the attention level that can and cannot be addressed.

To classify the divided attention in 3 category namely Low, Average and High divided attention, we have applied the following steps after collecting the data:

- Remove the inconsistent data from dataset.

- Label the data based on the mean and standard deviation of the attention score.
- Apply machine learning model to classify the attention type (Low, Average, High).
- Analyze the output and trends in academic performance and divided attention.

3.2 Function

In this work we have developed three distinct task which will have spatial identification test, color and number test (Figure 3.1), which will monitor the attention level by using visual effect and multi-tasking. A user has to press the specified key at instant, the target stimuli occur [11].
In this test, there is predefined input which will keeps on changing randomly at the time interval of 750 milliseconds. This whole process of test occur in order i.e., firstly angle determination test is done (task 1), then color selection test (task 2) and then number selection test (task 3) (Figure 3.1). Each test is of 3 seconds and this is repeated 20 times. If a user is unable to respond within that 6 seconds, either he missed it or unable to act, it will be considered as wrong outcome. If user is fast and smart enough to act decisively and press right key for that target stimuli, answer is recorded as true, otherwise false value is stored in database.

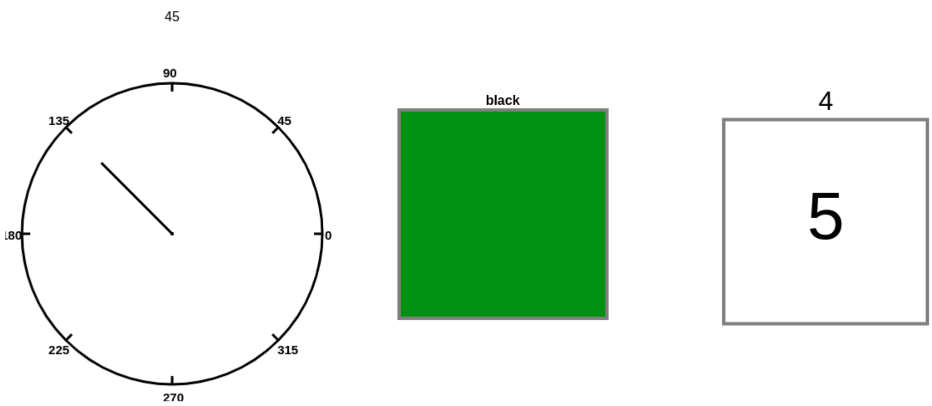

Figure 3.1: Window containing all 3 task.

3.2.1 Task 1

In first task, we try to measure the attention level of a user related to spatial movement of stimuli. In this test, an angle is generated randomly and it keeps on changing at each 750 milliseconds. A user is given input as particular angle (in degree) and he have to click the “left arrow" at the instant when that particular angle (target stimuli) is shown in the clock (Figure 3.2). This task run for 6 seconds only and user has to respond correctly within this 6 seconds. At the same instant, evaluation is done and the output is stored in database. And this task again run after task 2 and task 3 are performed. 20 records are created in this process.

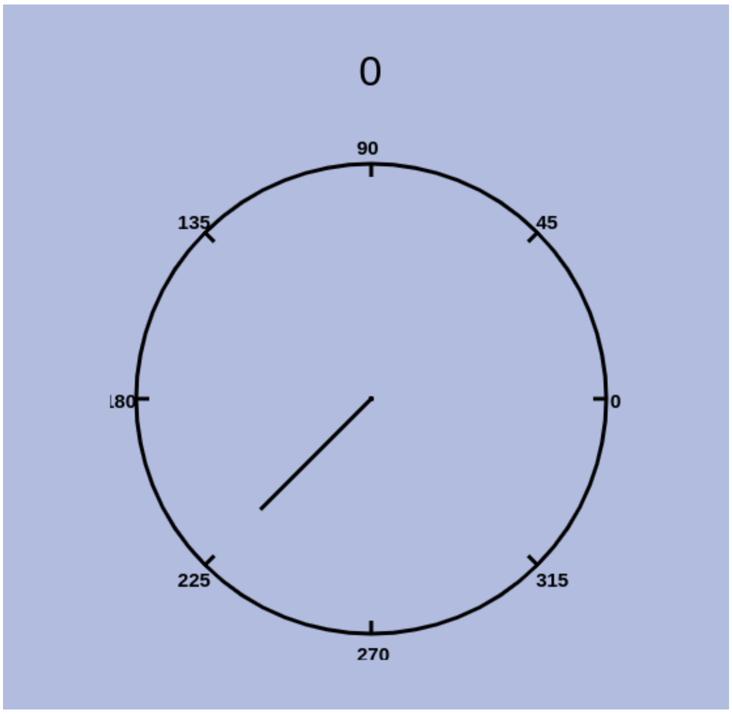

Figure 3.2: Preview of Task 1.

3.2.2 Task 2

In this task, we are concerned with chromatic stimulus behavioural process. We have to select a given color out of the rest of the colors (8 colors) which are generated randomly at regular interval of time and changes periodically at time interval of 750 milliseconds (Figure 3.3). We will use “up-arrow" for responding for the given color (target stimuli). If the time limit (i.e., 6 seconds for each question) is elapsed and the color is not selected then the question will be marked missed. For example, in Figure 3.3 target stimuli is gray and instant stimuli is blue.

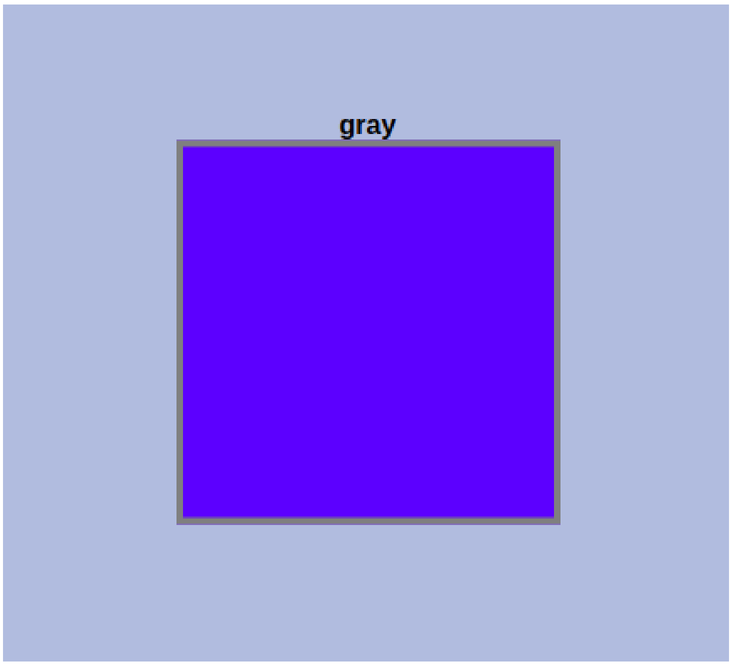

Figure 3.3: Preview of Task 2.

3.2.3 Task 3

In this game we are concerned with stimulus and response related to number game. We have to correctly select a number which is generated randomly using a pseudo number generator that keeps on changing every 750 milliseconds (ranging from 1-8 inclusive). We will use “right-arrow" for selecting the given target color. If the time limit (i.e., 6 seconds for each question) is exceeded and the number is not yet selected then the question will be marked missed. This task is also performed 20 times. For example, in given Figure 3.4, a user is asked to press right key when orange square box shows 5 as target stimuli is 5.

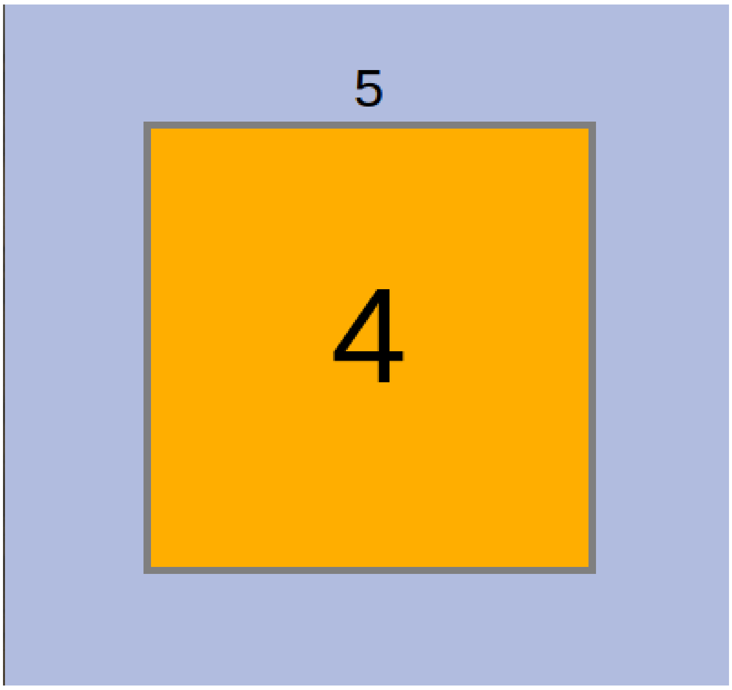

Figure 3.4: Preview of Task 3.

3.3 Labelling of Dataset

The dataset that is collected is not labeled so we have done statistical analysis on the data in order to label it as High, Average or Low divided attention. The steps for labeling a dataset is as follows :

1. Firstly, we have done the statistical analysis individually for each of the three cognitive tasks. We are using mean(μ) and standard deviation(σ) in order to differentiate between the three classes. Let the 3 cognitive tasks be task-a, task-b, and task-c then the corresponding statistical parameters for these are (μ_a, σ_a), (μ_b, σ_b), (μ_c, σ_c). We have also classified the performance in these individual tasks into 3 classes(High(H), Average(A), and Low(L)) as follows :
   H_a = above $\mu_a + \sigma_a$ A_a = between $\mu_a - \sigma_a$ and $\mu_a + \sigma_a$ L_a = below $\mu_a - \sigma_a$

   H_b = above $\mu_b + \sigma_b$ A_b = between $\mu_b - \sigma_b$ and $\mu_b + \sigma_b$ L_b = below $\mu_b - \sigma_b$

   H_c = above $\mu_c + \sigma_c$ A_c = between $\mu_c - \sigma_c$ and $\mu_c + \sigma_c$ L_c = below $\mu_c - \sigma_c$

2. Again we will do the statistical analysis but now for the combined cognitive task comprising of all the three sub-tasks a, b and c. The statistical parameters for this combined task are (μ, σ).

3. Then we will check for the consistency of the subject's performance in the combined cognitive task with the help of the performance of his individual tasks. By doing so all the inconsistent or irrelevant records (due to fatigue, boredom or habituation) will be filtered out.

4. We will categorize each record of the dataset in three classes of Divided Attention as follows :

   - High Divided Attention (results are above $\mu + \sigma$)
   - Average Divided Attention (results are between $\mu - \sigma$ and $\mu + \sigma$)
   - Low Divided Attention (result are below $\mu - \sigma$)

Scatter plot of Task-1, Task-2 and task-3 are shown in Figure 3.5, in which green bubble represent High attention score, red dot represent Average attention score, whereas blue bubble represent Low attention score.

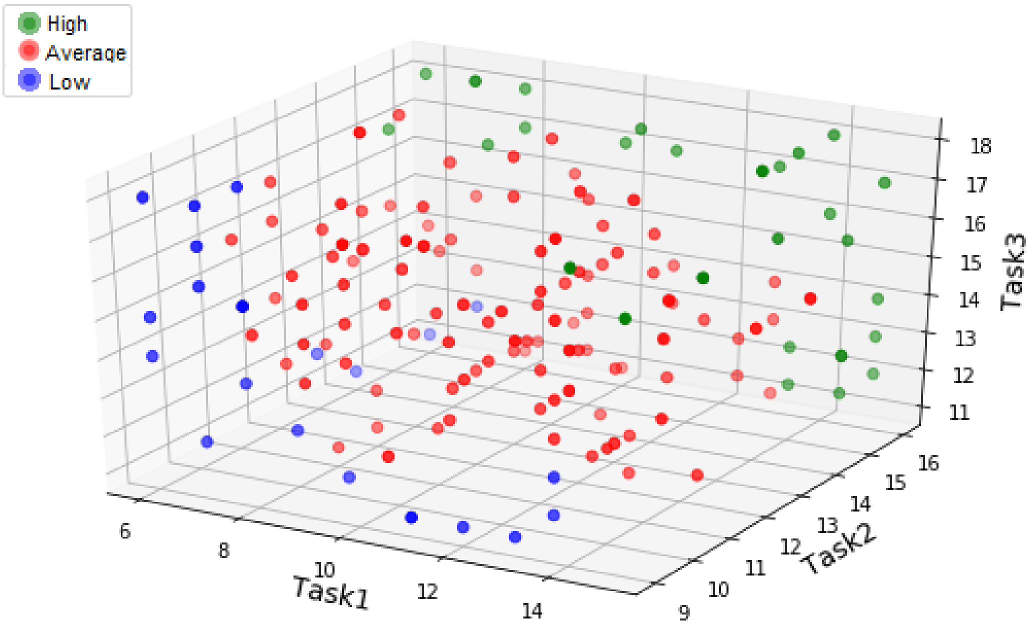

Figure 3.5: Scatter plot for all 3 tasks

Index	Task-1	Task-2	Task-3	Z
0	8	13	13	0
1	13	11	12	0
2	7	10	18	-1
3	8	14	11	0
4	11	16	17	1
5	14	15	12	1
6	9	10	16	0
7	13	12	11	0
8	9	9	15	0
9	8	15	17	1
10	12	13	11	0
11	15	16	15	1
12	15	14	15	1

Table 3.1 Labelled Dataset

Target Value Z (in table 3.1) is divided into 3 class namely -1, 0, 1 where,

- -1 corresponds to Low Divided Attention.
- 0 corresponds to Average Divided Attention.
- 1 corresponds to High Divided Attention.

Chapter 4

Classification model and Results

4.1 Classification of Divided Attention

In order to classify the Divided Attention of a subject, we have used some of the machine learning algorithms. We are using classification which is a technique for determining class the dependent belongs to based on the one or more independent variables. Here the classes are High, Average and Low and the features are the correct responses of the subject on the basis of 3 cognitive tasks. Before applying any classification algorithm we have split the dataset into two sets, one for training dataset(60%) and the other for testing data-set(40%) before training our model. Then we are employing three classification techniques:

4.1.1 Naive Bayes Classifier

A Naive Bayes classifier is a probabilistic machine learning model thatâĂŹs used for the classification task. The crux of the classifier is based on the Bayes theorem with the independence assumptions between predictors i.e., it assumes the presence of a feature in a class is unrelated to any other feature. Even if these features depend on each other or upon the existence of the other features, all of these properties independently. Thus, the name Naive Bayes [13].

Naive Bayes classifier is the fast, accurate and reliable algorithm. Naive Bayes classifiers have high accuracy and speed on large datasets. Naive Bayes classifier assumes that the effect of a particular feature in a class is independent of other features. Even if these features are interdependent, these features are still considered independently. This assumption simplifies computation, and that's why it is considered as naive. This assumption is called class conditional independence.

$$P(h|D) = \frac{P(D|h)P(h)}{P(D)}$$

- P(h): the probability of hypothesis h being true (regardless of the data). This is known as the prior probability of h.
- P(D): the probability of the data (regardless of the hypothesis). This is known as the prior probability.
- P(h|D): the probability of hypothesis h given the data D. This is known as posterior probability.

- P(D|h): the probability of data d given that the hypothesis h was true. This is known as the posterior probability.

Naive Bayes classifier calculates the probability of an event in the following steps:

1. Calculate the prior probability for given class labels.
2. Find Likelihood probability with each attribute for each class.
3. Put these value in Bayes Formula and calculate posterior probability.
4. See which class has a higher probability, given the input belongs to the higher probability class.

4.1.2 Support Vector Machine (SVM)

A Support Vector Machine (SVM) is a discriminative classifier formally defined by a separating hyperplane. In other words, given labeled training data (supervised learning), the algorithm outputs an optimal hyperplane which categorizes new examples. It is based on the concept of decision planes that define decision boundaries. A decision plane is one that separates between a set of objects having different class memberships [14]. SVM offers very high accuracy compared to other classifiers such as logistic regression, and decision trees.

The main objective is to segregate the given dataset in the best possible way. The distance between either nearest points is known as the margin. The objective is to select a hyperplane with the maximum possible margin between support vectors in the given dataset. SVM searches for the maximum marginal hyperplane in the following steps:

1. Generate hyperplanes which segregates the classes in the best way.
2. Select the right hyperplane with the maximum segregation from either nearest data points.

4.1.3 Random Forests

Random Forest Classifier is an ensemble algorithm based on bagging i.e., bootstrap aggregation. Ensemble methods combine more than one algorithms of the same or different kind for classifying objects i.e., an ensemble of SVM, Naive Bayes or Decision Trees. Random forests create decision trees on randomly selected data samples, gets a prediction from each tree and selects the best solution by means of voting [15]. It also provides a pretty good indicator of the feature importance.

Deep decision trees may suffer from overfitting, but random forests prevent from overfitting by creating trees on random subsets. The main reason is that it takes the average of all the predictions, which cancels out the biases. Random Forest adds additional randomness to the model while growing the trees. Instead of searching for the most important feature while splitting a node, it searches for the best feature among a random subset of features. This results in a wide diversity that generally results in a better model.

It technically is an ensemble method (based on the divide-and-conquer approach) of decision trees generated on a randomly split dataset. This collection of decision tree classifiers is also known as the forest. The individual decision trees are generated using an attribute selection indicator such as information gain, gain ratio, and Gini index for each attribute. Each tree depends on an independent random sample. In a classification problem, each tree votes and the most popular class is chosen as the final result. In the case of regression, the average of all the tree outputs is considered as the final result. It is simpler and more powerful compared to the other non-linear classification algorithms.

It works in four steps:

1. Select random samples from a given dataset.
2. Construct a decision tree for each sample and get a prediction.
3. Perform a vote for each predicted result.
4. Select the prediction result with the most votes as the final prediction.

4.2 Results

In order to classify the Divided Attention of a subject, we have employed three machine learning classification algorithms (SVM, Naive Bayes classifier and Random Forest). We have done a comparative analysis among them on the basis of their efficiency. From the analysis we can conclude that the efficiency of Random forest classifier is better as compared to SVM and Naive Bayes classifier. Apart from this, we have also plotted the confusion matrix of all the three classifiers that can be used to describe the performance of our classification model(or classifier) on a set of test data whose true values are known.

		predicted value		
		-1	**0**	**1**
True value	**-1**	2	6	0
	0	0	49	1
	1	0	7	7

Confusion Matrix for Naive Bayes Classifier.

From the above confusion matrix of Naive Bayes Classifier, we conclude that out of 8 instances of Low attention class, 2 of them are correctly predicted but 6 of them are incorrectly classified into Average attention class. For 50 instances of Average class, 49 are correctly classified but 1 instance is misclassified as High attention class. For 14 instances of High class attention, 7 of them are classified correctly but 7 is incorrectly classified as Average attention class. So, accuracy of Naive Bayes model is 80.57%.

True value \ predicted value	-1	0	1
-1	3	5	0
0	2	48	0
1	0	1	13

Confusion Matrix for SVM Classifier.

From the above confusion matrix of SVM Classifier, out of 8 instances of Low attention class, 3 instance are predicted correctly but 5 of them are incorrectly classified into Average attention class. For 50 instances of Average class, 48 are correctly classified but 2 instances is misclassified as Low attention class. For 14 instances of High class attention, 13 of them are classified correctly but 1 instance is incorrectly classified as Average attention class. So, performance of SVM model is 88.88%.

True value \ predicted value	-1	0	1
-1	4	4	0
0	1	49	0
1	0	2	12

Confusion Matrix for Random Forest Classifier.

Above confusion matrix of Random Forest Classifier indicate that for 8 instances of Low attention class, 4 instances are correctly predicted but 4 are incorrectly predicted into Average attention class. For 50 instances of Average class, 49 are predicted correctly but 1 instance is misclassified as Low attention class. For 14 instances of High class attention, 12 of them are predicted correctly but 2 instances is incorrectly predicted as Average attention class. So, performance of this model for our dataset is 90.27%.

We have found the accuracy of all three classifiers using the given dataset.

The accuracy of SVM classifier is 88.88%, for Naive Bayes classifier it is 80.55% and for Random Forest classifier the accuracy is 90.27% (Table 4.1). From these statistics we can conclude that Random Forest classifier is more accurate and hence better classifier for Divided Attention than SVM and Naive Bayes classification model.

Classifier	Accuracy
Naive Bayes	80.55
SVM	88.88
Random Forest	90.27

Table 4.1: Efficiency of implemented classifiers.

Chapter 5

Analysis on basis of divided attention

5.1 Trends in academic performance

This analysis examines the association between student's divided attention performance and their academic functioning. We will see whether a subject having high, low or average divided attention performs well or poorly in his academics. This study helps in examining whether there is a negative association between attention difficulties and their academic performance.

We have collected the data regarding their academic performance from all the students who performed the test for divided attention. For the analysis, we have plotted a histogram and scatter plot graph (Figure 5.1). From these graphs we can analyze that most of the students have average divided attention in contrast to low and high divided attention. Majority of the students with high divided attention have good academic performance while some have average and few of them have poor academic performance. The students with poor academic performance and high divided attention must have strong logical and analytical reasoning and high mental agility.

Most of the students with average divided attention have either good or average academic performance and the students with low divided attention have poor academic performance.
From these results (Figure 5.1), we can conclude that divided attention has a strong association with academic functioning and students with attention problems have a subsequent decline in their academics.

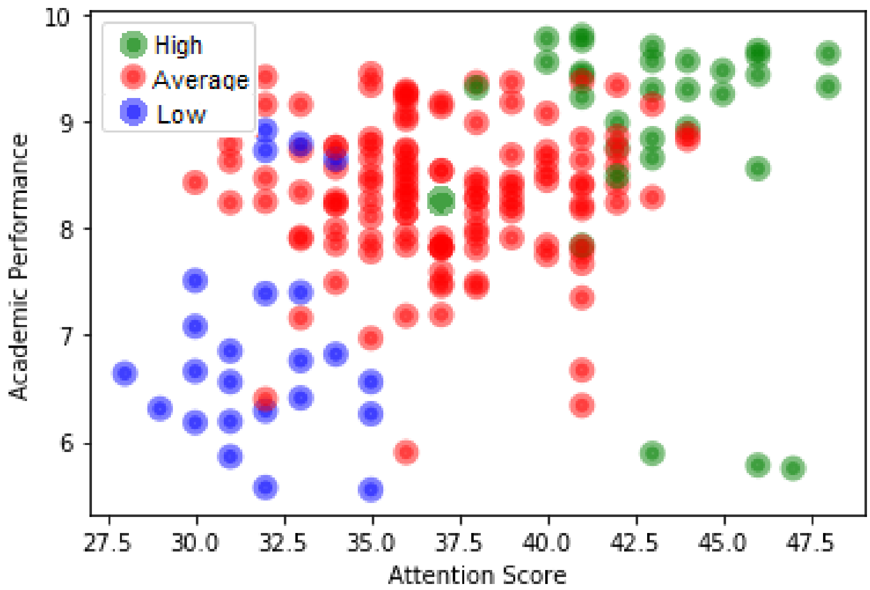

Figure 5.1: Plot of Attention Score and Academic Performance.

5.2 Analysis of Linear Perception and Divided Attention

All the ways in which we experience the world around us for example, we recognize our favorite food by its aroma and the way it looks, we recognize an orange by its round shape, citrus flavor, and its color, etc. It is through these sensory experiences that we interact with and interpret things in our world. Recognizing and interpreting sensory information, such as sound and smells, are all a part of perception.

Perception refers to the way sensory information is organized, interpreted, and consciously experienced. It also includes how we respond to the information. We can think of perception as a process where we take in sensory information from our environment and use that information in order to interact with our environment. Perception allows us to take the sensory information in and make it into something meaningful.

Here we have designed a linear perception device in which given a line of some fixed length (L) the subject has to slide a line accordingly to draw the length (L') with minimum error (Error = L' - L). We are taking the subject's performance error as a parameter to analyze the relationship between Linear Perception and their Divided Attention.

For the analysis, we have plotted a graph (Figure 5.2) between Divided Attention score and Linear Perception response (error).

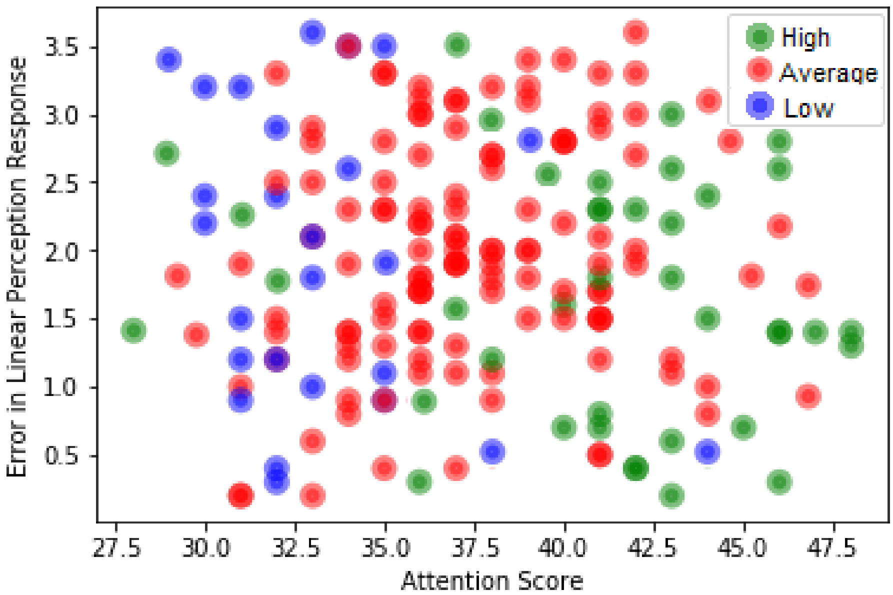

Figure 5.2: Plot of Attention Score and error in Linear Perception.

From Figure 5.2 we cannot observe any strong association between Linear Perception and Divided Attention. The possible causes may be due to insufficient dataset or the discrepancy in the subject's Divided Attention and most of the data we have collected corresponds to the subject with no attention difficulties. So this analysis can give a better result if we have more data and more feature parameters (especially data of the subject's facing with attention problems).

Chapter 6

Discussion

Divided attention is our brain's ability to attend 2 or more stimuli simultaneously. It allows us to process different information sources and successfully carry out multiple tasks at a time. Our ability to attend to multiple stimuli and do various tasks at a time does have its limits. We have developed a computer-based, user-friendly attention test for Divided Attention which consists of three games. Each game is independent and has its own cognitive requirements. These tests run in sequential order, periodically for about 9 minutes. After the test is completed we use the results of our test as dataset for our machine learning model. The dataset thus obtained is unlabelled so we label these dataset into 3 classes of Divided Attention as High, Low or Average by doing statistical analysis. By doing so all the inconsistent records are also filtered out. In order to classify the Divided Attention of a subject, we have employed three machine learning classification algorithms (SVM, Naive Bayes classifier and Random Forest) and done comparative analysis among them. We have also examined the association between student's divided attention performance and their academic functioning and established that students with attention problems have a subsequent decline in their academics. Apart from this, we have also studied the relationship between Linear Perception and their Divided Attention by using a linear perception device. It can be used as a cognitive assessment to measure attention deficits in patients and normal (healthy) persons.

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