P1. Hi, my name is Wonkwon Lee and I am glad to introduce my final year projects to folks today. I am studying about neurons and neuronal networks under supervisor Dr. Eva Lopez.

P2. To begin with, I would like to introduce about my project. The aim of my project is to model and analyse both single neurons and neuronal networks. I have read through various renowned papers to develop my background knowledge and familiarized myself to mathematical knowledges and currently using computer simulation. Furthermore, I will extend these models to investigate other dynamical behaviours in the brain.

P3. My goal is to model synapses based on the Hebb's rule and integrate the models with the neuronal networks to analyse how changes of the synaptic strength can affect the behaviours of networks. I will extend Wulfram Gerstner's mathematical models to simulate and analyse how pre- and postsynaptic activities change due to synaptic plasticity.

P4. To implement networks of neurons, we have start from a single neuron. First, we should start from understanding biophysical characteristics of a neuron. Then, we implement neuron models from simplified integrate-fire to complicated and extending ones. The last part is the cornerstone of this project, a transition from single neurons to networks. It is a bridge scales from a micrometers to centimeters, from single cells to cognition.

P5. Now let's talk about the most important question. So, what is a neuron? A neuron is a complicated nonlinear dynamical system that can receive, process, and transmit information. It generates electrical potentials across their cell membrane. And neuron spikes when membrane potential rapidly rises and falls.

As neuron is an electrically excitable cell, it can be simplified to mathematically model and can even be plotted. The graph here shows how membrane potential changes (and spikes) over time if any stimulation applied to a neuron. When membrane potential reaches action potential (spike), then voltage drops drastically, and finally reaches equilibrium.

P6. The word "synapse" comes from a Greek word "synapsis", meaning conjunction. As the name said, synapse is a junction between two neurons. It has a very interesting role in neuronal interaction. Synapse permits a transmitting neuron to pass an electrical signal to receiving neuron. In other words, synapses are the means by which neurons use to interact each other. When an action potential reaches to synapse, the input current flowing into transmitting neuron can cross the barrier of the two cell membranes and enter the receiving neuron. Therefore, the input currents of presynaptic spike can directly stimulate the postsynaptic neuron.

Furthermore, it is widely known that synapse plays an important role in the formation of memory. The connection between the two neurons is strengthened when both neurons are active at the same time. The strength of this connection results in the storage of information, and that is memory.

P7. Now that we have talked about biological characteristics of neurons, I will now start talking about how to model a single neuron. Mathematically, a neuron is a dynamical system in terms of input/output relations. The earliest integrate-fire neuron model was suggested in early 1900s, based on the law of capacitance. The equation on the right is just a time derivative of law of capacitance (Q=CV). Yes, the earliest integrate-fire model was simply a relationship between membrane current at the input stage and membrane voltage at the output stage.

P8. The neuron, however, is a far more complicated to be expressed as simple integrate-fire models. The problem of early model is that there is no time-dependent memory. If the model receives below-threshold signals at some time, it will retain that voltage boost forever until it fires again. Therefore, we add “Leaky” term on simplified integrate-fire model to describe the charges being slowly leaked over time through the cell membrane. Now the memory problem is solved; leak term reflects the diffusion of ions in the membrane when equilibrium is not reached in the cell.

P9. Unfortunately, there are still remaining limitations to leaky integrate-fire model. First of all, the LIF model is highly simplified that it neglects many aspects of neuronal dynamics. Also, the LIF model is linear, meaning that input from transmitting neurons or from current injection, is integrated linearly, regardless of the state of the receiving neuron. Finally, after each output spike, the membrane potential is reset, so that no memory of previous spikes is kept.

There are two nonlinear models: QIF suggested by Eugene Izhikevich and Exponential IF. Both models are fast and easy to simulate, but I decided to use Gerstner’s model. The reason why I decided to use EIF is because Wulfram Gerstner further expanded the model

P10. This neuron model is called AdEx model. Let me explain why adaptation matters what does it do. Unfortunately, a single equation is not sufficient enough to describe the variety of firing patterns of neurons. Therefore, we need to couple the voltage equation to show different firing patterns. Although QIF can be coupled with adaption equation, AdEx is relatively more accurate due to the modulation of the membrane potential.

As you see, the AdEx is consists of 2 equations: the first equation describes the dynamics of the membrane potential. The other describes the adaptation in terms of voltage. The Figure under the AdEx equation demonstrates adaptation and regular firing of the AdEx model in response to a input current in voltage **(top)** and in adaptation variable **(bottom)**. The figure on the right is Gerstner’s AdEx model classification, demonstrating multiple firing patterns in neurons. For each type, the neuron is stimulated with a step current with low or high amplitude. The models are classified by the steady-state firing behavior (vertically) and transient initiation pattern (horizontally).

The following 3 terms: tonic, initial burst, decay, are the main initiation patterns. Tonic is when initiation cannot be distinguished from the rest of spiking response, initial burst is when neuron initiates with greater frequency, and delay is when neuron responds after the delay. After the initial transient, there are another 3 major patterns: tonic, adapting, and burst. regularly spaced spikes (tonic); gradually increasing intervals (adapting); and alternation between short and long intervals. By using AdEx models, we can not only solve problems of early models but also analyze firing patterns.

P11. So far, I have tested different single neurons. The slide here demonstrates my preliminary result. The first graph is LIF model with injection of sinusoidal current. It generated 5 spikes. The second graph is EIF model without adaptation equation. The input was step current and it generates 7 spikes. The last graph is AdEx model with injection of step input current, generating 10 spikes. The AdEx model has phase plane representation, which displays the dynamical systems views of neuron.

According to the Gerstner's firing pattern classification, the left figure has initial burst at transient initiation and has tonic pattern for steady-state. Also let's compare with the phase plane representation. In the phase portrait, the graph has a series of direct resets followed by a detour reset. By using AdEx model, I could test different types of input current and compare their patterns.

P12. A neuronal network is not just a group of neurons gathering together. We need to consider several questions before we start implementing network.

Q1. The answer is completely arbitrary. However, we need two different populations of integrate-fire models: excitatory and inhibitory. It doesn't matter how much neurons we put, but need to maintain a ratio of 4:1. For example, a network of 10000 neurons is consists of 8000 excitatory and 2000 inhibitory.

Q2. I am going to use Oscillation is a prevalent phenomenon in biological neural networks. In recurrent networks, a state of non-synchronous activity is unstable in the absence of noise. By using oscillation, neurons tend to form clusters of cells that fire synchronously. Oscillations in random-connectivity networks show that each neuron fires nearly regularly and within a cluster, neurons are almost fully synchronized

Q3. I am going to let each neuron to have a certain number of connections with other neurons, firing at a fixed rate. Also, each connection will have a certain weight. Each neuron will have a certain number of connections with other neurons, firing at a fixed rate. Each connection will take a certain weight.

I am currently at this stage, and will successfully create networks of neurons by using above methods.

P13. My goal is to examine how synaptic plasticity affect neuronal network behaviours. Synapse plasticity is an ability of synapses to strengthen or weaken over time, in response to increases or decreases in their activity. The image explains about long-term potentiation(LTP), an example of the result of long-term plasticity. LTP is a persistent strengthening of synapses based on recent activities. The recent patterns of synaptic activity produce long-lasting increase in signal transmission between neurons.

The reason for LTP can be explained by spike-timing-dependent plasticity (STDP). STDP is a biological process that adjusts the connection strengths based on the relative timing of a neuron's output and input spikes. In other words, under the STDP process, if an input spike tends to occur before output spike, then the particular input becomes stronger.

In order to integrate STDP to neuronal network, I am going to use Hebbian rule to model STDP. Hebbian rule explains the adaptation of neurons during the learning process. According to the Hebbian rule, if presynaptic cell persistently stimulates the postsynaptic cell, synapses increase their efficiency. I am going to use mathematical formulation of Hebbian rule to integrate STDP model into neuronal networks and ultimately investigate long term neuronal networks behaviours.