Neural Spike Analysis Project

Taige Mueller

2025-03-17

Cori: Sessions 1-3

Forssmann: Sessions 4-7

Hench: Sessions 8-11

Lederberg: Sessions 12-18

Session 1 Introduction

Our study examines how brain activity and visual stimuli influence decision-making success in mice. Success is defined by the mice performing the desired action in response to visual cues.

In the experiment, mice were positioned with their front paws on a wheel, which they could rotate left or right. Visual stimuli were presented on boards with varying contrasts on the left and right sides. The goal was to determine whether the mice could make the correct decision based on these stimuli.

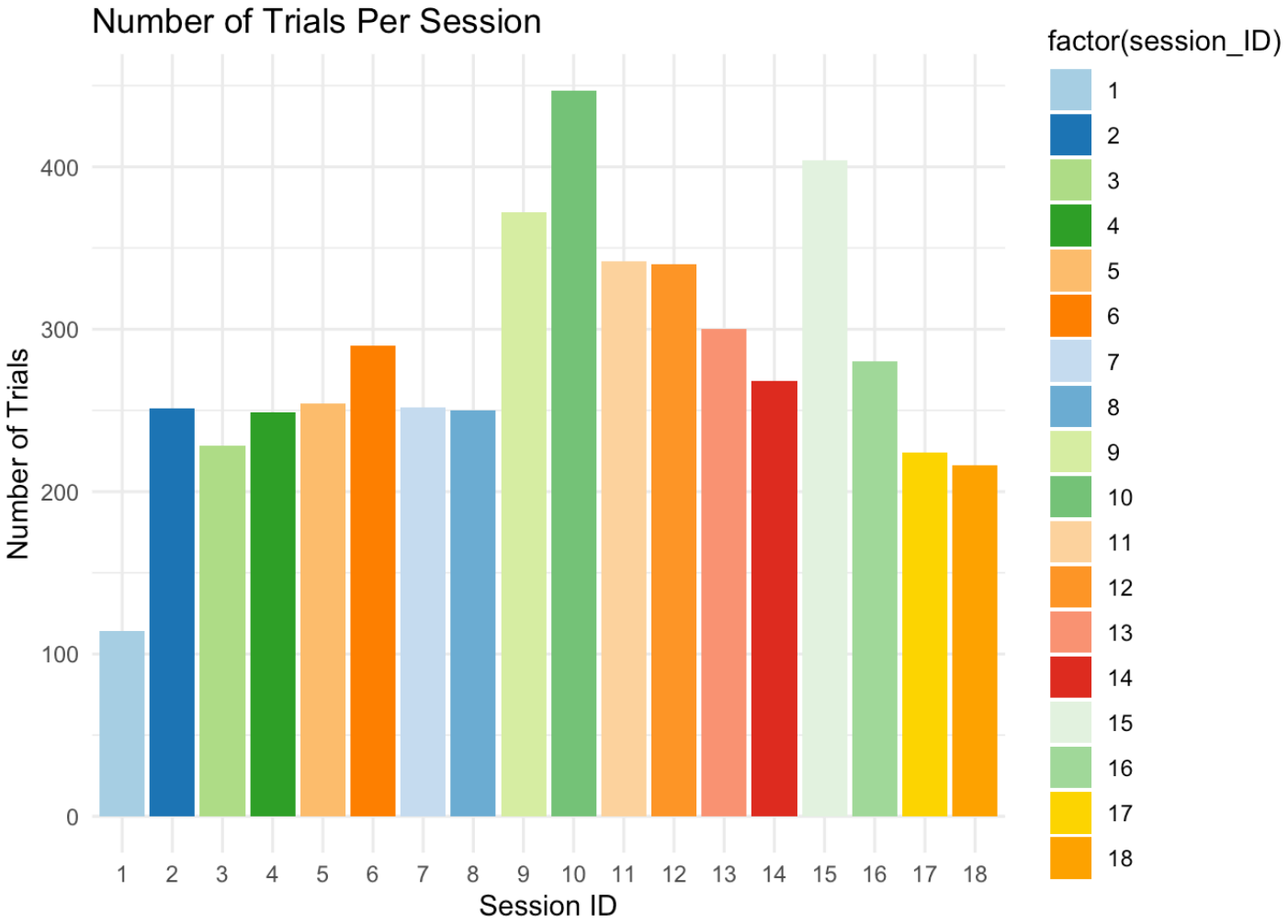
To analyze the factors influencing success or failure, we measured several key variables, including left contrast, right contrast, time bins for neural spikes, neural activity in the visual cortex, and the brain area involved.

For this report, we focus on four mice, Cori, Forssmann, Hench, and Lederberg. Each of whom participated in multiple testing sessions over 3 to 7 days. Cori had 3 sessions, Forssmann had 4, Hench had 4, and Lederberg had 7. Our objective is to investigate what impacts the success rate of correct decisions and how the recorded neural activity contributes to this outcome. We will conduct statistical analyses and explore our findings to gain deeper insights into this decision-making process.

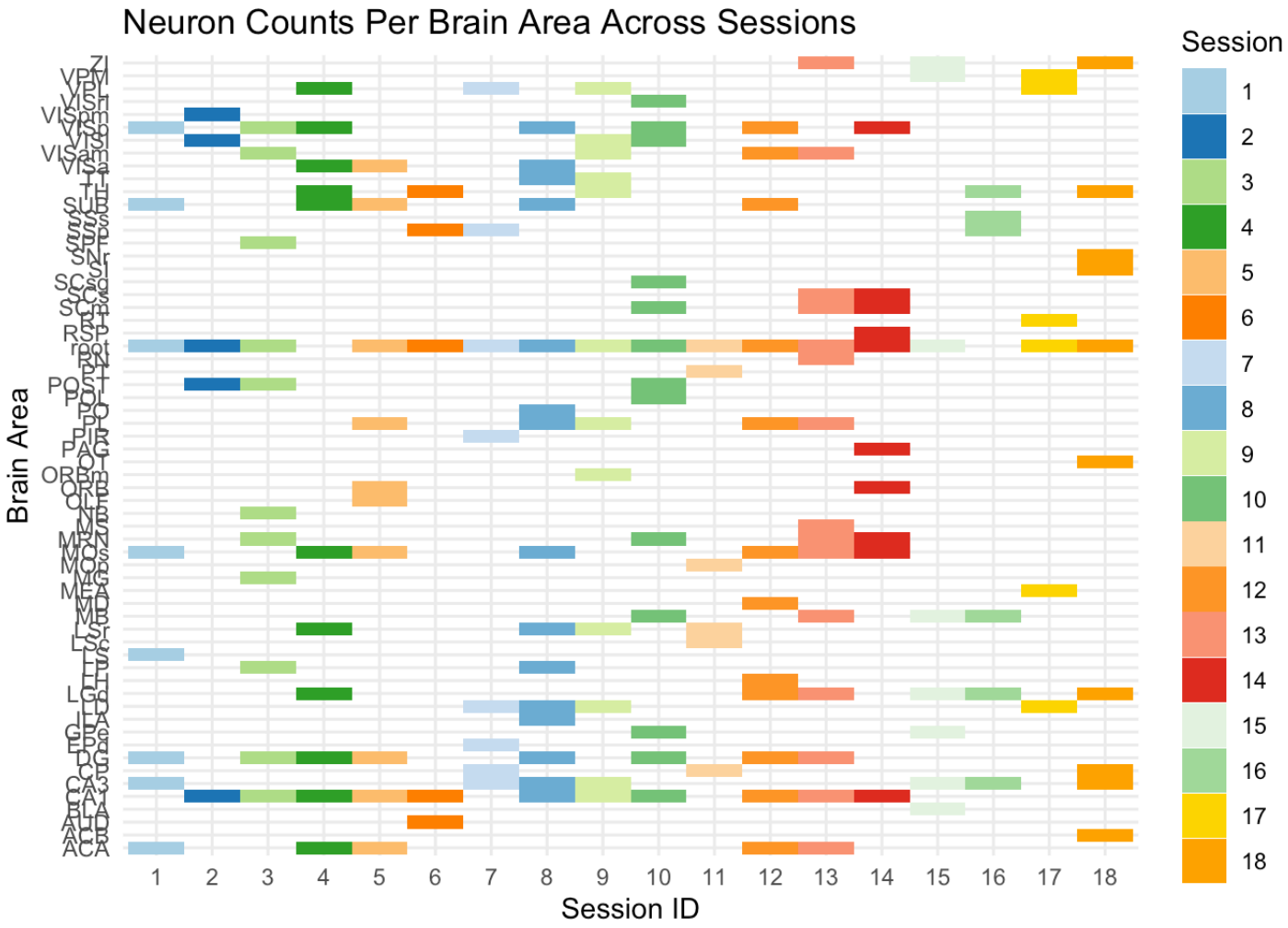
Session 2 Exploratory Analysis

In analyzing our data we found that the overall success rate accross all 18 sessions was 71%. This is a good percentage. It shows that the contrasts likely do have an important impact on the decision-making of the mice. We also found that there were 62 unique brain regions that were studied. The top five brain regions with the most neurons were root, TH, CA1, VISp and MOs. With root far exceeding the rest.

“contrast_left” “contrast_right” “feedback_type” “mouse_name” “brain_area” “date_exp” “spks” “time”

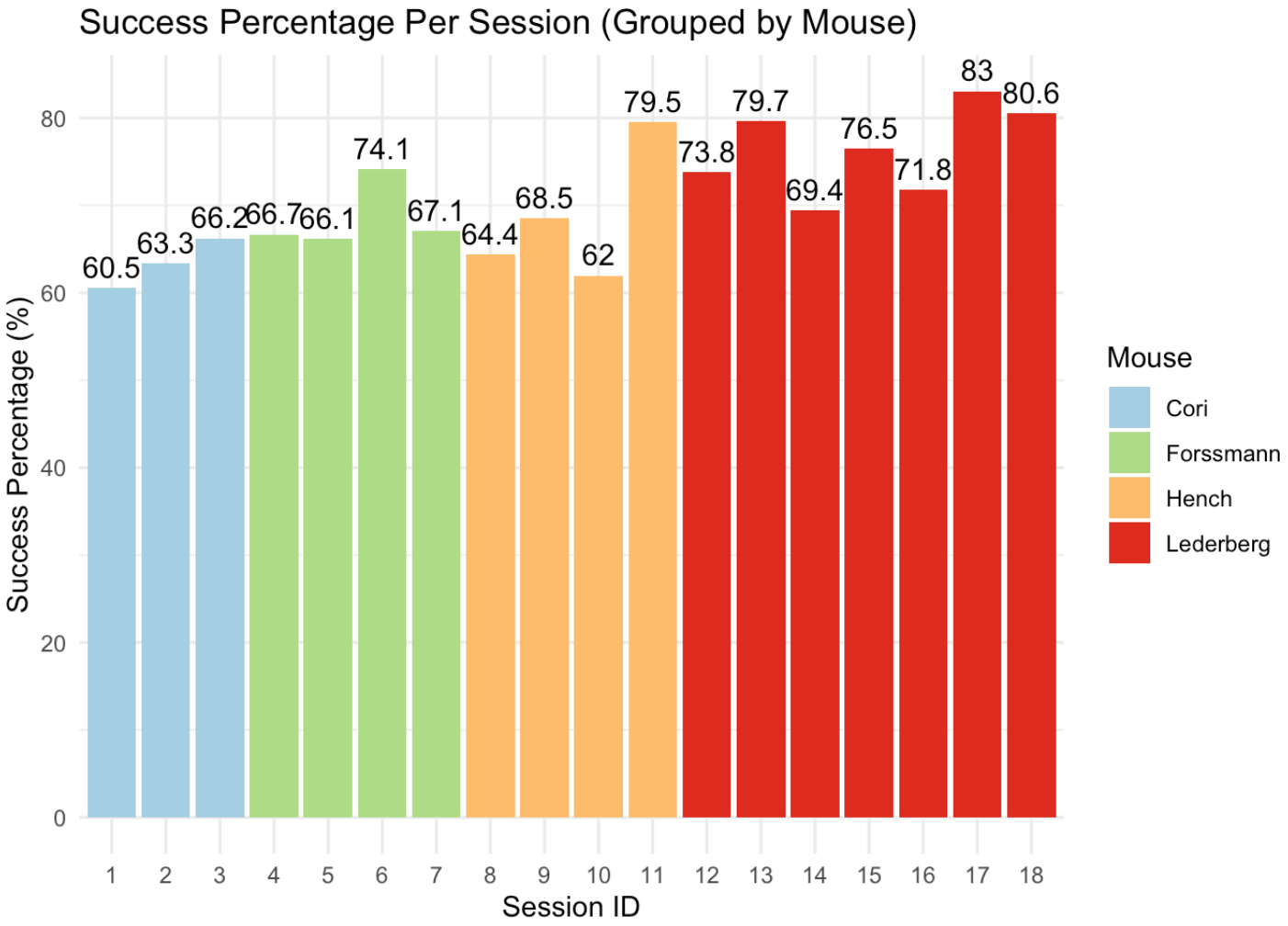


The above graph shows that the number of trials per session and mouse varied significantly.

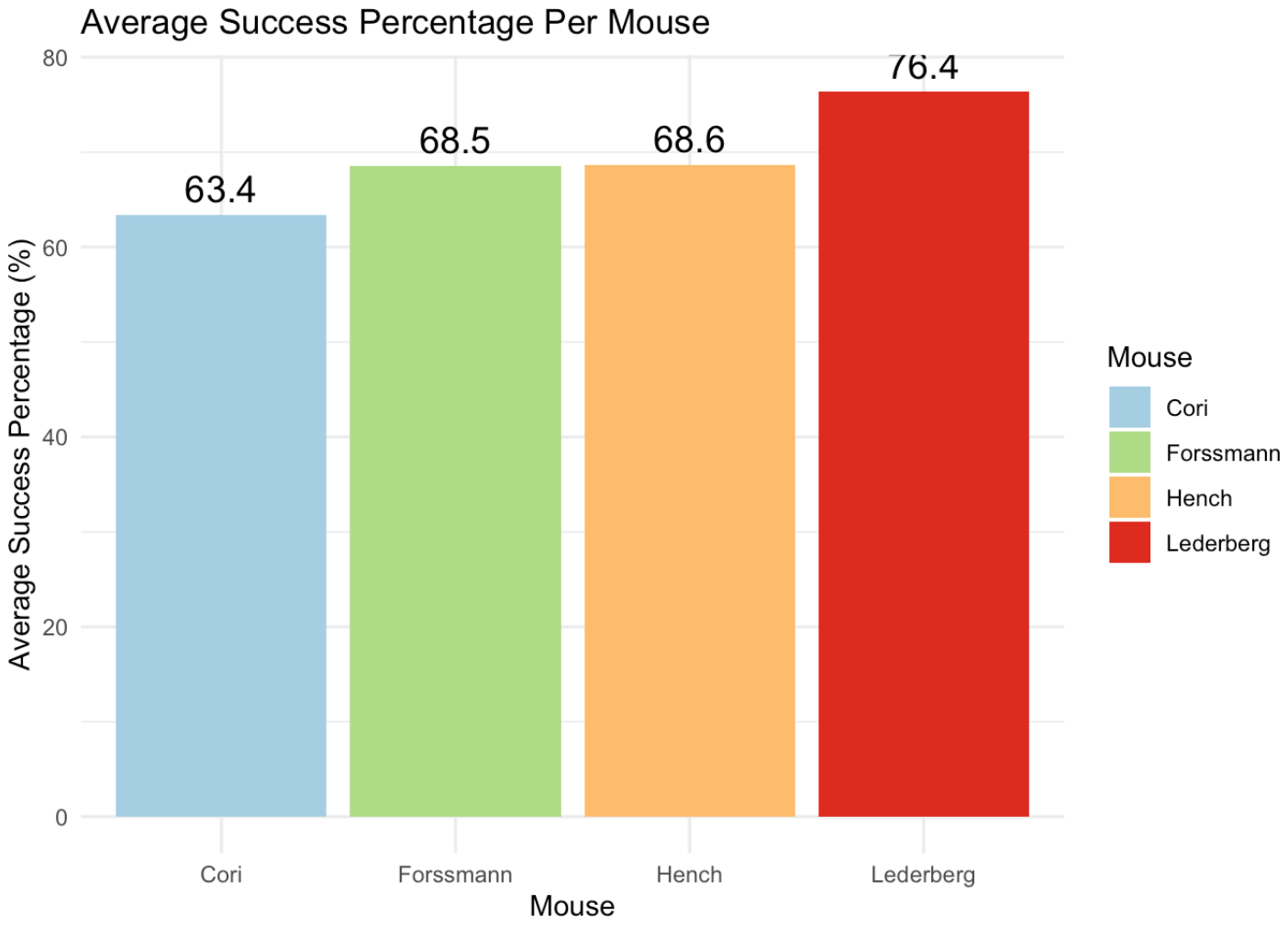


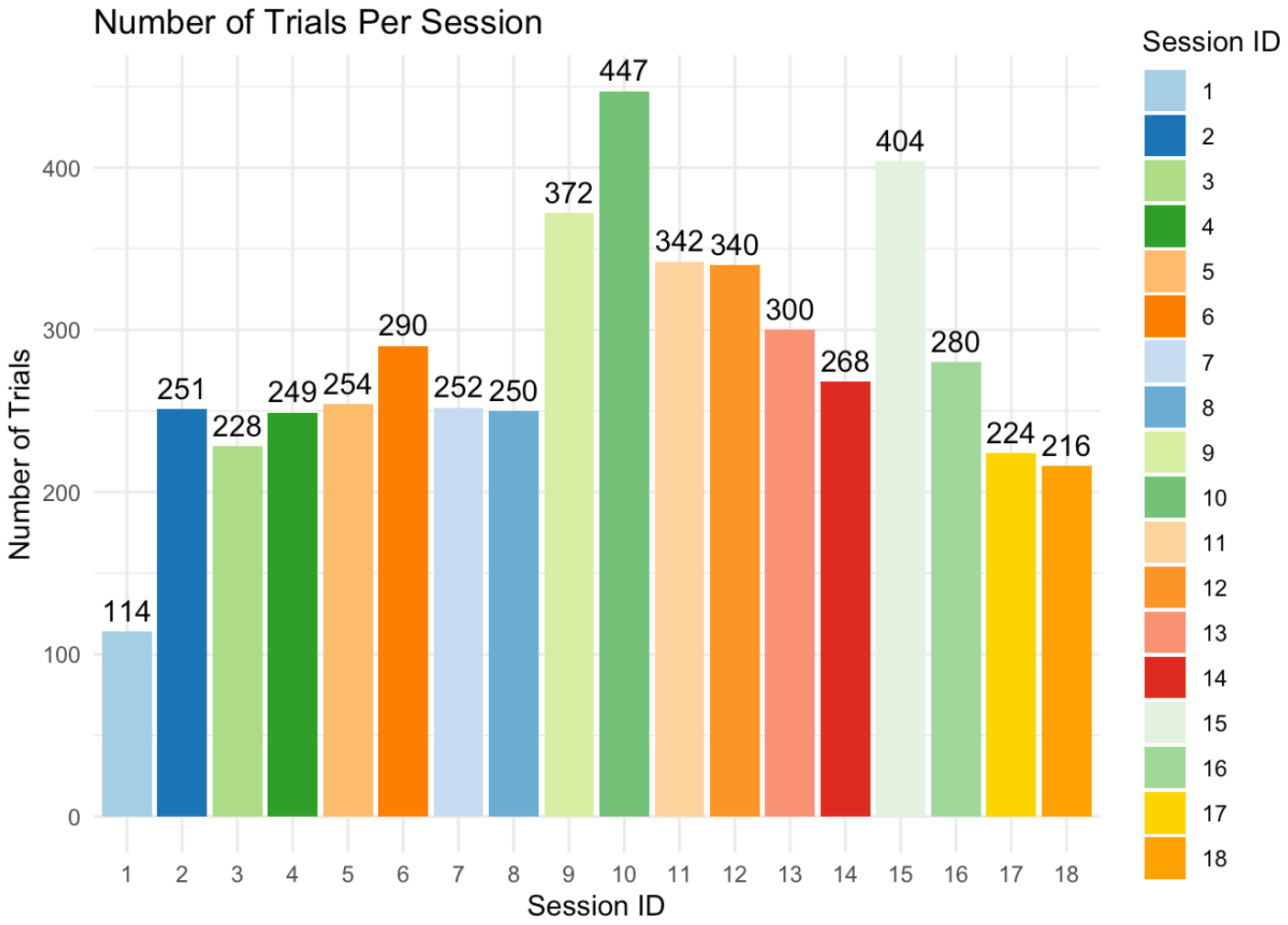
The brain areas also varied greatly accross the sessions. With some being much more popular than others.

Our success rates accross the sessions varied there was a slight upward trend of higher percentages towards the later sessions. This may be due to the on-average higher traial count as well.

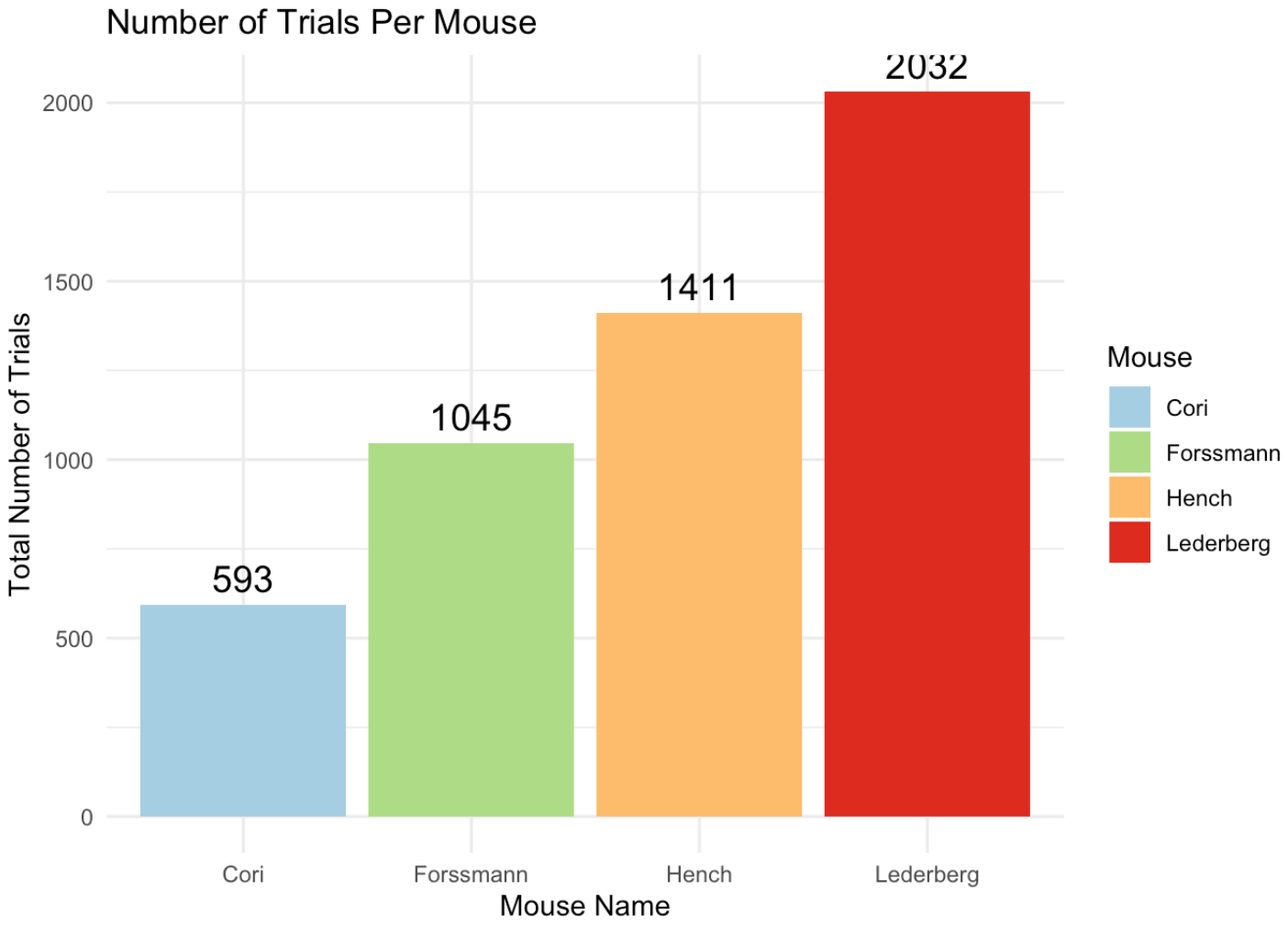


The mouse, Lederberg had the highest overall percentage of successes with Cori having the lowest. This further suggests that number of trials and sessions may impact success rate.


Average Success Percentage Per Mouse
Average Success Percentage (%)
80
60
40
20
0
63.4
68.5
68.6
76.4
Cori
Forssmann
Hench
Lederberg
Mouse
Mouse
Cori
Forssmann
Hench
Lederberg



Above is a graph showing the number of trials per session.



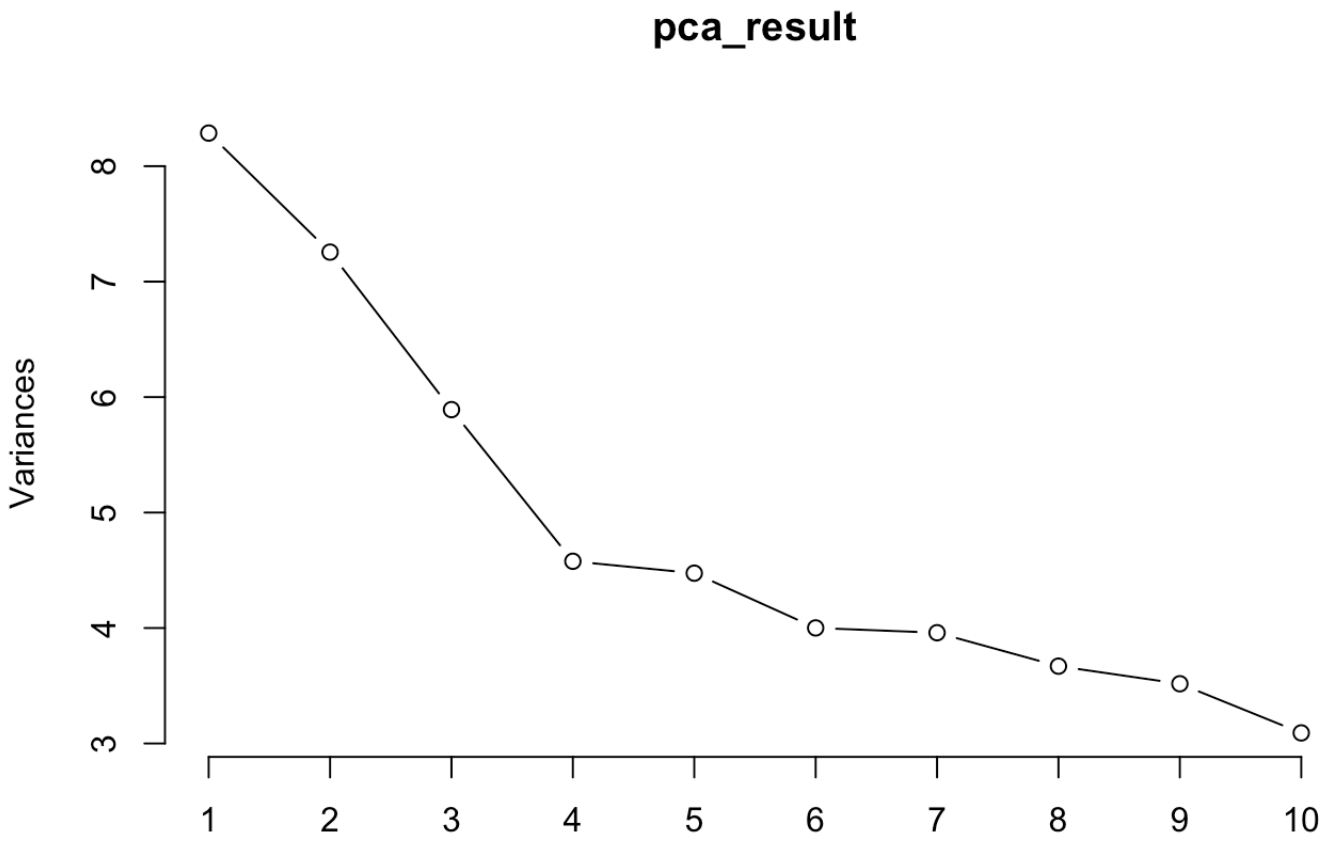
The number of trials varied greatly between the four mice. This may influence the success rate and other outcomes of study.

Session 3 Data Integration

Next we modified the data in preparation to prep it for model training. We used normalization. This step was simple and represents a base to our analysis.

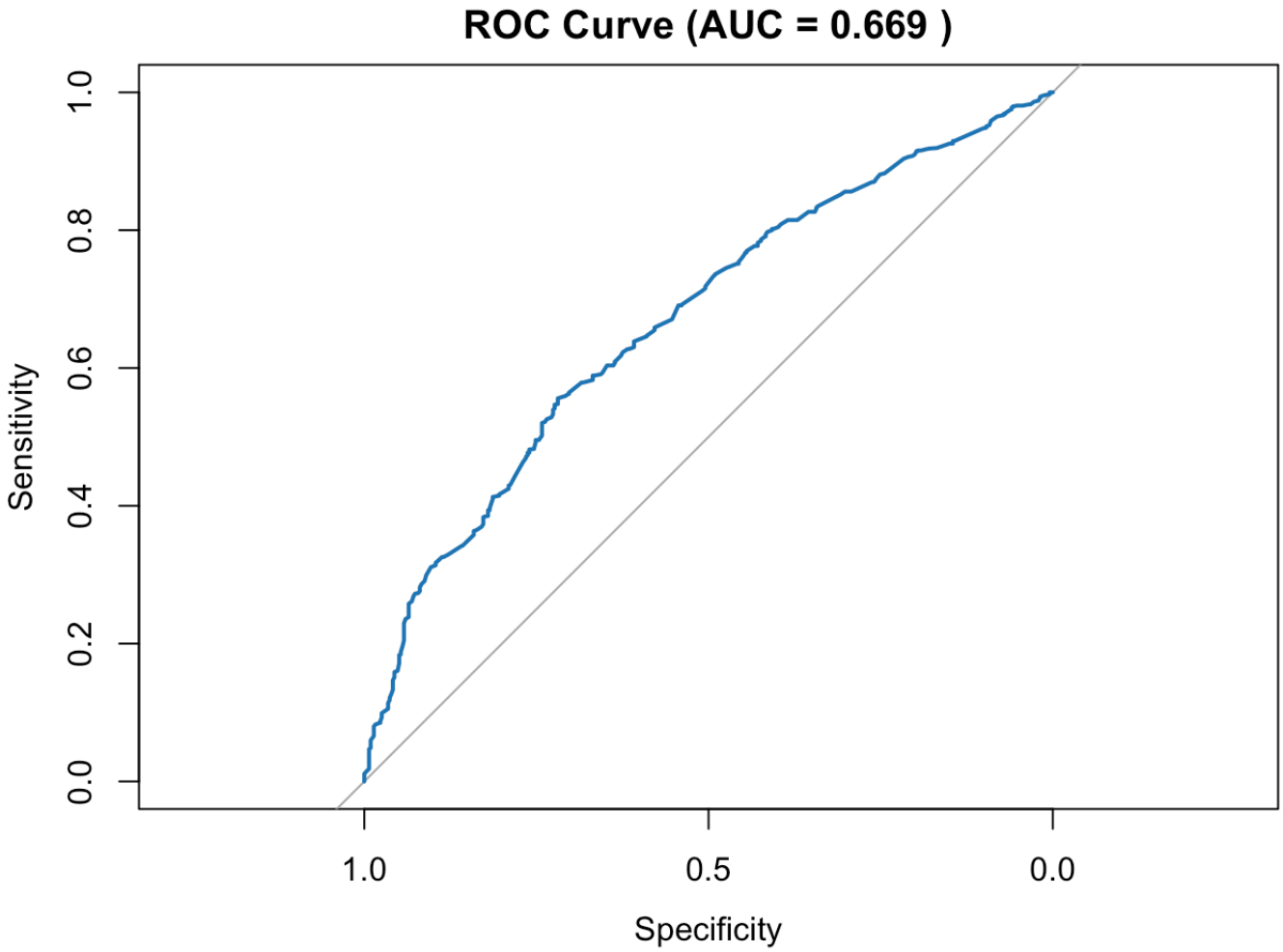
Section 4 Predictive Modeling

Next we built our predictive model. We merged the dataset to format. Using PCA and XGBoost Model Training.




```
## [1] "Test Accuracy: 70.6 %"
```

```
##           Actual
## Predicted    0    1
##         0   63   77
##         1  371 1013
```



Session 5 Test Data

This section was unsuccessful due to time restraints.

```
# # Convert test data into a dataframe for predictions
# test_trials_df <- bind_rows(lapply(seq_along(test_sessions), function(i) {
#   data.frame(
#     session_ID = i + 18,  # Assign new session IDs (assuming training data had 18 s
essions)
#     contrast_left = test_sessions[[i]]$contrast_left,
#     contrast_right = test_sessions[[i]]$contrast_right,
#     avg_neuron_spike_rate = mean(unlist(test_sessions[[i]]$spks), na.rm = TRUE),
#     num_neurons = length(unique(test_sessions[[i]]$brain_area))
#   )
# }))
#
# # Check test data structure
# print(head(test_trials_df))
#
#
# # Select same predictors used in training
# predictors <- c("contrast_left", "contrast_right", "avg_neuron_spike_rate")
#
# # Convert test data to matrix
# test_matrix <- as.matrix(test_trials_df[, predictors])
#
# # Create XGBoost DMatrix
# dtest_new <- xgb.DMatrix(data = test_matrix)
```

Discussion

This report is far from thurough. However we gained valuable insights and have a direction moving forward.

acknowledgements

https://chatgpt.com/share/67d8b3f7-7218-8001-ae9f-dfbc90b6a2b3 (https://chatgpt.com/share/67d8b3f7-7218-8001-ae9f-dfbc90b6a2b3)

Study Paper

https://discovery.ucl.ac.uk/id/eprint/10087006/1/Steinmetz%20et%20al%202019%20-%20Revised%20Manuscript.pdf (https://discovery.ucl.ac.uk/id/eprint/10087006/1/Steinmetz%20et%20al%202019%20-%20Revised%20Manuscript.pdf)