DECODING NEURAL INFORMATION FROM MONKEY'S BRAIN

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by

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to the

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CERTIFICATE

This is to certify that the work contained in this project report entitled "**Decoding Neural Information From Monkey's Brain**" submitted by **Hitesh Arora** (**Roll No.: 11010122**) to Department of Computer Science and Engineering, Indian Institute of Technology Guwahati towards the requirement of the bachelor thesis report has been carried out by him under my supervision.

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April 2015 Project Supervisor

ABSTRACT

To understand the functional architecture of brain, neuroscientists conduct experiments focused on specific brain functions while recording neural response from targeted brain regions. In the project, we analyse monkeys' brain data obtained from two different experiments, using machine learning based approach.

The first experiment aimed to understand monkey's behaviour in a free-eye scan task. We were able to decode the target position during an eye-movement of monkey, and compared it across three brain regions - Frontal Eye Field (FEF), Caudate Nucleus (CN), and Pre-Frontal Cortex (PFC). We found that the eye-movement information is directly encoded in FEF, but it seems to be abstractly represented in CN and PFC.

The second experiment aimed to find out if the cognitive functions of spatial working memory and task representation are distributed across regions of Pre-Frontal Cortex (PFC) and Posterior Parietal Cortex (PPC), or the co-activated regions are specialized for specific roles. We found that the brain region PFC is used for remembering the target stimulus and filtering distractors by both the monkeys, while the brain region PPC is only used by one of the monkeys. We also got some insights about the neural representations of stimuli across a trial.

Contents

Chapter 1

Introduction

Understanding how human brain works has fascinated mankind since long. Over the years, we have been making progress towards understanding brain, but still we havent been able to understand how exactly neural computations take place, how human intelligence still overpowers most learning algorithms and there are so many questions still unanswered.
But today, the opportunities for success in brain research are unprecedented. The availability of massive computing power, advanced and innovative technologies for recording brain data and strong support for brain research, has opened so many avenues to understand brain in a better way. Currently many researchers from different domains viz. computer science, neuroscience, cognitive science and psychology have joined hands to understand how is intelligence grounded in computation, how they develop during childhood and evolve through experience. Many big projects are already underway - The US governments BRAIN Initiative (Brain Research through Advancing Innovative Neurotechnologies) [7] , with the goal of mapping the activity of every neuron in the human brain; the Human Brain Project [8] funded by European Union with aim to simulate complete human brain on supercomputer; various projects by Center for Brains, Minds and Machines(CBMM), Allen Institute for Brain Science and many more researchers.

With the aim to understand the functionality of the brain, researchers design experiments and record data from human brain, using different methodologies viz. functional magnetic resonance imaging (fMRI), magnetoencephalography (MEG), electrophysiology etc. with each technology helping to answer specific questions. The objective is to correlate the behaviour of the subject (human or animal) with the neural data obtained and build models and theories, and validate them using further experiments. This is a research thrust strongly pursued in various research groups.

As part of my thesis project, we are working on analysing neural data from two different experiments in collaboration with Dr. Ethan Meyers, (CBMM, MIT). In the first one, we analyse neural data from monkeys brain as it performs a novel free-movement task. We wanted to find out if we can predict the pattern of monkey's eye-movements using neural data, and which brain regions contribute to these patterns and learning. We were able to decode eye-movement of monkey with high accuracy, and compared the information among all the three brain regions. The data has been made available by Dr. Theresa Dresrochers, (Brown University) and Graybiel Lab, MIT and we are extremely grateful to them for sharing the data.
In the second experiment, we worked on analysing spatial working memory in primates with two variations of the experiment. In this, two monkeys performed a task to remember the first or second of a sequence of two stimuli, and data was recorded from Pre-Frontal and Posterior Parietal Cortex. We found that the region PFC plays a role in remembering the target stimulus and filtering the distractor stimulus. But the region PPC was observed to be used only by one monkey, and not by the other. The data has been provided by Dr. Christos Constantinidis (Wake Forest University School of Medicine) and we are deeply thankful to him.

In Chapter 2, the technique of population decoding and methodologies are discussed. The first experiment is explained in detail in Chapter 3, and the second in Chapter 4 respectively, along with all the analysis and results.

Chapter 2

Background

To understand how our brains might be working, one of the important questions to answer is - *How is information encoded in our brains?* To solve this intriguing question, scientists started long back in 1950s, and one of the most famous experiments was Hubel and Weisels cat experiment [5] where they recorded from an electrode inserted into cats brain and discovered simple and complex cells (neurons).They both were even rewarded with Nobel Prize in Physiology or Medicine in 1981 for their immense contributions in the field. Over the years, the methods for recording brain signals have been advancing gradually with some of methods currently being used as electrophysiology, functional Magnetic Resonance Imaging (fMRI), and Magnetoencephalography(MEG). The most common used data analysis methods include the traditional statistics on the data, which are not very successful in answering complex questions about how neural activity codes information across time and if the information is contained in some invariant format. We will mainly focus on electrophysiology (neural spiking) data, though this technique can be applied to other types of data as well.

2.1 Population Decoding

Population decoding is one of the powerful methods used to analyse multivariate neural data based on the principle of cross-validation used in machine learning research, and is beginning to be widely used to analyse data[11][6]. The idea behind this method is based on an intuition that, one of the important computational functions that the brain should perform is to be able to reliably distinguish between different behaviourally relevant conditions in real time. If we can build a model (classifier) using the neural data and it is able to distinguish among a pre-defined set of conditions that were present when the neural recording, then we can say that the recorded neural activity or the corresponding brain region contains sufficient information to differentiate among the conditions present. But how can we be sure that our model captured the reliability in the data? Cross-validation comes to our rescue! If we can build model using only part of data and show that the same model works for distinguishing the same set of conditions in a new (test) data, then we can be much more confident that our the neural activity indeed had information which could enable brain to distinguish reliably. Moreover comparing different models can give us insight about how neurons might encode information. 2.1 explains the basic steps in analysis using an example.

2.2 Experimental Design

In our analysis, we assume that a human or animal subject is presented with different conditions while the experimenters record from multiple neurons with implanted electrodes across different trials. These conditions could be anything viz. different images, different object positions or shapes, the same objects under experimental manipulations (with or without attention) etc. To build a reliable model, multiple repetitions of each condition must be shown and the order of presentation should be randomized to avoid errors due to neuronal adaptations and non-stationarities in recordings.

2.3 Neural Spiking Data

We assume that spike extraction has been performed on the data recorded and we have the spike data as sequence of 1s and 0s on time scale, where 1s refer to the occurrence of spikes and 0s to non-occurrence of spikes. The temporal scale on which information is encoded is still not well understood, but better results have been obtained in many cases if we bin the data in intervals of hundreds of milliseconds, and take the average firing rate in the bin. If we are recording from multiple neurons during an experiment, then we treat neural response (usually the average firing rate) of each neuron as a feature, and concatenate the neural response of all the neurons to obtain a neural population

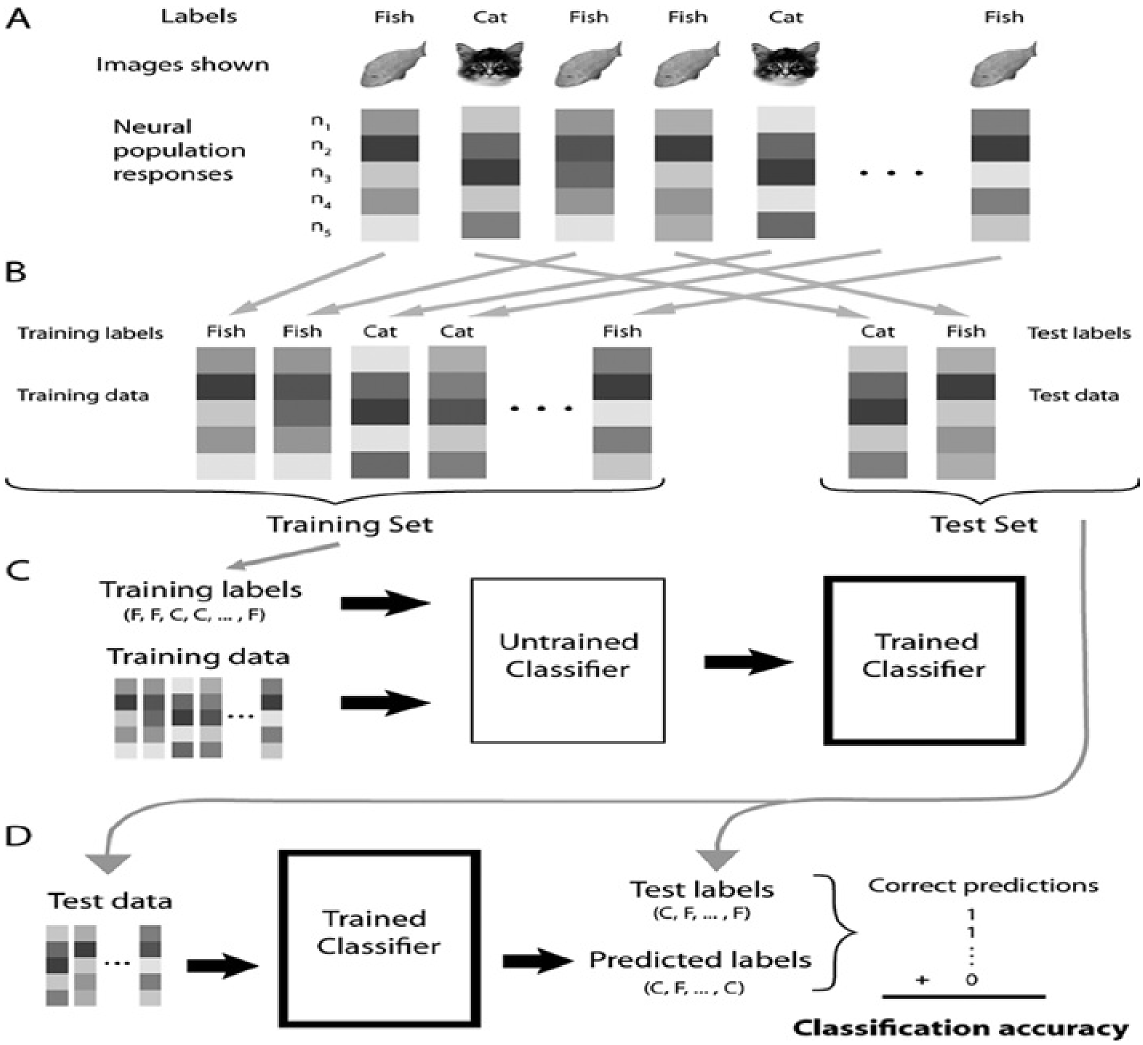


Figure 2.1: Basic steps involved in training and testing a classifier. (A) An illustration of an experiment in which an image of a cat and an image of a fish were shown in random order to a subject while simultaneous recordings were made from five neurons/channels. The grayscale level denotes the activity of each neuron/channel. (B) Data points and the corresponding labels are randomly selected to be in either the training set or in the test set. (C) The training data points and the training labels are passed to an untrained classifier that learns which neural activity is useful at predicting which image was shown thus becoming a trained classifier. (D) The test data are passed to the trained classifier, which produces predictions of which labels correspond to each unlabeled test data point. These predicted labels are then compared to the real test labels (i.e., the real labels that were presented when the test data were recorded) and the percent of correct predictions is calculated to give the total classification accuracy. Image courtesy [9]

response vector. Due to experimental challenges in recording from multiple electrodes simultaneously, a pseudo-population approach is used, wherein we concatenate responses of different neurons that were recorded when same stimulus or condition was shown, although they were recorded during different sessions, and not simultaneously. It has been shown, that we still can get useful insights using pseudo-populations as well.

2.4 Decoding process

In the cross validation step, the data is divided into training and test data. After some pre-processing, the training data is fed to a classifier to build to learn a model and then tested on the test set, to obtain a measure of prediction, which we term as decoding/classification accuracy. We repeat the process and choose the cross-validation splits randomly each time, and final calculate the average decoding accuracy. More analysis and testing can be done to explore possible encodings of the data possibly in an abstract/invariant way in higher-level brain regions. A very good source to learn about this method is the book chapter on Tutorial on Pattern Classification in Cell Recording by Ethan Meyers and Gabriel Krieman [9].

2.5 Neural Decoding Toolbox (NDT)

NDT is a toolbox in Matlab developed by Dr. Ethan Meyers that makes it much easier to apply population decoding analysis to neural data. We have used NDT for most of the data analysis and generation of results. For further details of NDT, please refer[10] or tutorials at http://www.readout.info/ .

Chapter 3

Free-eye viewing experiment

3.1 Motivation

How people or even animals make choices in day to day life? Are they optimal? Such questions led to formulation of many theories, and one of them is Reinforcement Learning (RL). RL mathematically formulates the process by which rewards and punishments affect the behaviours and decisions of a goal-seeking agent (person, animal or even robot) towards optimality. Many psychologists and neuroscientists have tested these ideas experimentally through various stimulus-response tasks [1] [3] , such as rodents trained to press a button or a sequence of buttons to get reward, or monkeys learn to distinguish between different images and respond by a particular action like eye movement. But in most of such experiments, the number of responses available are few, ratio of cost and benefit is explicit and a small range of relationship between rewards and agents response is imposed. This is in contrast to the real-life complex situations where no repetitive stimulus-response links are present, number of choices (responses) are large. To understand naturalistic learning and incorporate uncertainty, researchers at the Graybiel Lab at MIT designed an experiment and tested whether such behaviours could be explained by RL. [4]

3.2 Experiment Details

The experiment was conducted with two monkeys, (G and Y). In the experiment, eye positions were monitored using infrared eye tracking and neural recordings were collected from electrodes implanted in different brain regions of the monkeys.

3.2.1 Setup

During the experiment, each monkey was seated in front of a computer screen on which a grid of gray dots was shown initially and there were no behavioural requirements while gray dots were shown. After a delay (Start Delay, 1-2s), a grid of four or nine target dots turned green. The monkey could move its eyes freely in any way as long as its gaze remained in the green grid. After a variable delay (Delay Scan 1-2 s), one of the target dots was pseudorandomly baited (selected) with reward, and nothing was signalled in any way to the monkey. This delay was to prevent monkey from immediately completing the trial. Now, whenever the monkeys gaze entered the baited target, either by fixating or saccading through it, the green target grid was immediately turned back to the gray grid. After a variable delay (Reward Delay, mean 0.6s), the monkey was rewarded followed by Inter Trial Interval, and the trial ended. If the monkey moved its eyes outside the green target grid before capturing the baited target, the trial was aborted immediately and grid turned back to gray, and no reward was delivered.

The monkeys were given no explicit training and since a target was pseudo-randomly baited, no particular sequence of eye movements (saccades) implied getting rewarded. The experiment was performed during daily sessions across months, where each session included multiple trials. What do you expect? Would there be any pattern in the monkeys eye movements or would they be random?

3.2.2 Behavioural results

Despite complete lack of instruction on whether or how to move their eyes, the monkeys developed their own repetitive eye movement patterns to scan the grids, and performed the task approximately 70% correct across sessions. It was observed that the monkeys reached their maximum for reward per session, and minimum for eye travel distance during Reward Scan per trial for each session (cost) in the earlier trials itself, but still their pattens continued to evolve over time. As described in the paper, the optimal scanning pattern, in some way, was a loop pattern in which each target was visited once and the one among these with minimum total travel distance should be the optimal one.

Surprisingly the monkeys final patterns were optimal or near optimal, comparing among all possible patterns using exhaustive search algorithm.

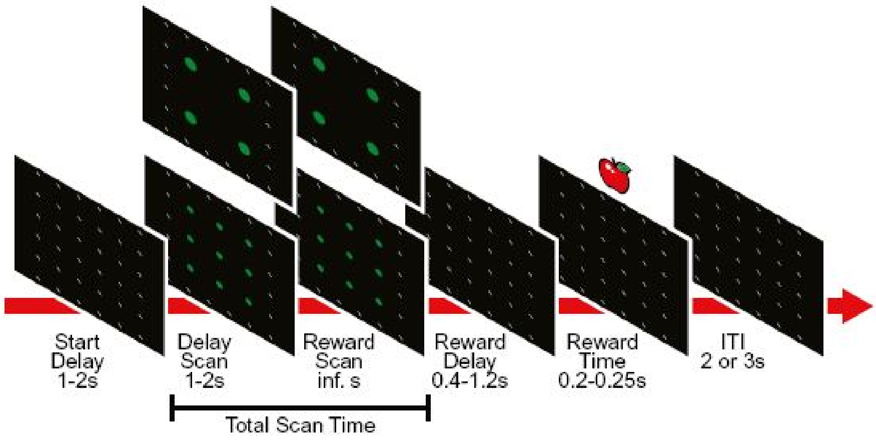


Figure 3.1: Schematic of the free-viewing scan task. There was no requirement for the monkeys eye position when the gray grid was displayed. After a variable Start Delay, the green target grid was presented indicating the start of the Scan Time. When the green target grid was displayed, and once the monkeys gaze entered the area defined by the green grid, the only requirement was that the eye position remained in that space. After the variable Delay Scan, the Reward Scan began when a randomly chosen target was baited without any indication to the monkey. There was no time limit on the duration of the Reward Scan. Once the monkey captured the baited target by fixating or saccading through it, the green grid immediately turned off and the trial proceeded through the remaining task periods as illustrated. If the monkeys eye position exited the green grid area before capturing the baited target, the trial was immediately aborted by extinguishing the green target grid, and no reward was delivered. Courtesy [4]

Moreover, the evolution of the pattern of eye movements of monkeys can be explained by trial-by-trial analysis of monkeys scan path transition probabilities and cost changes. It has been shown in paper that a reinforcement learning algorithm based on the explore-exploit principle very closely models monkeys behaviour, and the pattern of simulated agent closely resembled that of monkeys with appropriate parameters.

3.2.3 Data given

We were given all the data recordings to analyse the brain recordings and find out neural correlates of the observed monkeys behaviour. The neural recordings were made from 3 main regions of brain namely, Caudate Nucleus (CN), Pre-Frontal Cortex (PFC) and Frontal Eye Fields (FEF). The data included both eye-tracking data and neural spiking data across different sessions. For each session, the data for each trial included the timings for all events of interest viz. the start time, target on, find scan, target off, reward on, reward off, end time, baited target position, and result of the trial (success/failure). It had information for all fixations, and eye movements (saccades) with their positions and times. The timings for neural spikes along with the brain region it came from was also given. We were to analyse the 9-sized grid task.

3.3 Analysis

Given the above data, the questions that came to our mind were, can we predict the pattern of eye-movements made by monkey? How does the neural representation change as monkey continues to do the task across months? Which brain regions (neurons) play major role in learning?

3.3.1 Design of Analysis

We began by analysing if we can predict where the monkeys eye movement (saccade) at a point in time, so that later we could think about predicting a sequence of eye movements. As per the procedure in population decoding, we defined the condition (class label/stimulus) of a trial as the dot position towards which monkey made a saccade at a particular point of time (which we chose as 1st, 3rd, or 5th saccade after the Target On time). There were 10 class lables, 9 of them being the fixed green dot positions, and 10th of them to denote a position which wasnt exactly at any of the 9 dots. Since the experiment was carried out across different sessions, and in each session recordings were made from different electrodes, we used the concept of pseudo-populations to combine recordings from different sessions. Now to combine neurons, we first needed to compute the number of times each condition (stimulus) was presented to each neuron (site), and find out the number of time each condition was atleast presented for all the neuron sites.

Now choosing all possible neuron sites, with all possible conditions (class labels) left us with very few repetitions for each site (which means very less training data, though a longer feature vector). Hence we had to choose the optimal number of neuron sites, number of class labels to decode, and minimum number of repetitions for which each chosen label for each chosen neuron site. By doing analysis, we chose to take the top 5 of the class labels (which had the most number of repetitions), and keep the minimum number of repetitions for each class label as 10, we found the number of neuron sites which satisfied these conditions and chose them in decoding.

3.3.2 Data Preprocessing

First, the neural data was divided based on the brain region it belonged to viz. CN, FEF or PFC. Then the spike data was converted into raster format as is needed by the NDT. Each trial was labelled based on the position of 3rd saccade, and the data in each trial was aligned with the onset of 3rd saccade. Actually 3rd saccade is just taken here to explain, we could have taken any saccade, and we did for 1st and 5th saccade as well. Also the each trial was labelled with other information as well such as the start of saccade, saccade amplitude, direction, result of trial etc. which would be used in later analysis. Then the optimal bin size (time over which the average firing was calculated over) was found by running analysis over a range of bin sizes, and bin size of 250 ms was chosen. We took the sampling interval of 50 ms, which specified how frequently to calculate these firing rates. Now since different neurons could have different range of firing rates, to ensure that neurons with higher firing rates do not contribute more directly to decode results, z-score normalisation was carried out. The mean and standard deviation for each feature was found out using the training data, and then each neuron (feature) was normalized to have zero mean firing rate and a standard deviation of 1 in both training and test data.

3.3.3 Decoding Analysis

Then the decoding analysis was carried out using the procedure of cross-validation. For an iteration (resample run), a particular pseudo-population was chosen and then k-way cross-validation was done in which the classifier was trained and tested on different divisions of the data and average of decoding accuracy calculated. The entire process (resample runs) was repeated and each time new splits and new pseudo-populations were generated, until the change in average decoding accuracy was less than 0.5 of the already calculated decoding accuracy. Hence the procedure was repeated until convergence to get a value to decoding accuracy.

3.4 Results and discussions

2 types of plots are used in the results:

1. Classification Accuracy Vs Time Plot: Classification (decoding) accuracy of the chosen variable is plotted against time. (x,y) denotes that if we train the classifier at x time point (precisely time bin), and test at that time, y is the decoding accuracy we get. Time 0 (zero) is the onset time of event (saccade in this case) we are decoding.

2. TCT Plot : Temporal Cross Training Plot

The decoding accuracy results are plotted in an matrix where the y-axis indicates the time the classifier was trained and the x-axis indicates the time when the classifier was tested.

Parameters:

Bin Size = 250ms, Step Size = 50ms, Convergence Threshold = 0.5, Number of Class Labels used = 4, Variable decoded = Saccade To Position, Cross Validation Splits = 10 (1 repetition in each class), Classification Method= Using maximum correlation coefficient (These parameters were used in all results, unless specifically mentioned)

3.4.1 Decoding Accuracy For Each Brain Region

We began by analyzing if we can predict where the monkeys eye moves towards (saccade) at a point in time, so that later we could think about predicting a sequence of eye movements. We decoded the dot position towards which monkey made a saccade at a particular point of time (which we chose as 1st, 3rd, or 5th saccade after the Target On time).

a) **Frontal Eye Fields (FEF)**

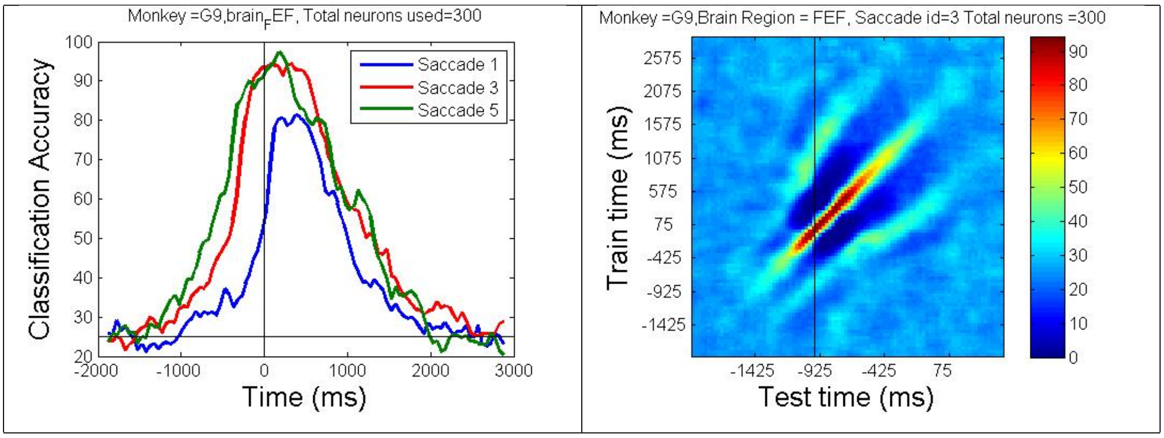


Table 3.1: Decoding Results: G9-PFC

- As expected, high decoding (classification) accuracy (90%) in FEF. It is in agreement with the fact the Frontal Eye Fields correspond directly to the eye movements and hence we were able to decode so effectively.

b) Caudate Nucleus

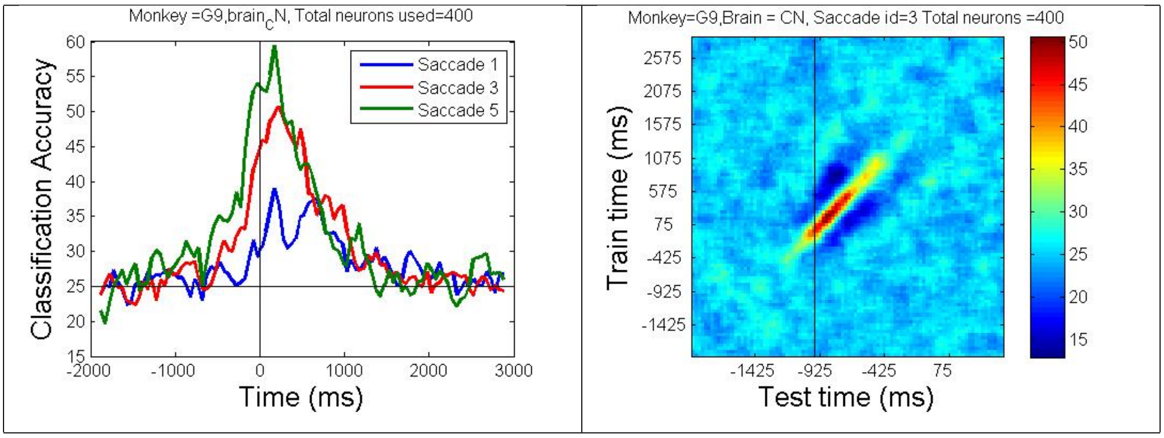


Table 3.2: Decoding Results: G9-PFC

- Around 50% decoding accuracy, despite the fact that large number of neuron sites are used. It might mean that the information of exact location where monkeys eyes move towards are not encoded in this region, but rather some abstract information regarding the path chosen.

- The peak in the decoding accuracy shifts towards left and higher as we decode the latter saccade.

c) Pre-Frontal Cortex (PFC)

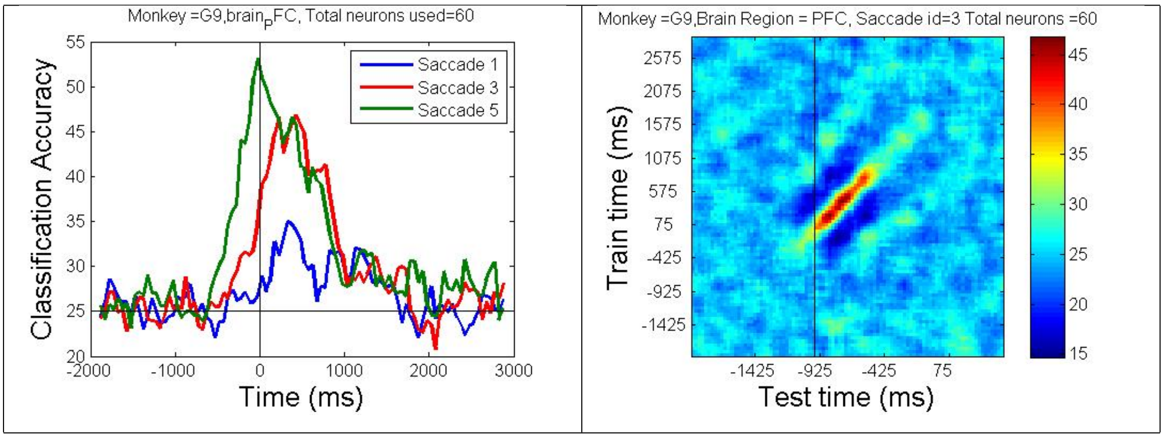


Table 3.3: Decoding Results: G9-PFC

- Similar observation as in CN, but the number of neuron sites are much lower in this case.

Following are observed in all brain regions:

- The peak in the decoding accuracy plot shifts towards left as we decode the latter saccade. It suggests that monkey might be deciding slightly earlier where to move its eyes.

- An interesting observation is the dark blue region (denoting below-chance decoding accuracy) parallel to diagonal in the TCT plots. It might mean that the neural responses during that times are anti-correlated to the neural responses during the time of targeted saccade.

- Also, the light blue color lines (above-chance decoding accuracy, but not too high) parallel to diagonal is observed. It might correspond to monkeys eye movement pattern or some correlation in the data.

3.4.2 Comparison of 3 brain regions

To compare decoding accuracies in FEF, CN and PFC, equal number of neuron sites and same parameters were chosen for decoding in all the 3 brain regions. The relative decoding accuracies can be clearly observed.

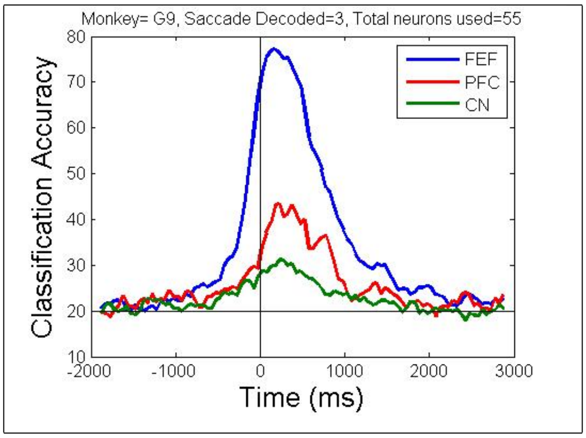


Table 3.4: Decoding Results: G9 -All brain regions, CV =15, Labels decoded = 5

3.4.3 Comparison between FEF and CN

Decoding accuracy of decoding 3rd saccade in FEF and CN, using large nunber of neuron sites (400) for both of the regions. It seems probable that the information of exact location where monkeys eyes move towards are not encoded in CN, but rather some abstract information regarding the path chosen.

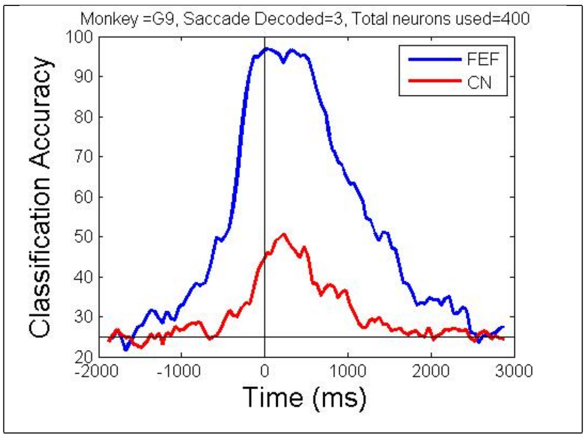


Table 3.5: Decoding Results: G9 -FEF vs CN

3.5 Conclusion and Future Directions

We verified that the FEF brain region contains information regarding each saccade by getting very high decoding accuracy. It seems that Caudate Nucleus does not represent the saccade information directly, rather stores some other information in abstract form, which was observed by low decoding accuracy despite large number of neurons. The TCT plots hinted that the representation of saccade towards a location could be anti-correlated to representation of fixating that location, shown by dark blue lines parallel to diagonal. But this would be to be verified with more analysis.

The next question to answer could be to find out how neural representations change across sessions. It could be done by comparing the decoding accuracies in groups of sessions and finding how it changes across months. Another thing that would be interested to see is if we can decode a sequence of saccades, and find how ahead in time we can decode, which would imply how much ahead in time the monkey plans. The major challenge in this is the fact that number of repetitions of a particular sequence of saccades is not very much, which would need to be overcome.

Many earlier studies have tried to find out how the brain translates the driving factors and signals based on Reinforcement learning into behaviour, and tried to examine potential locations of RL component variables in the brain (11,12). The state values, action values, and rewards which define a RL model have been found in the CN of monkeys and mice in various experiments. However most of the experiments included acquisition of few associations between stimulus and task, rather than the slow, and naturalistic acquisition of habit as happened in the case of monkeys. It would be worth investigating if RL variables for such behaviours are also represented in the CN of monkeys.

Chapter 4

Spatial Working Memory Task

4.1 Motivation

To understand working of brain, it becomes important to identify brain regions involved in different tasks performed by brain, and the contributions of each brain region. Cognitive functions of spatial working memory and task switching are two of the most important and frequently used functions of brain. The neurons in the areas of the association cortex, particularly prefrontal cortex (PFC) and posterior parietal cortex (PPC) have been found to exhibit neural correlates of these functions **??**. However it is not clear if the cognitive functions are completely distributed across different brain regions working in parallel, or co-activated regions are specialized for specific roles **??**. Previous experiments training animals to remember first of a sequence of stimuli have found prefrontal cortex to better represent the location of target stimulus and filter distractors**??**. Posterior parietal cortex was observed to mainly represent the most recent stimulus shown, be it a distractor or target**??**. Moreover some studies have found significant deficits in maintaining task information in memory and task switching after prefrontal lesions, making PFC critical for task information**??**. However, it is unclear if the functional specialization of PFC to filter distractors extends to stimuli shown earlier in sequence, when the subjects (animals) are cued to remember subsequent stimuli. To answer these questions, researchers at Constantinidis lab at Wake Forest University School of Medicine, USA designed an experiment in which monkeys were trained to remember either the first or second of two stimuli presented in sequence. It could also help to reveal how different task rules affect neural representation of stimulus and distract information.

4.2 Experiment Details

The experiment was done with two rhesus monkeys (named GRU and HEC), and neural recordings were collected from dorsolateral prefrontal cortex (areas 8a and 46), and Posterior Parietal Cortex (areas 7a and LIP). The tasks used were Oculomotor Delayed Response (ODR) task variations **??**, where monkey had to remember and make an eye movement to either the first or second stimuli shown.

4.2.1 Setup

On the computer screen, a small white or blue square (fixation point) is located at the center and color denotes the task type. As the task begins, the monkey has to fixate on the center white/blue square for 1 sec, after which the first stimulus (white square of size 1.5°) is shown for 0.5 sec. This is followed by 1.5 sec delay, after which the second stimulus (white square of size 1.5°) is shown. After the second delay period of 1.5 sec, monkeys have to saccade (make eye-movement) depending on task type:
1. *Stimulus Remember 1* Task (denoted by white fixation point) -
Saccade to location of first stimulus.
2. *Stimulus Remember 2* Task (denoted by blue fixation point) -
Saccade to location of second stimulus.
A reward of fruit juice was given to monkeys after making saccade to the correct location.

4.2.2 Experiment variations

The above rules remaining same, two variations of the experiment were carried out listed below.

1. **ODR diametric**

-The first stimulus is displayed pseudo-randomly at one of the eight positions as shown in figure 4.1.

-The second stimulus is displayed at a location diametric to the first stimuli.

2. **ODR variation**

It is explained in figure 4.2. -The first stimulus is displayed at one of the two locations:

(i) In the receptive field

(ii) Diametric to receptive field

The receptive field of the neurons was mapped using a single stimulus ODR task.

-The second stimulus is displayed at the following locations relative to first stimulus's location:

(i) 0° (same as first stimulus's location)

(ii) 45°

(iii) 90°

(iv) 180°

(v) No second stimulus was shown

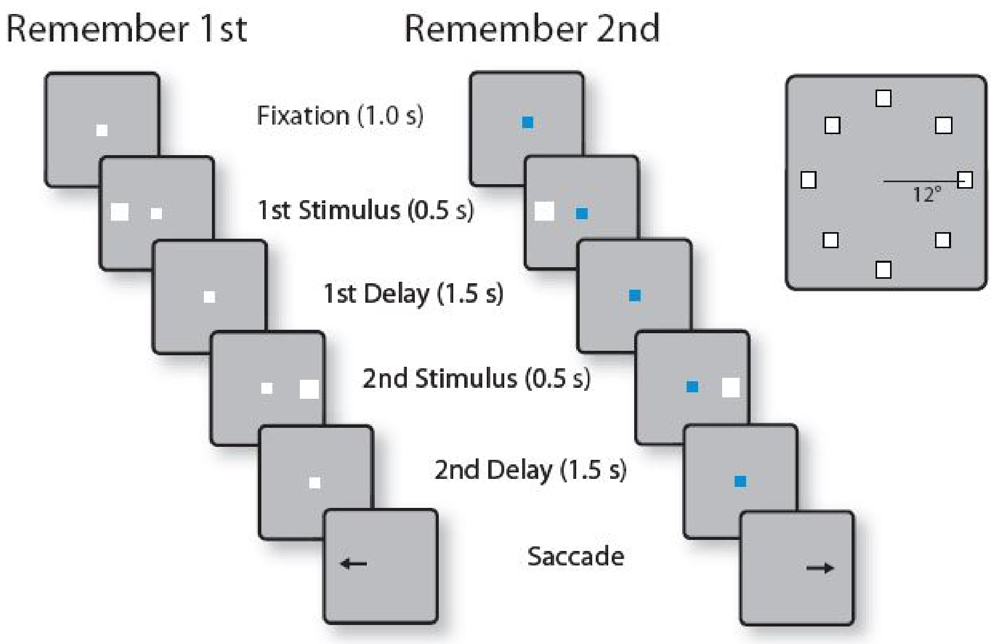


Figure 4.1: Successive frames illustrate the sequence of stimulus presentations in the behavioral tasks. In the remember-1st task (left), the white color of the fixation point instructed the monkeys that the 1st stimulus should be remembered. After the 2 stimulus presentations, with delay periods intervening between them, the fixation point turned off and that cued the animal to make an eye movement towards the direction of the 1st stimulus. In the remember- 2nd task (middle), the blue fixation point (dark gray) instructed them to remember and saccade to the location of the 2nd stimulus. The 1st stimulus in either task could appear at 1 of 8 locations arranged on a ring of 12 eccentricity (right). The 2nd stimulus appeared always diametric to the 1st. Courtesy [12]

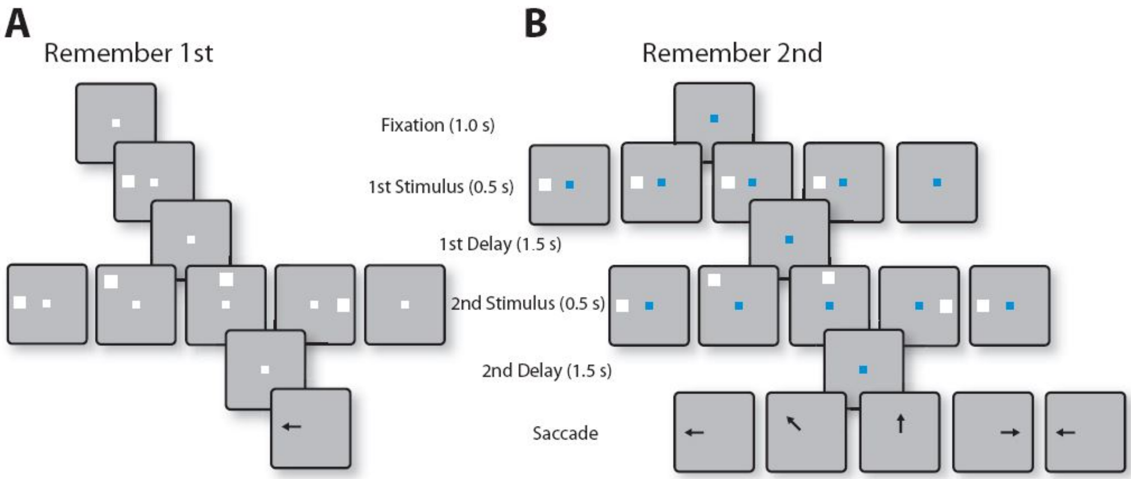


Figure 4.2: Successive frames illustrate the sequence of stimulus presentations in the randomized distractor tasks. A: in the remember-1st task, the 1st stimulus could appear at 1 of 2 locations; one typically in the receptive field of the neuron under study (shown as left location) and its diametric (not shown). Each 1st stimulus could be followed by 5 randomly interleaved conditions: a 2nd stimulus at the same location as the 1st, at a location offset by 45, 90, or 180, or no 2nd stimulus (null condition). The monkey was required to make an eye movement to the 1st stimulus, regardless of the location of the distractor. B: in the remember-2nd task, the 1st stimulus (which was now a distractor) could again appear at 1 of the 2 locations, followed by a 2nd stimulus at the same possible locations relative to the 1st, as in the remember-1st task. The null condition in the remember-2nd task involved no stimulus presentation during the 1st interval. The monkey was required to make an eye movement to the location of the 2nd stimulus. Courtesy [12]

4.2.3 Behavioural results

After training, both the monkeys learned to perform both the tasks. In [], it can be seen that the percentage of correct trials i.e. the behavioural performance of monkey HEC is better than monkey GRU in most cases.

4.2.4 Data given

We were given neural data and find out neural correlates of the observed monkeys behaviour. The neural recordings were made from 2 main regions of brain namely, Prefrontal Cortex (PFC) and Posterior Parietal Cortex (PPC).

ODR Diametric Task:

Monkey	Neurons in PFC	Neurons in PPC
GRU	42	178
HEC	148	166

ODR Variation Task:

Monkey	Neurons in PFC	Neurons in PPC
GRU	115	151
HEC	90	84

For each session, the data for each trial included the timings for all events of interest viz. onsets of stimuli, delay periods and locations of the stimuli. The timings for neural spikes along with the brain region it came from was also given. The data for only the correct trials was included in the analysis.

4.3 Analysis

The questions which we wanted to answer were-
Which location is represented by neurons in each brain region in both task types - remember 1st stimulus and remember 2nd stimulus?
Which brain region better represents the location of target stimulus as compared to distractor stimulus?

4.3.1 Design of Analysis

To find out which location is represented by each brain region, we analysed if we can predict the location of stimuli (first/second) from the neural data using population decoding analysis.

ODR Diametric Experiment:
To decode the location of first stimulus, we defined class label of a trial as the location of

first stimulus which could take one of the eight values - {'N','S','E','W,'NE','NW','SE','SW'}. Similarly, the location of second stimulus was chosen as the class label to decode location of second stimulus. As the second stimulus was always diametric to the first stimulus, it could take one of the same eight values.

ODR Variation Experiment

To decode the location of first stimulus, we defined class label of a trial as the location of first stimulus which could one of the two values -
{In receptive field, Not in receptive field}
The location of the second stimulus was chosen as the class label to decode location of second stimulus. In this case, the possible locations for second stimulus chosen were 0°, 90° or 180° relative to first stimulus. Since both the monkeys didn't perform well in case of 45°, we didn't consider it in the analysis. Also, the case of second stimulus being not shown was not considered as we wanted to decode location of second stimulus.

In both the above experiments, the decoding was done for both task types - *Stimulus Remember 1* and *Stimulus Remember 2*, keeping all the parameters same to compare them.

4.3.2 Decoding Procedure

As the experiments were carried out across different sessions, we used the concept of pseudo-population to combine data from different neurons. Hence we computed the number of times each condition (class label) was presented to each neuron and obtained the number of neurons sites and repetitions in each case. Based on their analysis, we chose the optimal number of neurons and repetitions in our decoding procedure.

The neural spikes times were converted into raster format as required by the Neural Decoding Toolbox. Then bin size analysis was done on a range of bin sizes from 150ms to 650ms. The bin size of 500ms was chosen, and a sampling interval of 50ms. Z-score normalization of the data was carried out, where each neuron's firing rate (feature) was normalized to have zero mean firing rate with standard deviation of 1.

Finally, the decoding analysis using the cross-validation procedures in NDT were carried out using max-correlation coefficient classifier.

4.4 Results and Discussions

The analysis was done on each brain region for both the monkeys for both the experiment variations as explained in the previous section. We obtained the following results. In each of the classification accuracy plots, blue line denotes the remember 1st task, while red line denotes the remember 2nd task. The horizontal line denotes the chance accuracy.

4.4.1 ODR Diametric Experiment

1. **Monkey - GRU, Brain region - PFC**

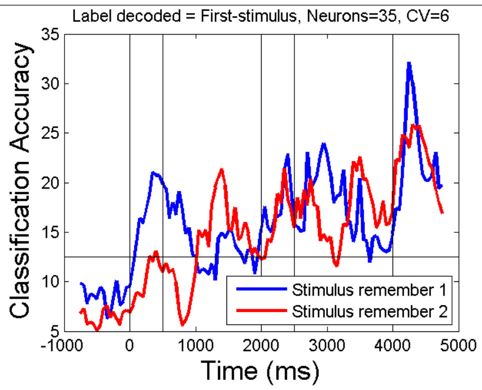
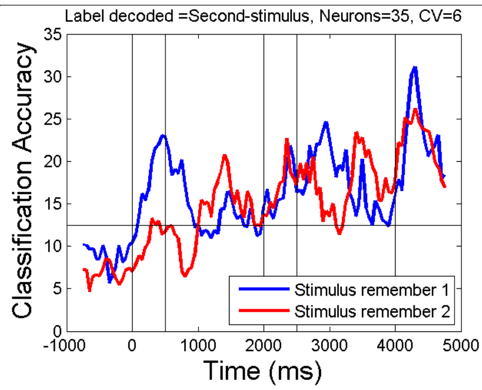
First Stimulus Decoded	Second Stimulus Decoded
	

Table 4.1: Decoding Results: GRU-PFC

It seems that very less information about the stimulus locations is represented in the PFC neurons in GRU. The number of neurons being very less (35) seems to be strong reason for such low decoding accuracy. A small peak in the last 1000 seconds indicate that the neural representation when monkey is making a saccade has some information about the stimulus location.

2. **Monkey - GRU, Brain region - PPC**

In this case, a decoding accuracy around 35 to 40 % is obtained in decoding the first stimulus in both the tasks. The decoding accuracy is high only during the time stimulus is shown, and is low during the delay periods. On a first look, it looks surprising why both the graphs are similar given that different stimuli are being decoded. But on a deeper thought, we can see that this should have been the case, as the second stimulus location is always diametric to the first stimulus location.

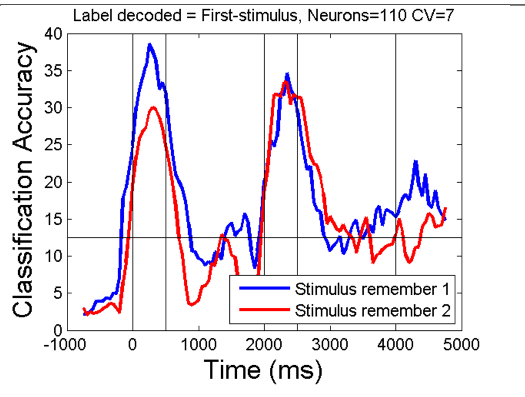
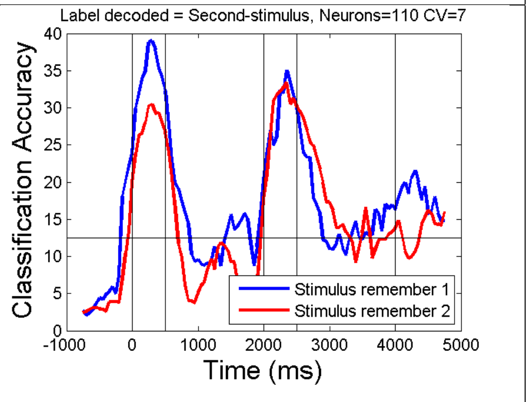
First Stimulus Decoded	Second Stimulus Decoded
	

Table 4.2: Decoding Results: GRU-PPC

The plot shows decoding accuracy obtained when training and testing is done at the same time bin, while the class label is either first stimulus location or the second. Now the neural representation during second stimulus presentation is likely to encode second stimulus location. It can be observed in the graph, that when we train our model using neural representation during second stimulus presentation, but label the location as first stimulus location (which is essentially diametric to the second stimulus location), we get high decoding accuracy. Though the neural data represents second stimulus, we can use it to tell the location of the first stimulus, as there is one-to-one mapping between the first and second stimuli locations.

3. **Monkey - HEC, Brain region - PFC**

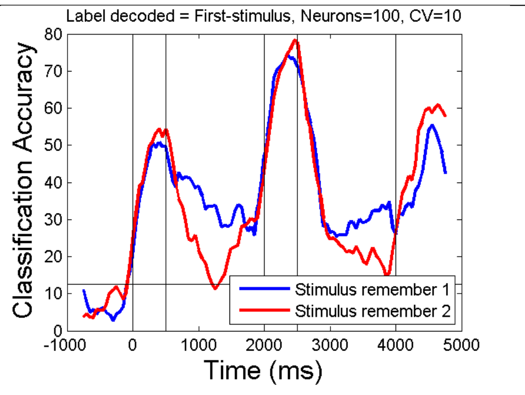
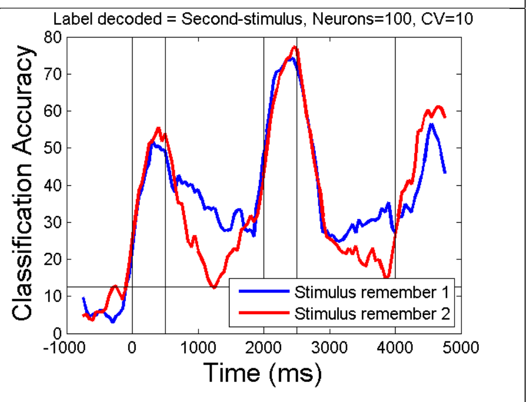
First Stimulus Decoded	Second Stimulus Decoded
	

Table 4.3: Decoding Results: HEC-PFC

In HEC monkey as well, similar plots are obtained for both task types. In this case, quite high decoding accuracy of 80% is obtained during second stimulus presentation and 50% is obtained during first stimulus presentation. Moreover, during the delay period there is 30-40 % accuracy in *Stimulus Remember 1* task, showing that PFC neurons remember the representation.

A question raised by similar plots in both the task types is whether the neural representation of first and second stimuli locations are correlated, given the locations of both of them are diametric. What would happen if we train from neural data when first stimulus is shown, but test when second stimulus is shown? We'll look into this analyses later.

4. **Monkey - HEC, Brain region - PPC**

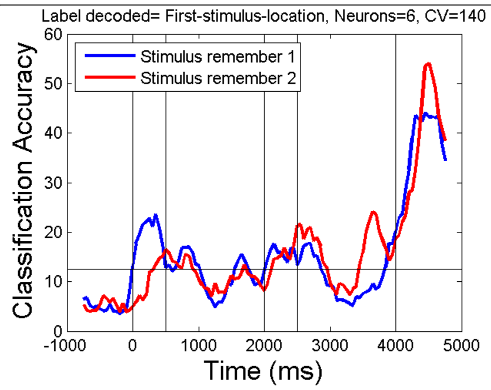
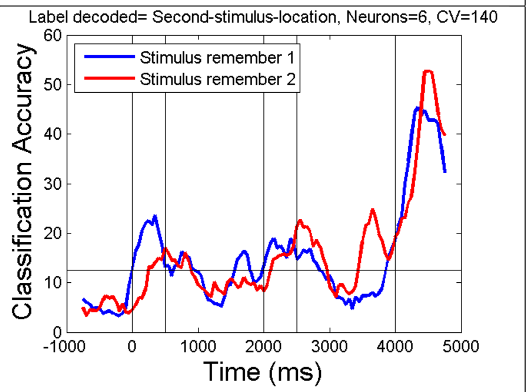
First Stimulus Decoded	Second Stimulus Decoded
	

Table 4.4: Decoding Results: HEC-PPC

Even though the number of neurons are high(140), plot predicts that no information regarding stimulus locations is present PPC neurons in HEC.

5. **First Stimulus Decoded, Brain region - PFC and PPC Combined**

This analysis is done to understand how monkey would do the cognitive task. A monkey would get response from both the brain regions and it will act based on the combined response. From the plots, it seems that HEC is better able to represent the stimulus location than GRU, which is also observed in the behaviour results in [12]. But it should be noted that there is a difference in the number of cross-validation splits used in these plots, which is due to the difference in available data for both monkeys.

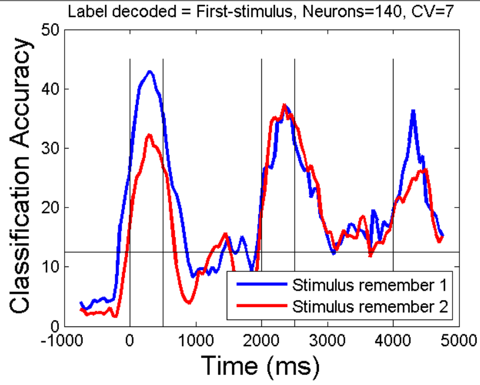
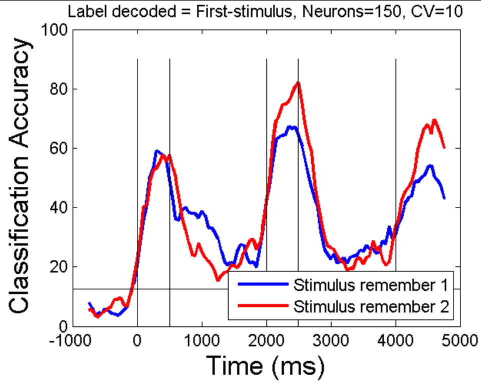
Monkey GRU	Monkey HEC
	

Table 4.5: Decoding Results: Both brain regions combined

6. **TCT Plots: First Stimulus Decoded, *Stimulus Remember 1* Task**

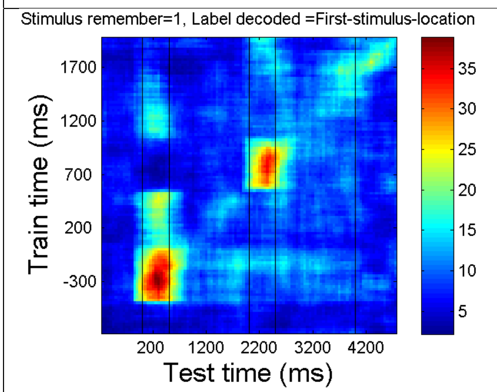
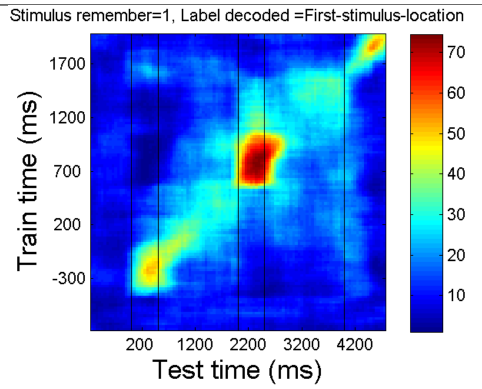
Monkey GRU - PPC	Monkey HEC - PFC
	

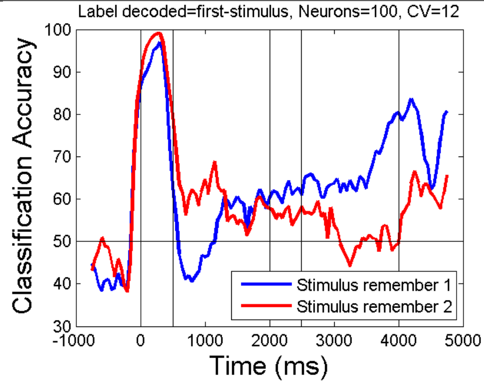
Table 4.6: Temporal Cross Training (TCT) Plots: Both brain regions combined

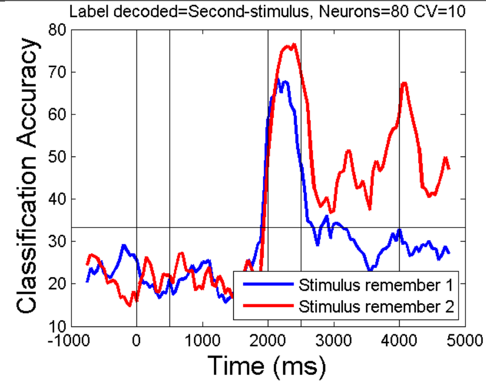
These plots answer the question that the neural representations of first stimulus location and second stimulus locations are not correlated, and moreover seem to be anti-correlated. We can observe that if the model is trained with neural data during the first stimulus presentation, while tested with neural data during the second stimulus presentation, we get below-chance decoding accuracy (shown by dark-blue color). Hence they are probably anti-correlated.

4.4.2 ODR Variation Experiment

In the ODR Variation experiment, the second stimulus can't be predicted from the location of first stimulus. Hence it would be interested to see the results of this experiment.

1. **Monkey - GRU, Brain region - PFC**

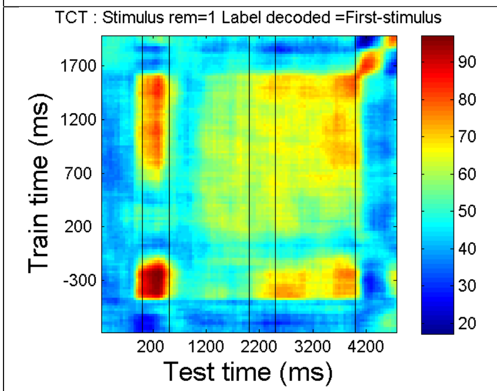
<table>
<tr><th>First Stimulus Decoded</th><th>Second Stimulus Decoded</th></tr>
<tr><td>


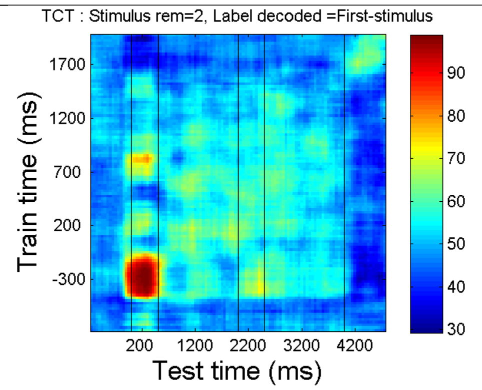
</td><td>


</td></tr>
</table>

Table 4.7: Decoding Results: GRU-PFC

It can be observed that decoding is higher when we decode the stimulus that is to be remembered. It can also be seen that information of stimulus to be remembered is also present during the delay period before the saccade is made. Though during the time any stimulus is shown, the decoding for that stimulus is high, after that time the decoding of the stimulus to be remembered is high. We can say the PFC here is remembering the target stimulus and filtering the distractor stimulus.

<table>
<tr><th>Stimulus Remember 1</th><th>Stimulus Remember 2</th></tr>
<tr><td>


</td><td>


</td></tr>
</table>

Table 4.8: Temporal Cross Training (TCT) Plots: GRU PFC - First stimulus decoded

For further analysis, we plot the TCT plots and observe that the representation of the stimulus to be remembered in the second delay period is similar to the initial representation when stimulus was shown. This can be observed by the red color in the plot, for the second-delay duration. On the other hand, when decoding the distractor stimulus no red color is observed in the plot apart for the stimulus presentation time.

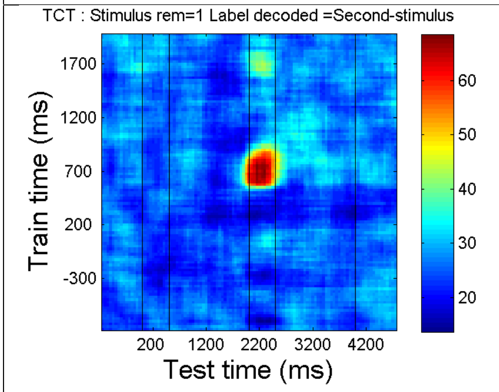
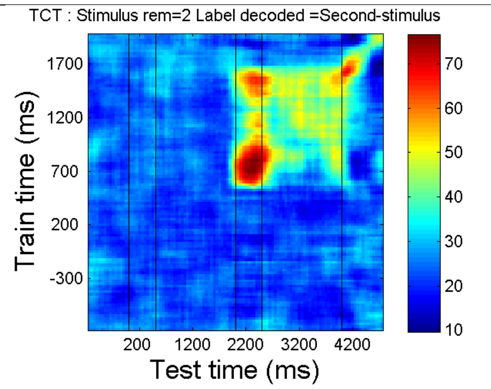
Stimulus Remember 1	*Stimulus Remember 2*
	

Table 4.9: Temporal Cross Training (TCT) Plots: GRU PFC - Second stimulus decoded

2. **Monkey - GRU, Brain region - PPC**

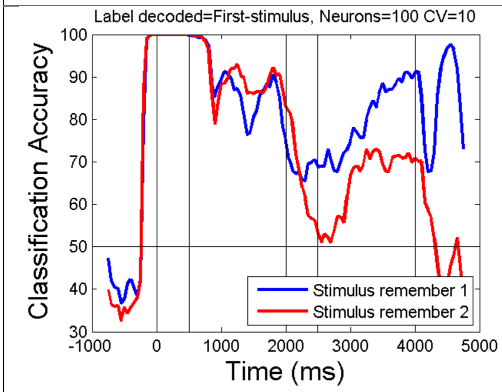
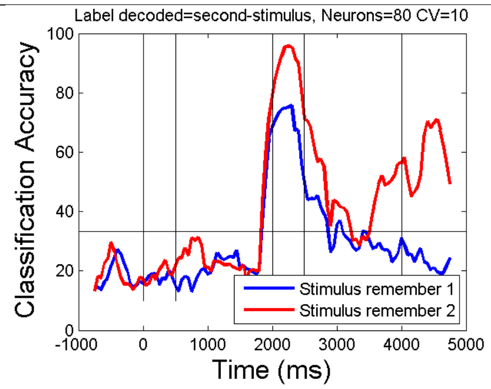
First Stimulus Decoded	Second Stimulus Decoded
	

Table 4.10: Decoding Results: GRU-PPC

In the PPC region as well, similar patten is observed where stimulus to be remembered is better decoded. Comparing with the PFC region, the decoding accuracy for remembered stimuli is higher in PPC regions.

3. **Monkey - HEC, Brain region - PFC**

In this monkey, the PFC remembers the first stimulus location until the second stimulus is shown for both the task types. If first stimulus is to be remembered it keeps the representation same, else it remembers the second stimulus location. This monkey seems to behave differently from the first monkey and may be this is the reason it performs better. Similar TCT plots are obtained for this monkey and brain region as well.

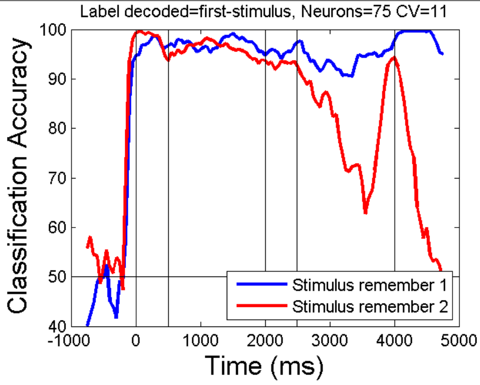
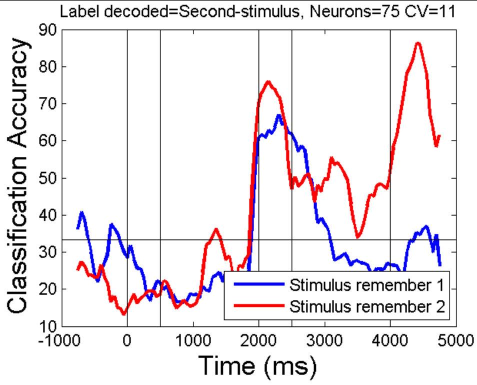
First Stimulus Decoded	Second Stimulus Decoded
	

Table 4.11: Decoding Results: HEC-PFC

4. **Monkey - HEC, Brain region - PPC**

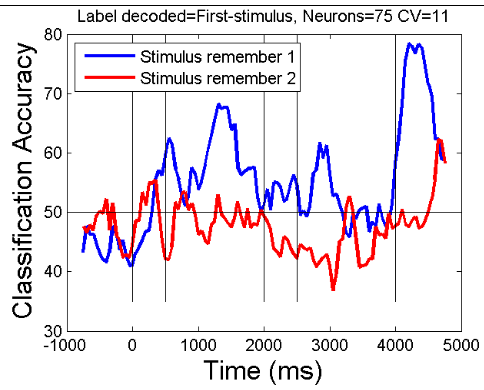
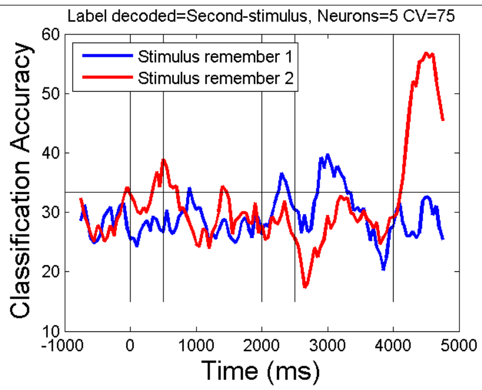
First Stimulus Decoded	Second Stimulus Decoded
	

Table 4.12: Decoding Results: HEC-PPC

It seems that this monkey does not use its PPC region for the task, as observed from the low decoding accuracy despite sufficient number of neurons. This result is in agreement with the results obtained in ODR Diametric Experiment, where chance decoding accuracy was obtained in the PPC region.

4.5 Conclusion and Future Directions

In the ODR Diametric experiment, since both the stimulus locations were directly dependent on the other, none of the stimulus could be regarded as the distractor stimulus. In monkey GRU, we observed decoding accuracy is high in PPC, while low in PFC where lack of sufficient training data (neurons) seems to be the reason. In monkey HEC, despite sufficient neurons in PPC region, low decoding is observed. But when we combined both the regions, similar decoding accuracy was obtained for both the monkeys. So it seems probable that HEC uses only its PFC region to perform the task.

From the ODR Variation experiment, we observed that both regions PFC and PPC in GRU monkey filter the distractor and remember the target stimulus with high accuracy. In HEC monkey, though PFC represents the target stimulus with very high decoding accuracy, we observe again low decoding accuracy in PPC. This could be due to two reasons. Either the neural recordings were obtained from the incorrect neurons, or there is no information represented in PPC. The monkey HEC might only be using its PFC region for performing the tasks.

The result that both the monkeys use PFC region verifies the result obtained in previous researches that PFC is the region which plays a role in remembering location of stimulus actively held in memory and resisting effect of distractors [2]. But the role of PPC is not clear, as it seems to be used by monkey GRU, but not by monkey HEC.

Understanding how the task information affects the stimulus representation is one of the things that could be worked on in future. It could be done by training the model on same stimulus in *Stimulus Remember 1* task and testing on same stimulus in *Stimulus Remember 2* task. It would also be interesting to compare the stimulus representation between both experiments.

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