Psychophysics

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Contents

Psychometric function, Threshold, PSE

The following link takes you to a psychophysical experiment. A red plus will be presented at the center of screen and a dot will appear on the right or on the left side of the fixation point. Your task is to indicate whether the dot appeared on the left or on the right side of the fixation point.

- Plot your psychometric function.

Physchometric function is as follows:

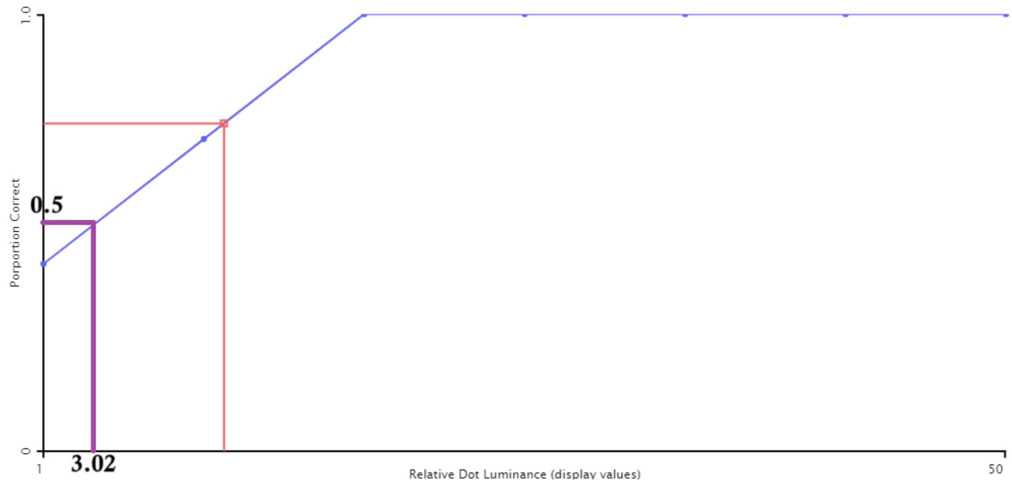


Figure 1: Psychometric function

- Find the threshold and PSE.

Now to find PSE, we should find the luminance on x-axis which makes proprtion correct = 0.5.

Threshold	PSE
10.19	3.02

Method and Stimulus Setting

Type of Method	Forced-Choice
Number of Levels of Relative Dot Luminance	7
Number of Repetitions	7
Minimum Value of Relative Dot Luminance	1
Maximuim Value of Relative Dot Luminance	50
Dot Diameter(Pixels)	4
Dot Position(Diam of Fix Mark)	5.0
Background Level(Display Values)	175

Sensevity Index, Criterion and ROC Curve

The following link takes you to a psychophysical experiment. On each trial, dots will start moving from the outer edge. On some trials, one of the dots moves faster than the others. Your task is to say whether there is a faster dot on the screen.

- Calculate your sensitivity index $d' = z(H) - z(F)$ and criterion $c = -0.5[z(H) + z(F)]$.

	Present	Not Present
Happened	0.75	0.11
Did not Happen	0.25	0.89

$$d' = z(\text{Hit}) - z(\text{False Alarm}) = z(0.75) - z(0.11) = 0.67 - (-1.22) \quad \rightarrow \quad d' = 1.89$$

$$c = -\tfrac{1}{2}(z(\text{Hit}) + z(\text{False Alaram})) = -\tfrac{1}{2}(0.67 - 1.22) \quad \rightarrow \quad c = 0.275$$

- Using the ROC curve, describe your performance.

Firstly, we implemnet following `MATLAB` code.

```matlab
% Given data points
hit = 0.75;
false_alarm = 0.11;

% Plot the ROC curve
figure;
plot([0, 1], [0, 1], '--');  % Diagonal line (random classifier)
hold on;
plot(false_alarm, hit, 'go', 'MarkerSize', 4);  % Data point
title('ROC Curve', 'Interpreter', 'latex');
xlabel('False alarm', 'Interpreter', 'latex');
ylabel('Hit', 'Interpreter', 'latex');
grid on;
legend('Our Trial', 'Data Point');
hold off;
```

Source Code 1: ROC Curve

Now, by using following plot and as we have $d' = 1.89$, we can find `AUC`.

$$d' = \sqrt{2} \times \text{qnorm}(AUC) \quad \rightarrow \quad \text{qnorm}(AUC) = \frac{1.89}{\sqrt{2}} \quad \rightarrow \quad AUC = 0.9207$$

Which is near to 1 and it is good for our trial.

Method and Stimulus Setting

Number of Trials	40
Percantage of Trial wit a Signal	50
Number of Background Dots	25
Relative Speed of Sytimulus	1.0
Duration of Stimulus	2.0

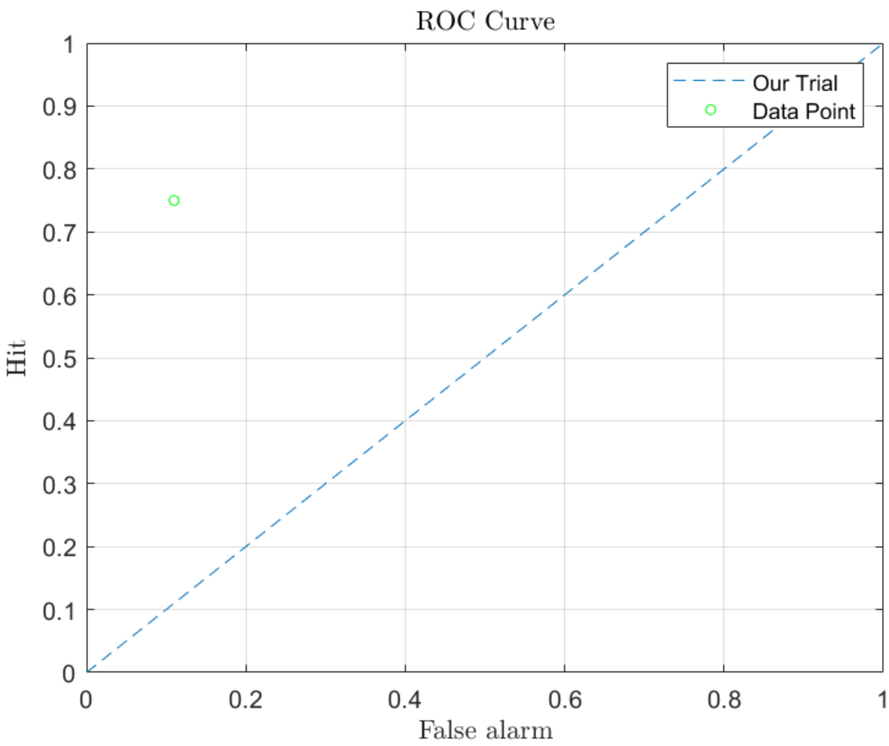
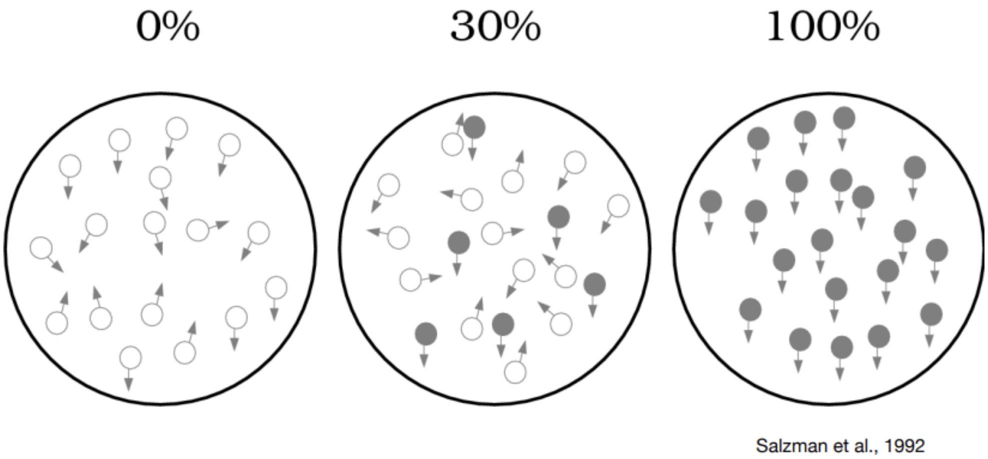


Figure 2: ROC Curve

Visual Motion Discrimination Task

Visual motion discrimination task is studied using a two alternative forced choice task. The stimuli are random dots moving in different directions. If all the dots move in the same direction, the motion strength (coherence) is 100becomes more random, the motion strength is reduced. The participant's task is to choose the direction of movement.



- Sketch the psychometric function. How would the psychometric function of an ideal observer (with zero noise) look like?

Psychometric Function

The psychometric function typically exhibits an S-shaped curve. It relates the strength of the motion signal (e.g., coherence level) to the observer's performance (e.g., proportion of correct responses). Here's how it looks:

- Threshold Region (Midpoint):
  - The middle part of the curve corresponds to the threshold region.
  - At this point, the observer's performance is around 50% (chance level).
  - The threshold represents the stimulus strength required for the observer to discriminate motion reliably.
- Slope:
  - The steepness of the curve (slope) reflects the observer's sensitivity to the motion signal.
  - A steeper slope indicates higher sensitivity (better discrimination ability).
- Asymptotes:
  - The curve approaches asymptotes (near 0% and 100% performance).
  - The lower asymptote represents performance when the motion signal is absent.
  - The upper asymptote represents performance when the motion signal is strong.

Ideal Observer (Zero Noise):

An ideal observer with zero noise would have the following characteristics:

- Perfect Sensitivity:
  - The ideal observer would have infinite sensitivity (infinite slope).
  - It could discriminate motion signals even at extremely low strengths.
- Threshold at Zero Coherence:
  - The threshold would be at zero coherence (no motion signal required for discrimination).
  - The psychometric function would intersect the x-axis (coherence) at zero.
- Perfect Performance:
  - The upper asymptote would be at 100% performance (perfect discrimination).
  - The ideal observer would achieve 100% correct responses even with weak motion signals.

In summary, the psychometric function for an ideal observer (with zero noise) would be a vertical line intersecting the x-axis at zero coherence, followed by a horizontal line at 100% performance.

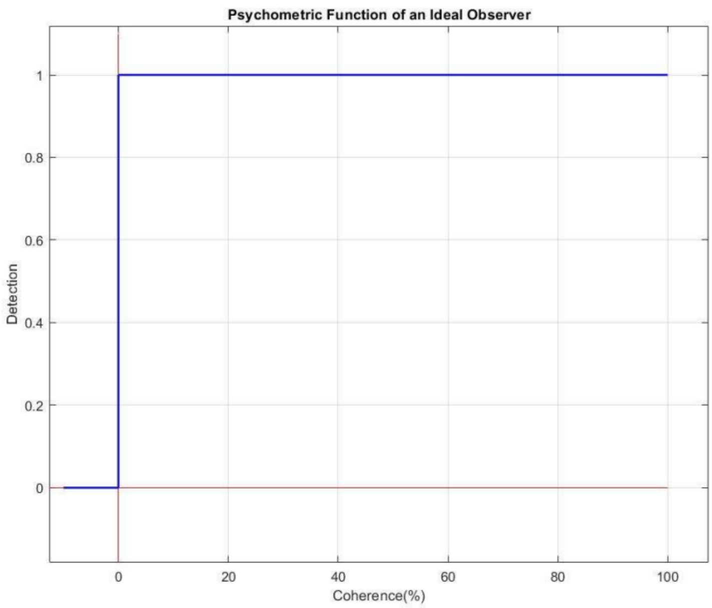


Figure 3: Ideal Observer Physchometric Function

In order to study the motion aftereffect, an adapter stimulus is added to the motion discrimination task. In other words, The experiment is started by showing a dot motion stimulus that is always moving in one direction and then another dot motion stimulus is presented.

- Using the psychometric curves try to explain the effect of stimulus adapter on the motion discrimination.

Motion Aftereffect and Adapter Stimulus

The motion aftereffect (MAE) is a perceptual phenomenon where prolonged exposure to motion in one direction leads to the illusion of motion in the opposite direction for stationary objects.

Experimental Setup: To study MAE, researchers use an experimental setup involving an **adapter stimulus**:

- The observer is presented with a dot motion stimulus that always moves in one specific direction (the adapter).
- After adaptation to the adapter stimulus, a **test stimulus** (another dot motion stimulus) is presented.
- The test stimulus can move in either the same direction as the adapter (congruent) or the opposite direction (incongruent).

Psychometric Curves: Psychometric curves describe how an observer's performance (e.g., accuracy or proportion of correct responses) varies with the strength of a motion signal (e.g., coherence level). The adapter effects on the motion discrimination:

- **Threshold Shift:**
  - The psychometric curve with the adapter stimulus may shift left or right along the coherence axis.
  - If the adapter and test stimuli are congruent (same direction), the threshold for motion discrimination may decrease (leftward shift).
  - If the adapter and test stimuli are incongruent (opposite directions), the threshold may increase (rightward shift).
- **Sensitivity Changes:**
  - The steepness of the curve (slope) indicates sensitivity to motion.
  - Adaptation can alter sensitivity due to neural changes in motion-selective neurons.
- **Ideal Observer (Zero Noise):**
  - An ideal observer (with zero noise) would show perfect adaptation.
  - The psychometric curve would shift precisely to match the adapter direction.
  - Sensitivity would remain high, and the threshold would be near zero coherence.

In summary, the addition of an adapter stimulus affects motion discrimination by altering the observer's sensitivity and threshold. The psychometric curves provide insights into the neural mechanisms underlying the MAE and motion processing.

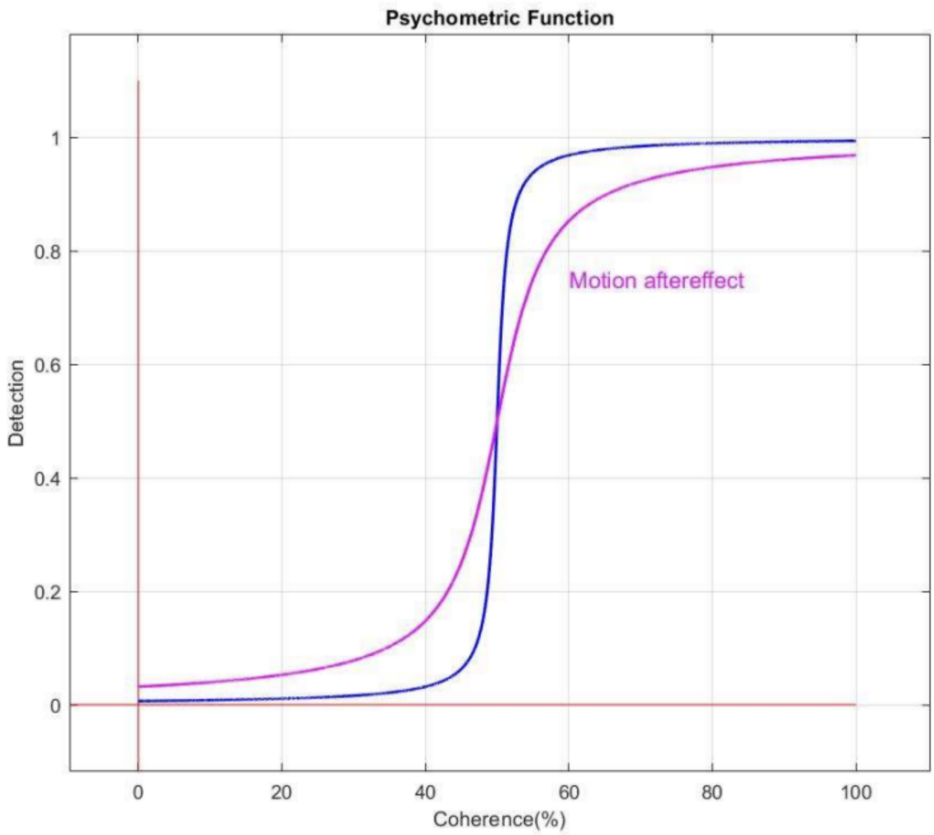


Figure 4: Physchometric Function

Dyschronometria

Dyschronometria is a condition of cerebellar dysfunction in which an individual cannot accurately estimate the amount of time that has passed (i.e., distorted time perception). Propose an experimental design to investigate the perception of duration in these patients. The design should consist of the following. In addition, explain your rationale for choosing these methods.

- Hypothesis
- Participants
- Stimuli
- Task procedure
- Experimental conditions
- Experimental method

Experimental Design: Investigating Duration Perception in Dyschronometria

- **Hypothesis**
  - Individuals with dyschronometria will exhibit distorted time perception.
  - Their estimates of time duration will be inaccurate.
- **Participants**
  - We will recruit a group of individuals diagnosed with dyschronometria.
  - A control group of healthy participants without cerebellar dysfunction will also be included.
- **Stimuli**
  - The stimuli will consist of visual and auditory time intervals.
  - These intervals will vary in duration (e.g., milliseconds to seconds).
- **Task Procedure**
  1. Baseline Measurement:
     - Participants will perform a duration estimation task without any adaptation.
     - They will judge the duration of presented intervals.
  2. Adaptation Phase:
     - Participants will be exposed to prolonged time intervals (e.g., visual or auditory stimuli) to induce adaptation.
  3. Test Phase:
     - Participants will perform the duration estimation task again immediately after the adaptation phase.
     - We will compare their duration judgments with those from the baseline.

- **Experimental Conditions**
  - Adaptation Condition:
    - Participants experience prolonged time intervals during adaptation.
    - We expect distorted duration perception after adaptation.
  - Control Condition:
    - Healthy participants undergo the same procedure without adaptation.
    - Their duration judgments serve as a reference.
- **Experimental Method**
  - We will use a within-subjects design.
  - The order of conditions (adaptation vs. control) will be counterbalanced across participants.
- **Rationale**
  - Adaptation mimics real-world situations.
  - Within-subjects design allows direct comparison.
  - Control group provides a baseline for normal duration perception.
- **Conclusion:** This experimental design will help us understand how dyschronometria affects time perception and shed light on the underlying neural mechanisms.

Mean RT, Accuracy, and Learning Curve

In the following experiment, participants' goal was to learn the best response (arbitrarily labeled "Yes" and "No") for each stimulus. Participants used up and down arrow keys to make "Yes" and "No" responses, respectively. Reward-associated stimuli led to a win of 0.35$onaveragewhenYeswasselectedandasmalllossof$0.05 when "No" was selected. Loss-associated stimuli led to a neutral outcome of 0.00$whenNowasselectedand$0.25 when "Yes" was selected. These associations were probabilistic such that the best response led to the best outcome 80% of the time during training. If no response was recorded, at feedback, a warning was given: "Too late or wrong key! 0.50$andparticipantslost$0.50. In a single reward learning trial, a stimulus was first presented with the options "Yes" and "No" above and below the image, respectively. Participants had 2 s to make a choice. After the full 2 s choice period, a 1 s blank screen inter-trial interval (ITI) preceded feedback presentation. Feedback was presented in text for 1.5 s, leading to a total trial duration of 4.5 s. After the feedback, an ITI of duration 2 preceded the next trial (min, 0.50 s; max, 3.5 s), where in the last 0.25 s before the next trial, the fixation cross turned from white to black. "

Figure 5: Wimmer GE, Li JK, Gorgolewski KJ, Poldrack RA. Reward Learning over Weeks Versus Minutes Increases the Neural Representation of Value in the Human Brain. J Neurosci. 2018 Aug 29;38(35):7649-7666. doi: 10.1523/JNEUROSCI.0075-18.2018. Epub 2018 Jul 30. PMID: 30061189; PMCID: PMC6113901.

The following link takes you to the results of the training task. You will need the following columns:
"reaction time" : response time for each trial.
"correct" : correct or incorrect response given reward/loss status of a stimulus.
"stimvalue": value of stimulus, where 0 = loss-associated stimulus; 1 = medium value (mean 0.25$reward)and2 = highvalue(mean$0.45 reward).

- Plot the average response time and accuracy for reward and loss-associated stimuli.

Firstly, we implemnet following `MATLAB` code to find data from `.csv` file and organize them and find what is suitable for this part.

```
% Specify the path to your CSV file
csvFilePath = 'study.csv';

% Read the CSV file into a table
table = readtable(csvFilePath);

% Extract relevant columns
stim_value = table2array(table(:,9));
```

```
    correct = table2array(table(:,7));
    reaction_time = table2array(table(:,6));

    % Create logical indices for reward and loss-associated stimuli
    reward_indices = (((stim_value == 1) | (stim_value == 2)) & (~isnan(
   correct)) & (~isnan(reaction_time)));
    loss_indices = ((stim_value == 0) & (~isnan(correct)) & (~isnan(
   reaction_time)));

    reward_accuracy = table{reward_indices, 'correct'};
    loss_accuracy = table{loss_indices, 'correct'};

    % Calculate mean reaction times for reward and loss-associated stimuli
    reward_mean_reaction_time = mean(table{reward_indices, 'reactiontime'});
    loss_mean_reaction_time = mean(table{loss_indices, 'reactiontime'});

    % Calculate mean accuracy for reward and loss-associated stimuli
    reward_mean_accuracy = mean(reward_accuracy);
    loss_mean_accuracy = mean(loss_accuracy);

    % Display the results
    disp(['Reward Mean Reaction Time: ', num2str(reward_mean_reaction_time)]);
    disp(['Loss Mean Reaction Time: ', num2str(loss_mean_reaction_time)]);
    disp(['Reward Mean Accuracy: ', num2str(reward_mean_accuracy)]);
    disp(['Loss Mean Accuracy: ', num2str(loss_mean_accuracy)]);

    % Data
    categories = {'Reward', 'Loss'};
    mean_reaction_times = [reward_mean_reaction_time, loss_mean_reaction_time
   ];
    mean_accuracy = [reward_mean_accuracy, loss_mean_accuracy];

    % Create a bar plot
    subplot(1,2,1)
    bar(mean_reaction_times, 'FaceColor', [0.2 0.2 0.5]);
    xticks(1:2);
    xticklabels(categories);
    xlabel('Condition', 'Interpreter','latex');
    ylabel('Mean Reaction Time', 'Interpreter','latex');
    title('Comparison of Mean Reaction Time', 'Interpreter','latex');
    ylim([0.6, 1.0]);

    % Create a bar plot
    subplot(1,2,2)
    bar(mean_accuracy, 'FaceColor', [0.2 0.2 0.5]);
    xticks(1:2);
    xticklabels(categories);
    xlabel('Condition', 'Interpreter','latex');
    ylabel('Mean Reaction Time', 'Interpreter','latex');
    title('Comparison of Mean Accuracy', 'Interpreter','latex');
    ylim([0.6, 1.0]);
```

Source Code 2: Bar Plot

Now, we can compare mean reaction time, and mean accuracy for both reward and loss-associated stimuli.

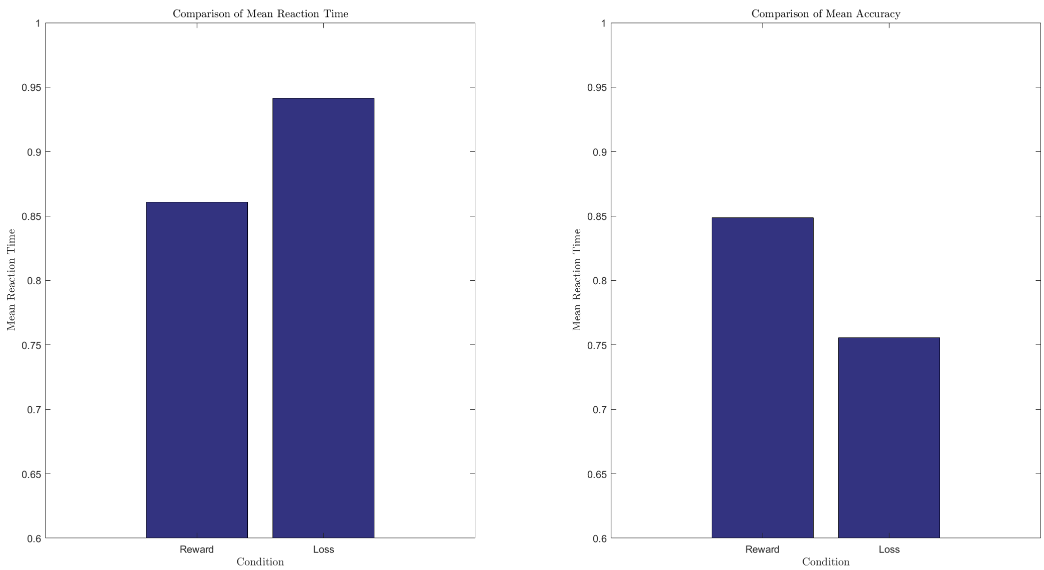


Figure 6: Comparison of Mean Accuracy and Mean RT

- Plot the learning curves for reward vs. loss-associated stimuli.

Now, we implement following code to plot learning curves. We plot to learning curve which one of them is for accuracy and the other for cumulative.

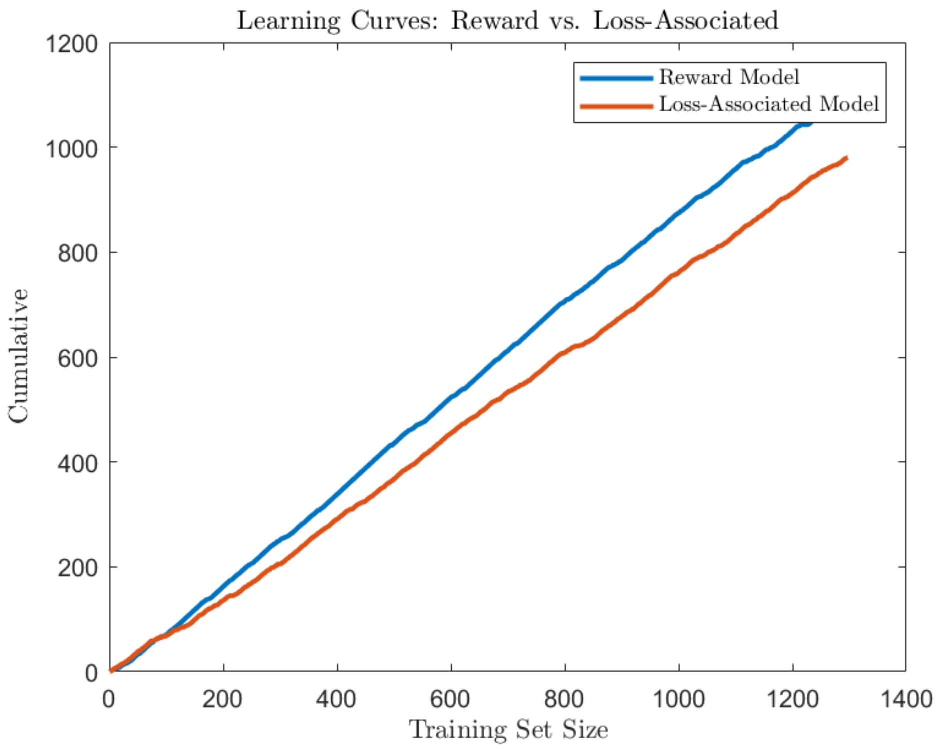


Figure 7: Cumulative Learning Curve

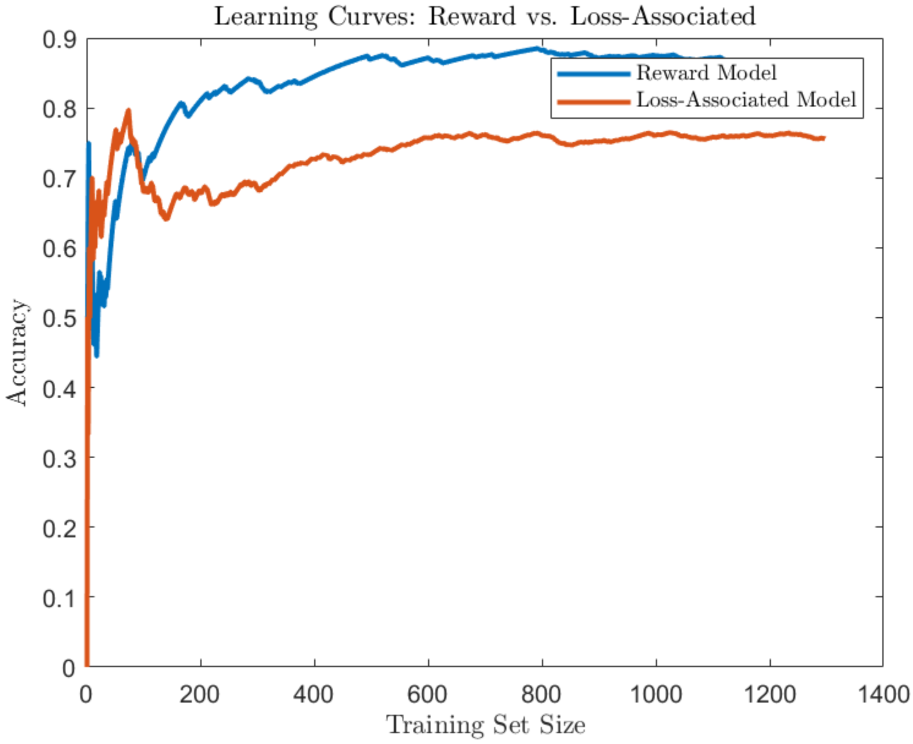


Figure 8: Accuracy Learning Curve

Derivation of Sensitivity

Derivation of Sensitivity (d') (Solution 1)

- **Definition of** d':
  - In signal detection theory, d' represents the sensitivity of an observer to discriminate between two stimuli or conditions. It is defined as the difference in means between the signal-present and signal-absent distributions, normalized by the standard deviation of the noise distribution.
  - Mathematically, d' is given by:

    $$d' = \frac{\mu_{\text{signal}} - \mu_{\text{noise}}}{\sigma_{\text{noise}}}$$

    Where:
    * μ_{signal} is the mean of the signal-present distribution.
    * μ_{noise} is the mean of the signal-absent (noise) distribution.
    * σ_{noise} is the standard deviation of the noise distribution.
- **Definition of** $z(H)$ **and** $z(F)$:
  - In signal detection theory, $z(H)$ and $z(F)$ represent the z-scores of hits (correct detections) and false alarms (incorrect detections), respectively. These z-scores are calculated based on the probabilities of hits and false alarms.
  - Mathematically, $z(H)$ and $z(F)$ are given by:

    $$z(H) = \Phi^{-1}(H) \quad , \quad z(F) = \Phi^{-1}(F)$$

    Where:
    * H is the proportion of hits.
    * F is the proportion of false alarms.
    * Φ^{-1} is the inverse cumulative distribution function (CDF) of the standard normal distribution.
- **Derivation**:
  - To prove $d' = z(H) - z(F)$, we need to show that the expression for d' matches the difference between $z(H)$ and $z(F)$.
  - Let's rewrite d' using the definitions of $z(H)$ and $z(F)$:

    $$d' = \frac{\mu_{\text{signal}} - \mu_{\text{noise}}}{\sigma_{\text{noise}}} = \frac{\Phi^{-1}(H) - \Phi^{-1}(F)}{1} = \Phi^{-1}(H) - \Phi^{-1}(F)$$

    Since the standard deviation of the noise distribution is 1 in z-score calculations, we can simplify d' to $\Phi^{-1}(H) - \Phi^{-1}(F)$.
  - This matches the expression for $d' = z(H) - z(F)$, thus proving the relationship.

Derivation of Sensitivity (d') (Solution 2)

Given two Gaussian probability density functions (PDFs) for two different states S1 and S2, we can denote them as follows:

$$p(x|S1) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu_1)^2}{2\sigma^2}} \tag{1}$$

and

$$p(x|S2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu_2)^2}{2\sigma^2}} \tag{2}$$

where: - μ_1 and μ_2 are the means of the distributions for S1 and S2 respectively, - σ is the standard deviation, which is the same for both distributions (as per the assumption of equal variance).

The likelihood ratio for these two states is given by:

$$\Lambda(x) = \frac{p(x|S1)}{p(x|S2)} \tag{3}$$

Taking the natural logarithm on both sides, we get:

$$ln(\Lambda(x)) = ln\left(\frac{p(x|S1)}{p(x|S2)}\right) \tag{4}$$

Substituting the PDFs, we get:

$$ln(\Lambda(x)) = ln\left(\frac{\frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu_1)^2}{2\sigma^2}}}{\frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu_2)^2}{2\sigma^2}}}\right) \tag{5}$$

Simplifying, we get:

$$ln(\Lambda(x)) = \frac{(x-\mu_2)^2 - (x-\mu_1)^2}{2\sigma^2} \tag{6}$$

This can be further simplified to:

$$ln(\Lambda(x)) = \frac{(\mu_1-\mu_2)x + (\mu_2^2 - \mu_1^2)}{2\sigma^2} \tag{7}$$

Now, we can define $z(x)$ as the log-likelihood ratio, i.e., $z(x) = ln(\Lambda(x))$. We can also define d' as the difference between the means normalized by the standard deviation, i.e., $d' = \frac{\mu_1-\mu_2}{\sigma}$.

From the above, we can see that $z(x)$ is a linear function of x with a slope of d', and hence the relationship between d' and $z(x)$ can be written as:

$$d' = z(H) - z(F) \tag{8}$$

where H and F are the hypotheses corresponding to states S1 and S2 respectively. This is the relationship you asked for.