Part 1:

Aim: Simulation of evidence accumulation model and studying the relationship between accuracy and reaction time (RT) in decision making

We can represent a discrete version of diffusion drift model (DDM) for evidence accumulation as follows (Ratcliff, 1978):

$$dX = Bdt + \sigma dW$$

Here, dX represents the change in evidence (decision variable) during the time step dt
B is a constant bias that directs the evidence total over time
dW, represents a discretized Brownian motion term. Simply put, a Brownian motion is a random walk in which steps follow a Gaussian distribution. Formally, the Brownian motion term is characterized by three properties:
1. W(0) = 0
2. W(t) is continuous in t
3. For any two values of t, t1, and t2, the difference between W(t1) and W(t2) follows an independent normal distribution with mean 0 and variance equal to the difference t2-t1.
Consequently, one important aspect of the Brownian motion term is its scaling with respect to time. Since dW follows an N(0, dt) distribution, increasing or decreasing the time step size increases or decreases the variance of the random portion of the walk. The scalar scaling constant σ allows for adjustments to uncertainty. To complete the simple model, we need a start point x0. In most cases, we will choose a value of 0 for x0, so that a positive accumulation will indicate a positive choice.
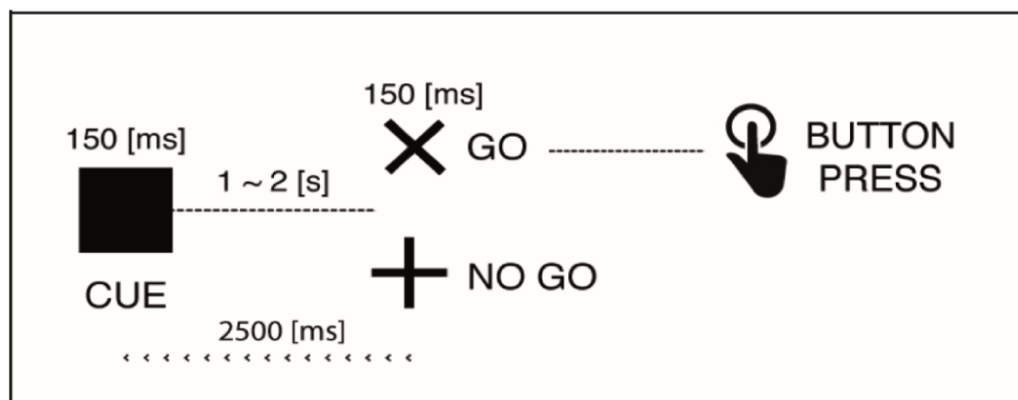
The general form of a Go/No Go task

Question 1: Write a simple simulation for Go/No Go task with a fixed time interval. This would correspond to presenting a stimulus and requiring the research participant to select a choice at the end of the time interval. Name this function as **simple_model**. The function accepts bias term, sigma, dt and time interval as the inputs and gives the choice as the output.

Question 2: Simulate 20 choice experiments, each 1 second long, with B=1 per second, σ=1, dt=0.1 second. What is the distribution of results? Modify **simple_model** to return the decision variable (x) as well as the

resulting choice. Examine the time course of the evidence for B=1, B=10, B=0, B=0.1, and B= -1 over a 10-second trial.

Question 3: Explore how the time interval influences the error rate. Generate 10 trials each for tasks ranging in duration from 0.5 to 10 seconds. Use parameters B=0.1 per second, σ=1, dt=0.1 second. Assume that a positive response is correct. How does Error Rate change with time?

Question 4: We would like to explore the probability distribution of decision variable at some time t. So, calculate the expected value and variance of decision variable in the main formula. Generate evidence trajectories for 10 trials over 10 seconds with parameters B=0.1 per second, σ=1, dt=0.1 second. Calculate mean and variance over time. Plot the trajectories, mean trajectory, and one standard deviation above and below the mean. Compare the trajectories to the expected value.

Question 5: Write a function **simple_model2** that accepts bias, time limit, and start point, and that returns the choice. **simple_model2** should use cdf function of normal distribution to calculate the probability of being above or below the start point without iterating through a trajectory. Once a probability of the decision variable total being above or below the start point is calculated, a draw from a uniform random distribution can be used to choose an option.

Question 6: In the previous parts, the time interval was fixed. But, to have this option to calculate the reaction time, here we simulate a situation of free response. Write a function **two_choice_trial** that accepts five parameters: positive and negative thresholds θ+ and θ-, a variance for accumulation error σ, a start value x0, and a bias B. The function should use the discrete time representation of the decision process by calculating values for the total evidence at successive time intervals until evidence exceeds a threshold. The time at the threshold crossing is the reaction time. The function should return both the reaction time and 1 or -1 for the response.

Question 7: Now, let's explore the relationship between error rate (ER) and reaction time (RT). Generate a large number of trials using a free response decision paradigm. Choose a relatively small bias. Plot a red point at (RT, 1) for each correct response (assuming that a response in the direction of the bias is correct), where RT is the response time. Plot a blue point at (RT, -1) for each incorrect response. Does the distribution of points say anything about the relationship between RT and ER?

Race diffusion model, an extension of drift diffusion model:

Question 8: The discrete version of the diffusion drift model can accommodate a two threshold paradigm, but even with two thresholds, the single iterator allows for only a single set of bias and variance values. Under some two choice scenarios, the race model may be a better match. Under the race model, each of the two choices has an independent iterator and threshold. The first process whose accumulated evidence exceeds its threshold is the choice of the system. This choice "wins the race". Write a MATLAB code, **race_trial**, to simulate this race model.

Question 9: Extend **race_trial** to accept a fixed time interval, and to return the best choice if the total time reaches the maximum interval without a clear winner.

Part 2:

Aim: Implementing the model proposed by Shadlen and Newsome (2001) for the interaction between area MT and LIP

The function **lip_activity** ahead models the activity of a single LIP neuron with fixed probabilities for its corresponding excitatory and inhibitory MT neurons.

```
function rt = lip_activity(MT_p_values,LIP_weights,LIP_threshold)
% Parameters:
% MT_p_values - a vector with 2 elements, firing probabilities for the
% excitatory and inhibitory neurons, resp.
% LIP_weights - a length 2 vector of weighting factors for the evidence
% from the excitatory (positive) and
% inhibitory (negative) neurons
% LIP_threshold - the LIP firing rate that represents the choice threshold criterion
% use fixed time scale of 1 ms
dt = 0.001;
N = [0 0]; % plus is first, minus is second
rate = 0.0;
LIP_event_times = [];
while rate < LIP_threshold
    t = t + 0.001;
    dN = rand(2) < MT_p_values;
    N = N + dN;
    p_LIP = sum(N.*LIP_weights);
    LIP_event = rand < p_LIP;
    _event_times = [LIP_event_times t];
    % check LIP mean rate for last M spikes
    rate = M/(t - LIP_event_times(N_LIP - M));
end
rt = t;
end
```

Question 1: Modify **lip_activity** to return the event times for the simulated LIP neuron. Modify the function to capture and return the event times for the two MT neurons. Generate a sample set of coordinated MT and LIP simulated event times and examine them as a raster. How do the patterns of activity differ?

Question 2: write a simulation of MT-LIP neurons
Write code to simulate the effect of presenting a directionally oriented stimulus during intervals of time. This will involve generating a time series where the value at each step is an orientation or a value that indicates the absence of a stimulus.
You need to allow the probability of firing for the two MT neurons in the model to change with time, based on the orientation of any presented stimulus.
The model should include two MT neurons and two LIP neurons. Each MT neuron should have feed forward connections to both LIP neurons, one excitatory and one inhibitory.
Generate activity patterns for both MT neurons and both LIP neurons for various stimulus presentations.