SPIKING NEURAL NETWORKS

ICT in Intelligent Networks

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- Artificial Neural Networks - the first step towards true artificial intelligence
- An attempt to replicate the human brain through computational algorithms
- Evolution of the neural network architecture
- Generations of neural networks

➢ First Generation - the Perceptron algorithm (1958) - able to perform binary classification of data

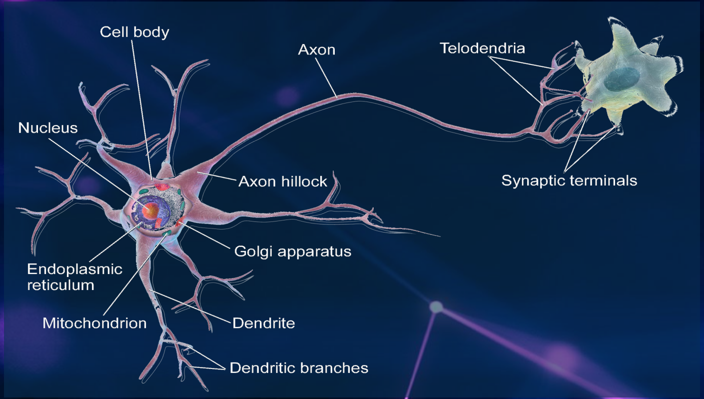
➢ Second Generation - Multi-layer neural network architecture, multiple different types of neurons, deep learning - able to perform significantly more complex tasks

➢ Third generation - the future of artificial intelligence, but what does it entail?

SPIKING NEURAL NETWORKS

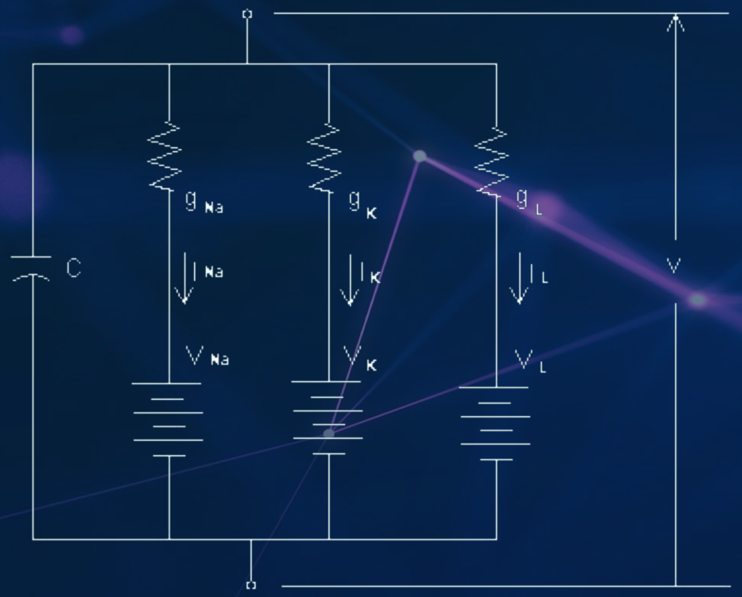
SPIKING NEURAL NETWORKS - THE FUTURE OF AI?

- Biological neurons - how do they work?!
- Voltage spikes
- Receptive field
- Neural communication
- Refractory period



COMPUTATIONAL MODELS OF NEURONS

- Hodgkin and Huxley model (1952)
- Simplification of neurons as an electrical circuit
- Based on the most common ions used in generation of action potentials
- Implement leaky current to simulate refractory period



SOLVING THE CIRCUIT

- Using Ohm's Law we get the equations at (1):

- By using the current - voltage relations we reach the expressions given at (2):

- The parameters g_{K_bar} and g_{Na_bar} are constant, while *n*, *m* and *h* vary according to the following differential equations:

$$I_{Na} = g_{Na} (E - E_{Na})$$
$$I_K = g_K (E - E_K)$$
$$I_L = g_L (E - E_L)$$

(1)

$$I_{Na} = g_{Na} (V - V_{Na}) = g_{Na} (E_{Na} - E_R)$$
$$I_K = g_K (V - V_K) = g_K (E_K - E_R)$$
$$I_L = g_L (V - V_L) = g_L (E_L - E_R)$$
$$V = E - E_R$$

$$g_k = g_{K\_bar}\, n^4 \qquad g_{Na} = m^3 h$$
$$g_{Na\_bar}$$

(2)

SOLVING THE CIRCUIT

$$\frac{dn}{dt} = \alpha_n(1-n) - \beta_n n$$

$$\frac{dm}{dt} = \alpha_m(1-m) - \beta_m m$$

$$\frac{dh}{dt} = \alpha_h(1-h) - \beta_h h$$

- The Hodgkin - Huxley model is a great achievement for 20th century biophysics
- Not suitable for large scale simulation of spiking neural network
- It can be modified/improved in two ways

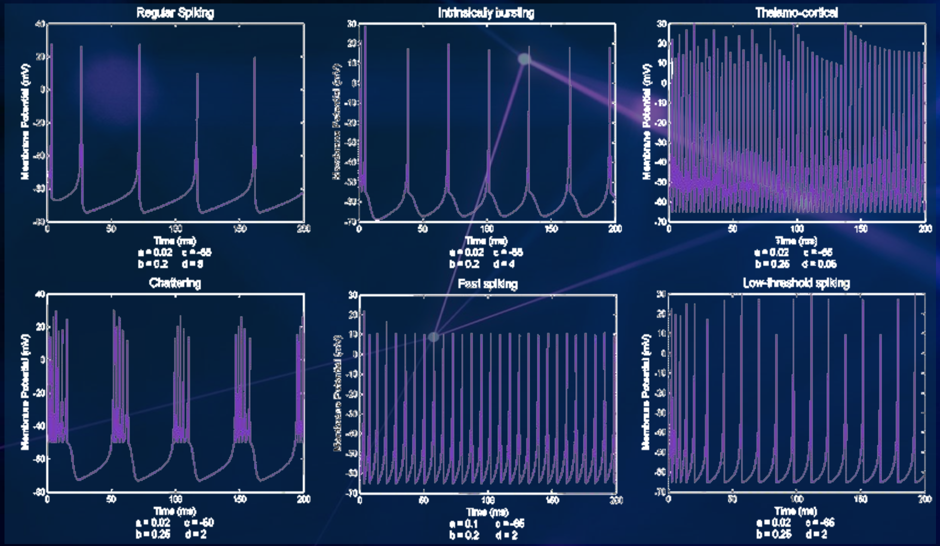
IMPROVING THE MODEL FOR AI

- Create a more detailed model:
  - more types of ion channels
  - incorporate factors that influence conductance
  - take the shape of the neuron into account

- Pros:
  - higher detail allows for more realistic behaviour
  - closest model to a real biological neuron
- Cons:
  - much more computationally expensive
  - impractical for data science due to extremely slow simulations

IMPROVING THE MODEL FOR AI

- Alternative method: use spiking patterns!
- Just one spike doesn't carry enough data
- 1D vector of membrane voltage values in accordance to time carries much more information
- Different types of spiking patterns



INTEGRATE-AND-FIRE MODEL

- One of the first computational models of a biological neuron (1907)
- Simple differential equation that uses the equation for capacitor current to simulate a voltage spike (1)
- Can be improved by incorporating a refractory period t_{ref} making the model more realistic (2)
- Not biologically accurate due to no time-dependent memory

$$I(t) = C_m \frac{dV_m(t)}{dt} \qquad (1)$$

$$f(I) = \frac{I}{C_m V_{th} + t_{ref} I} \qquad (2)$$

LEAKY INTEGRATE-AND-FIRE

- Improvement of the basic integrate-and-fire model
- Modification of the equation by adding a 'leak' term to the membrane potential to solve the memory problem (1)
- The firing frequency no longer increases linearly as the input current increases (2)

$$I(t) - \frac{V_m(t)}{R_m} = C_m \frac{dV_m(t)}{dt} \qquad (1)$$

$$f(I) = \begin{cases} 0, & I \leq I_{\text{th}} \\ \left[t_{\text{ref}} - R_{\text{m}} C_{\text{m}} \log\left(1 - \frac{V_{\text{th}}}{I R_{\text{m}}}\right)\right]^{-1}, & I > I_{\text{th}} \end{cases} \qquad (2)$$

IZHIKEVICH NEURONS

- Simple implementation of spiking neurons by Eugene M. Izhikevich
- Combines the Hodgkin - Huxley biologically plausible dynamics with integrate-and-fire computationally efficient neurons
- Using bifurcation methodologies, we can reduce the equations of the Hodgkin - Huxley model:

$$C_m \frac{dv}{dt} = k(v - v_r)(v - v_t) - u + I$$

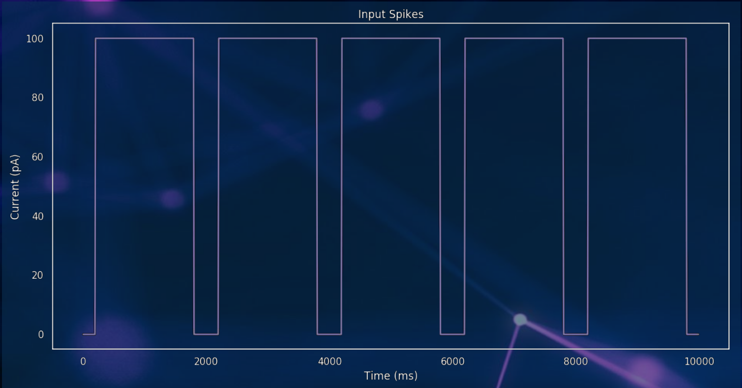
$$\frac{du}{dt} = a[b(v - v_r) - u]$$

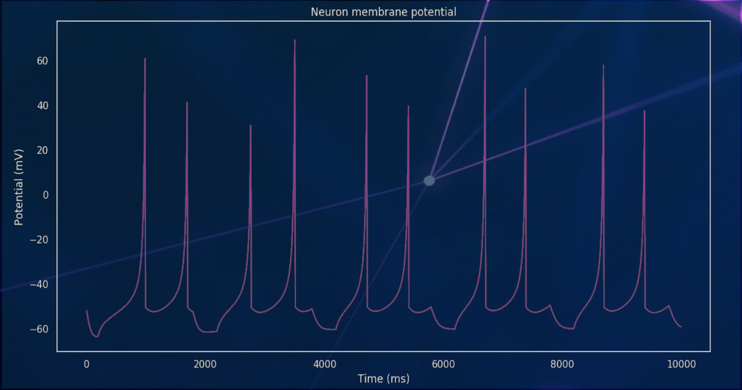
→ Using auxiliary after-spike resetting:

if v ≥ 30mV, then reset:
v = c
u = u + d

IZHIKEVICH NEURONS

- The parameter *a* describes the time-scale of the recovery variable *u*. Smaller values ⟶ slower recovery
- The parameter *b* describes the sensitivity of the recovery variable *u*
- The parameter *c* describes the after-spike reset value of the membrane voltage *v*
- The parameter *d* describes the after-spike reset of the recovery variable *u*
- The parameter C_m describes the membrane capacitance
- The parameter v_r is the resting membrane potential while v_t is the instantaneous threshold potential
- The parameter *k* is a constant defined as *1/R* where *R* is the membrane resistance





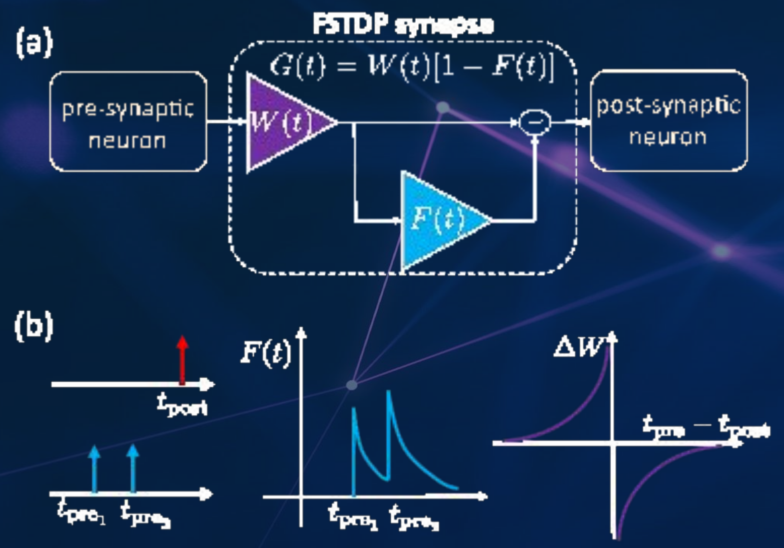
a = 0.03 [kHz]
b = -2 [S]
c = -50 [mV]
d = 100 [pA]
C_m = 100 [pF]
k = 0.7 [S]
v_r = -60 [mV]
v_t = -40 [mV]

TRAINING SPIKING NEURAL NETWORKS

- Backpropagation - the training algorithm for second generation neural networks
- Can it be used in the third generation?
- Possible, but most likely not the way forward
- Biological training algorithms - how do our brains learn?
- Spike-timing-dependent plasticity (STDP)

SPIKE-TIMING-DEPENDENT PLASTICITY

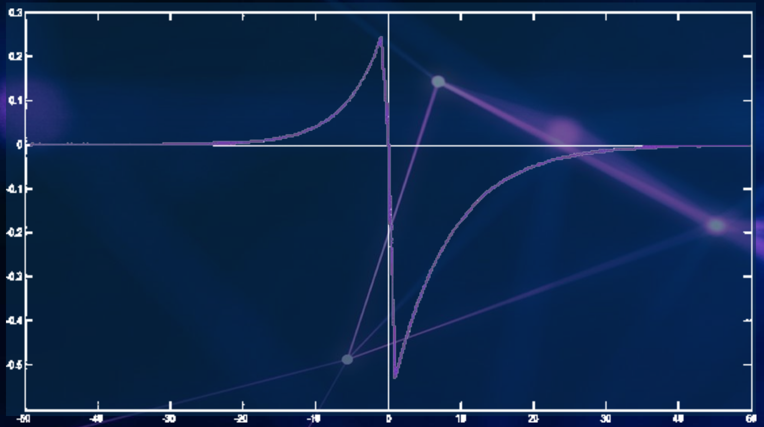
- Biological process that adjusts the strength of connections between neurons
- Adjustment of connections based on relative timing of a neuron's input and output action potentials (spikes)
- Inputs more likely to be the cause of the post-synaptic neuron's excitation are made even more likely to contribute in the future
- Can this process be used for Spiking Neural Networks?



SPIKE-TIMING-DEPENDENT PLASTICITY

- Yes, it can!
- However, a simplified interpretation is used
- An approximation of a classical asymmetric reinforcement curve present in biological neurons is used, taking time units as variables
- The equations for calculating the weight changes are as follows:

$$\mathrm{STDP}(\Delta t) = \Delta w = \begin{cases} A^{-}\exp^{*}\left(\frac{\Delta t}{\tau^{-}}\right), & \text{if\textasciitilde\textasciitilde}\Delta t \leq -2 \\ 0, & \text{if\textasciitilde\textasciitilde} -2 < \Delta t < 2 \\ A^{+}\exp^{*}\left(\frac{\Delta t}{\tau^{+}}\right), & \text{if\textasciitilde\textasciitilde}\Delta t \geq 2 \end{cases}$$



$$w_{\text{new}} = \begin{cases} w_{\text{old}} + \sigma\Delta w(w_{\max} - w_{\text{old}}), & \text{if } \Delta w > 0 \\ w_{\text{old}} + \sigma\Delta w(w_{\text{old}} - w_{\min}), & \text{if } \Delta w \leq 0 \end{cases}$$

WHAT DOES THE FUTURE HOLD?

- The advancement of computational power will lead to the possibility of more detailed models of biological neurons
- Every year we are closer to a true-to-concept biologically accurate artificial neural network
- Spiking Neural Networks could be the way towards General Artificial Intelligence and possibly more


THANK YOU FOR YOUR ATTENTION!