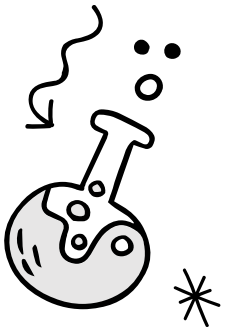
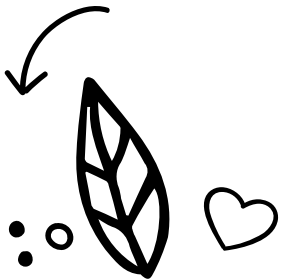


# Effects of the Distribution of Synaptic Strength on the Spiking Dynamics in a Network of Spiking Neurons

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# ★ Outline



1

**What is a Network?**  
*The Basics*

2

**Long-tailed Neuronal Spikes**  
*The Motivation*

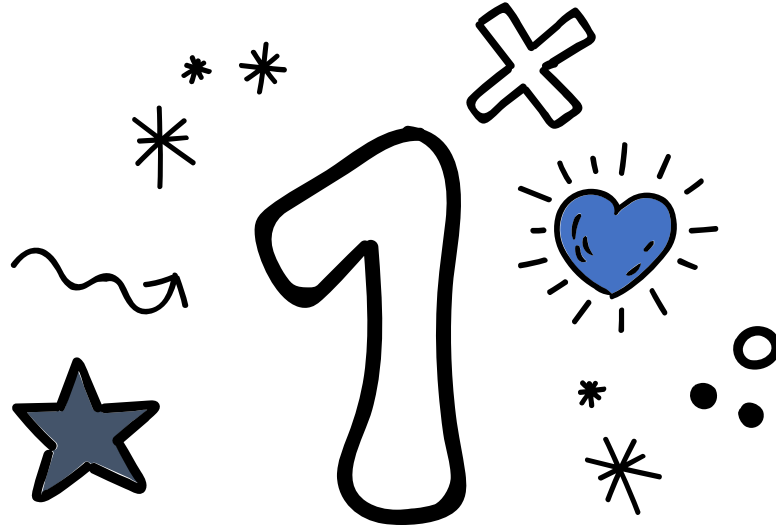
3

**Synaptic Spiking Model**  
*Model Implementation*

4

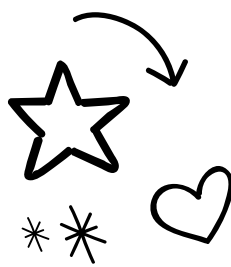
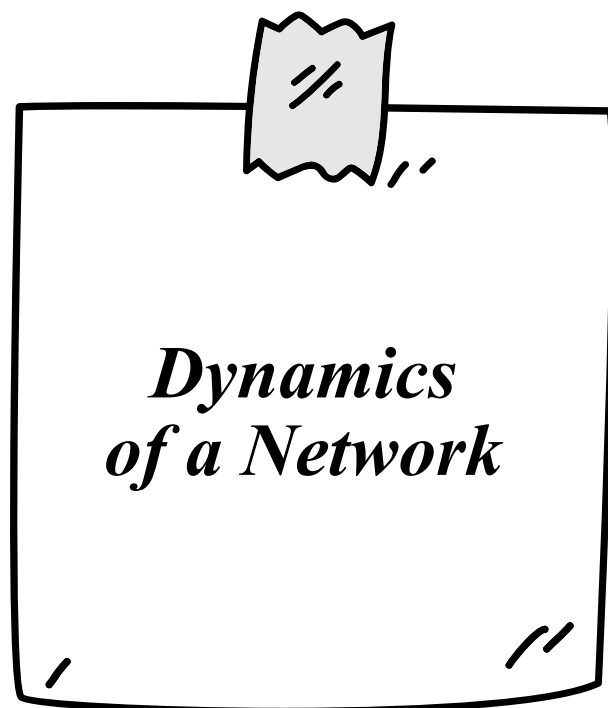
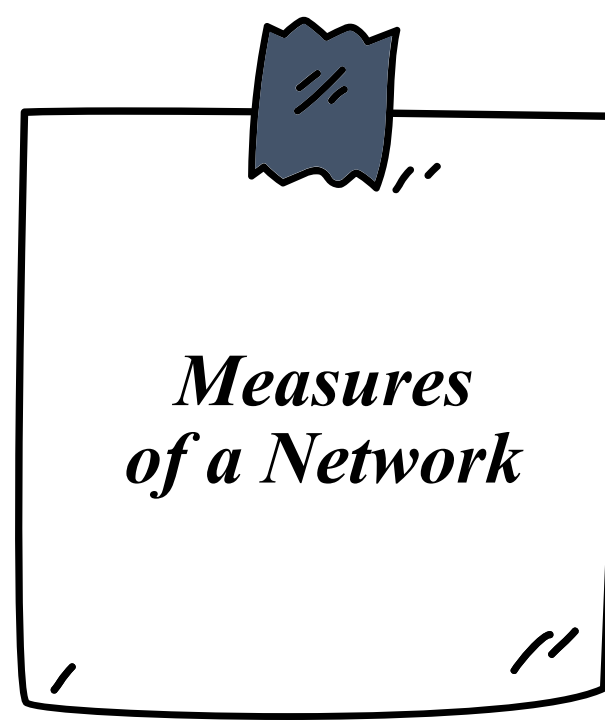
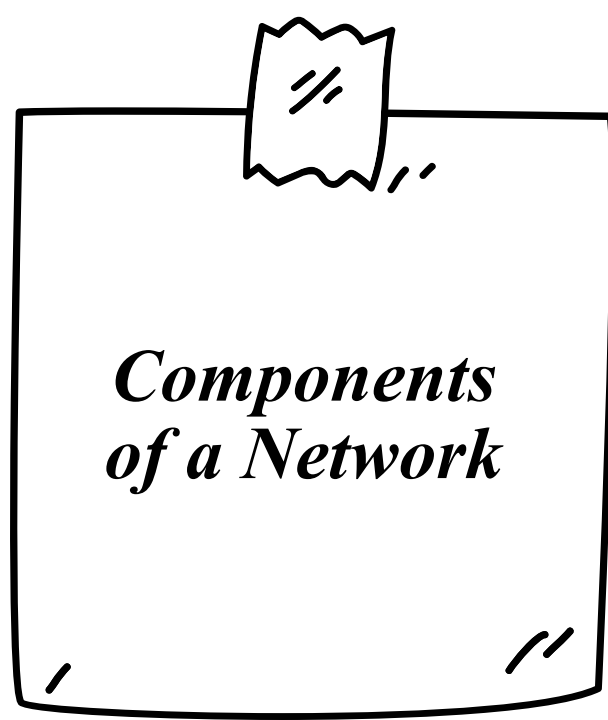
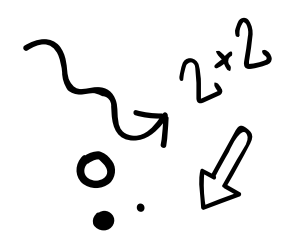
**What Explain the Spikes?**  
*Analysis & Discussion*

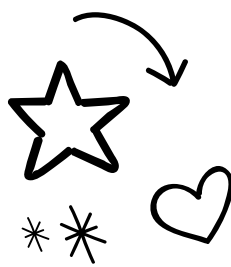
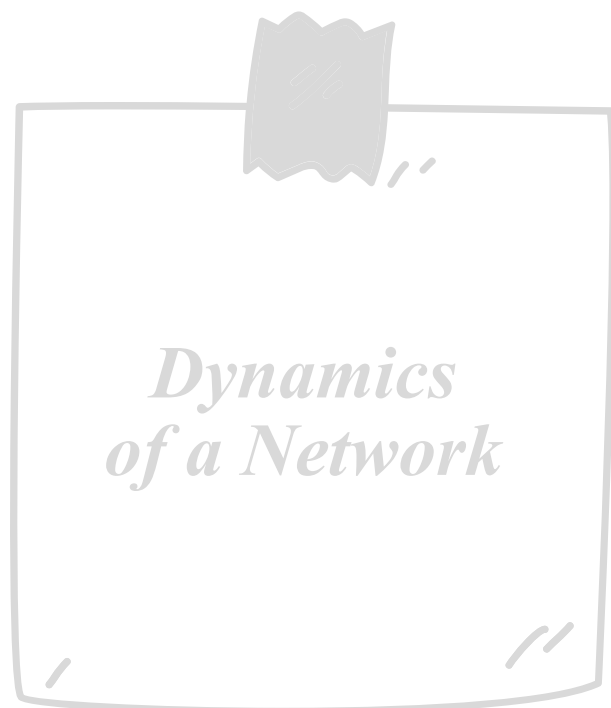
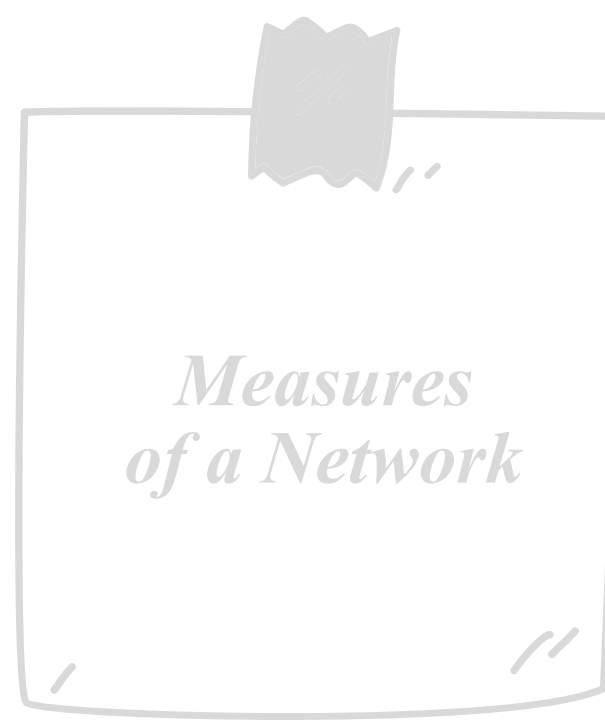
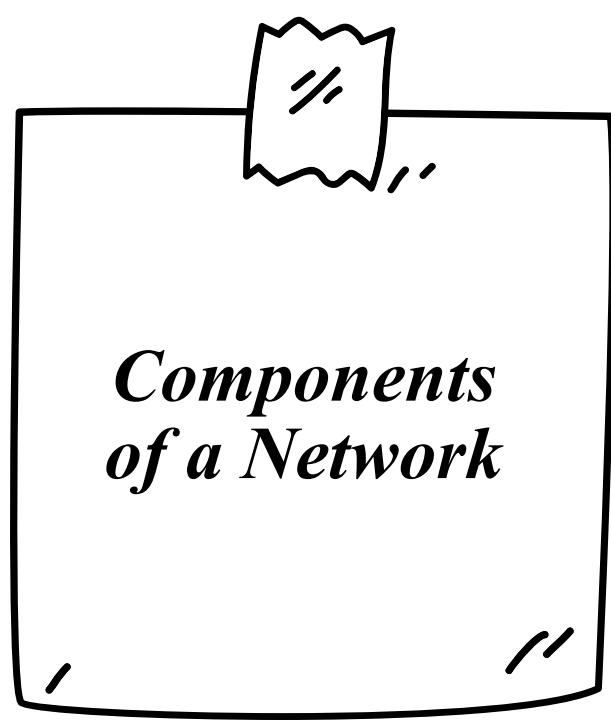
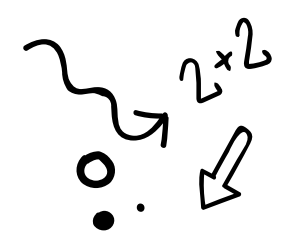




# **What is a Network?**

## ***The Basics***



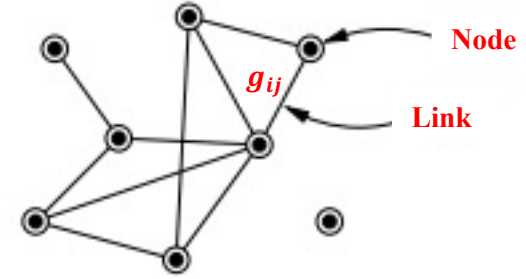


# 1. What is a Network?

- A network models a system with interacting individual components, and consists of **nodes**, **links** and **coupling strengths**

	Representation	Notation
<b>Node</b>	Individual component <i>e.g.</i> Neuron	$i$ , where $1 \leq i \leq N$ with $N$ = total no. of nodes
<b>Directed Link</b>	Mutual interaction <i>e.g.</i> Linkage btw. neurons	$A_{ij} = 1$ if node $j$ links to $i$ and 0 otherwise
<b>Coupling Strength</b>	Strength of interaction <i>e.g.</i> Synaptic weight	$g_{ij} \neq 0$ if node $j$ links to $i$ and 0 otherwise

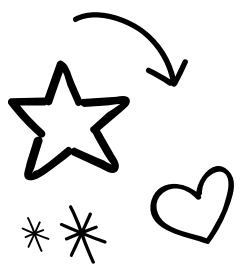
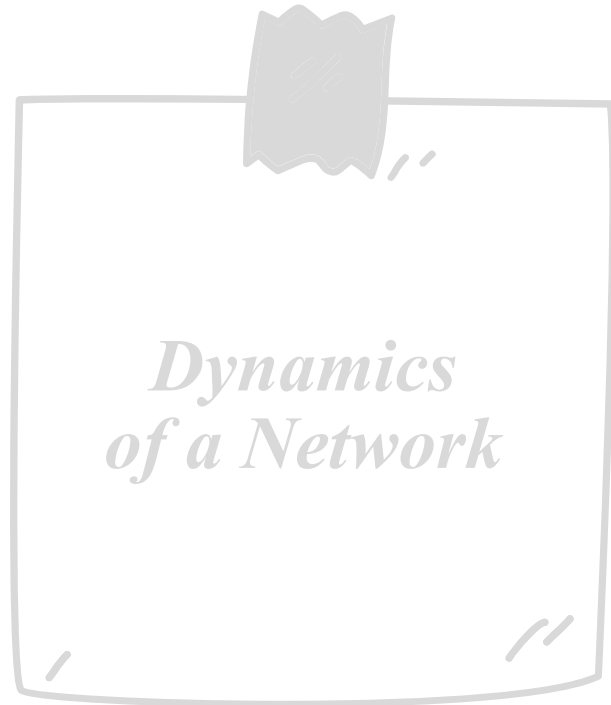
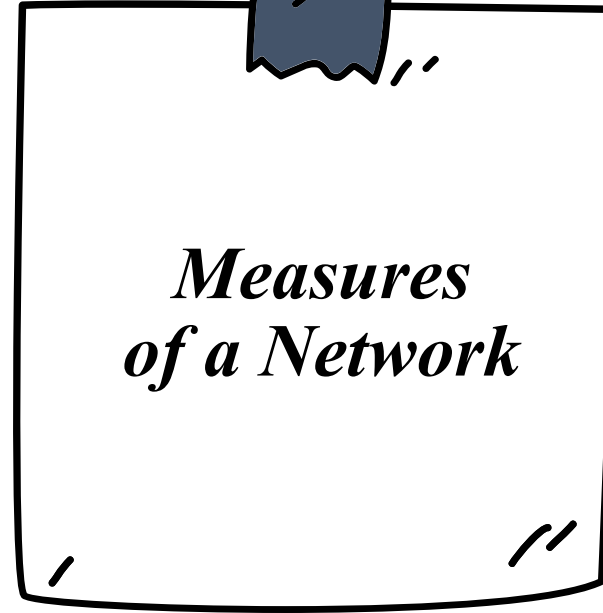
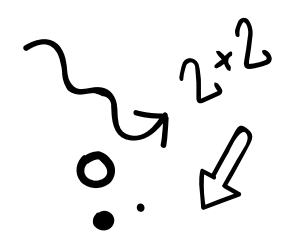
# 1. What is a Network?



- Coupling strength matrix **G** contains all  $g_{ij}$
- **G** is the most crucial piece of information about a network
  - ∴ it *fully* specifies the network structure, *i.e.*, **connectivity & interaction**

Features of <b>G</b>	
<b>0-Diagonal</b>	Nodes not self-connecting $\Rightarrow$ Diagonal entries $\equiv 0$ and $N(N - 1)$ possible directed links
<b>Sparsity</b>	Ratio btw. no. of directed links & $N(N - 1)$ <i>Note:</i> Most real networks are sparse
<b>Non-Symmetry</b>	Directed network $\Rightarrow g_{ij} \neq g_{ji}$ in general

- **G** has high theoretical importance but, in practice, is difficult to extract
  - $\Rightarrow$  Requires network reconstruction techniques



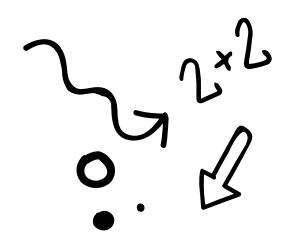


# 1. What is a Network?

- Network measures *summarize* the network structure
- This project focuses on **degree** and **strength**

Network Measure	Mathematical	Computational
In/Out-Degree	$k_{\text{in}}(i) = \sum_j \mathbb{I}(g_{ij} \neq 0)$	Count the non-zero entries in the <i>i</i> th <i>row</i> of <b>G</b>
	$k_{\text{out}}(i) = \sum_j \mathbb{I}(g_{ji} \neq 0)$	Count the non-zero entries in the <i>i</i> th <i>column</i> of <b>G</b>
In/Out-Strength	$s_{\text{in}}(i) = \sum_j g_{ij} / k_{\text{in}}(i)$	Average the non-zero entries in the <i>i</i> th <i>row</i> of <b>G</b>
	$s_{\text{out}}(i) = \sum_j g_{ji} / k_{\text{out}}(i)$	Average the non-zero entries in the <i>i</i> th <i>column</i> of <b>G</b>

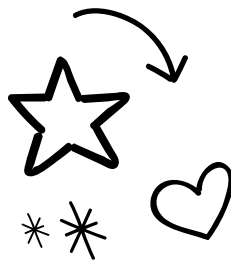
- Other finer measures:  $k_{\text{in}}^+(i) = \sum_j \mathbb{I}(g_{ij} > 0)$  and  $s_{\text{in}}^+(i) = \sum_j g_{ij} \mathbb{I}(g_{ij} > 0) / k_{\text{in}}^+(i)$   
⇒ Constructed by replacing the argument in the indicator function with the desired condition



*Components  
of a Network*

*Measures  
of a Network*

*Dynamics  
of a Network*



# 1. What is a Network?

- Network **dynamics** associates with network **structure** through a set of  $N$  dynamical equations, with the most *generic* form

$$\frac{d\mathbf{x}_i}{dt} = F(\{x_i(t)\}_{i=1:N}, \mathbf{G}, \boldsymbol{\eta}_i, \dots),$$

where  $\mathbf{x}_i$  is the state of node  $i$ , and

$\boldsymbol{\eta}_i$  is the noise term with covariance matrix  $\mathbf{D}$

- Numerically solved given suitable initial conditions  $\{x_i(0)\}_{i=1:N}$
- **Specifying a Network Model.** We require  $F, \mathbf{G}, \mathbf{D}$
- Time series  $\{x_i(t)\}_{i=1:N}$  form the **network dynamics**



# Long-tailed Neuronal Spikes

## *The Motivation*

## 2. Long-tailed Neuronal Spikes

- A network reconstruction method is applied to the *empirical neuronal time series* of cultures of rat embryonic cortices (25 days in vitro) to estimate the *coupling strengths*  $g_{ij}$ , leading to the following dataset

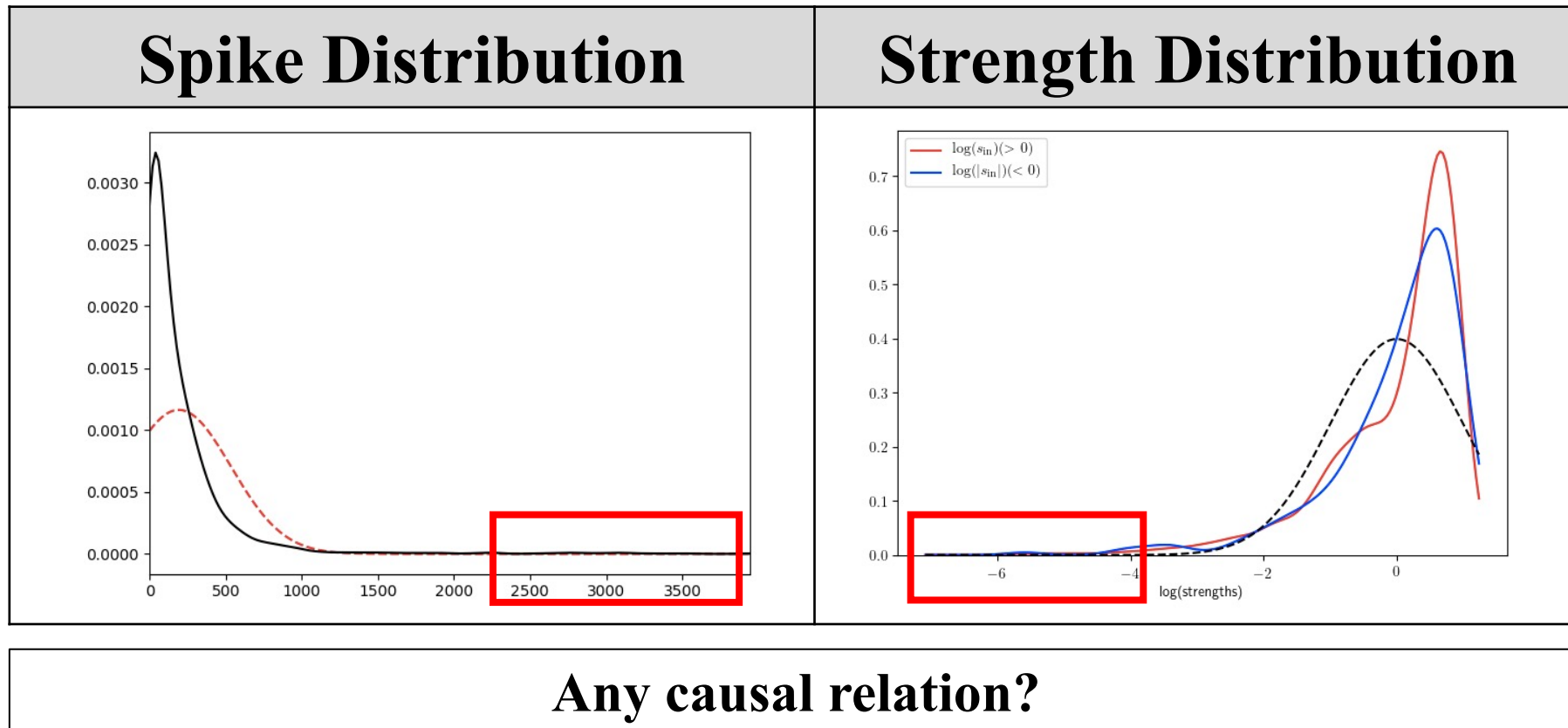
Node $i$	Node $j$	$g_{ij}$
1	196	0.0208720006
1	266	0.0156720001
1	267	0.0218959991
$\vdots$	$\vdots$	$\vdots$
2	1	-0.0234200004
2	21	-0.00388139999
2	23	-0.00472760014
$\vdots$	$\vdots$	$\vdots$
4095	4094	0.0089673996

- 4095 electrodes for data collection  $\Rightarrow$  4095 nodes in the giant network
- (Order)  $g_{ij} \sim 10^{-3}$  to  $10^{-2}$
- (Sign)  $g_{ij}$  can be +ve or -ve
- Sparse network with 1.4% sparsity
- Forms the foundation of *all* later simulations

## 2. Long-tailed Neuronal Spikes

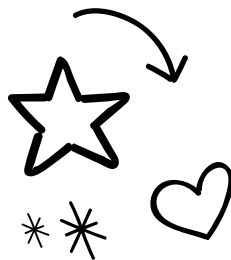
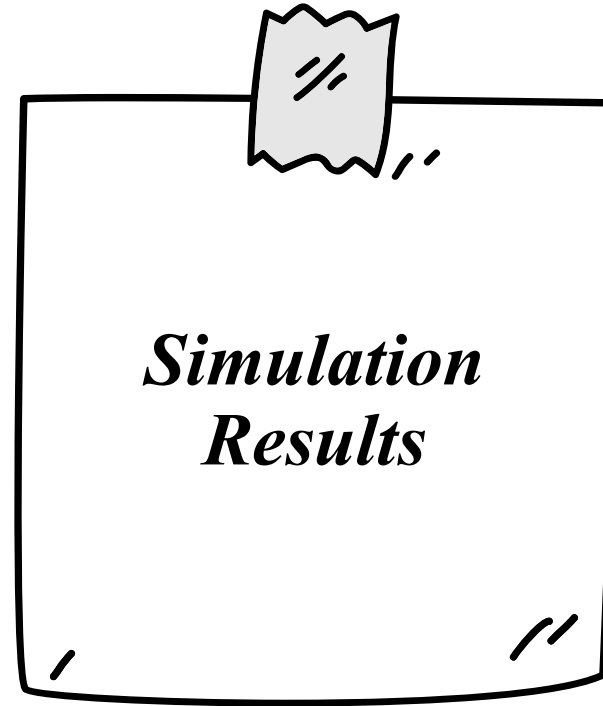
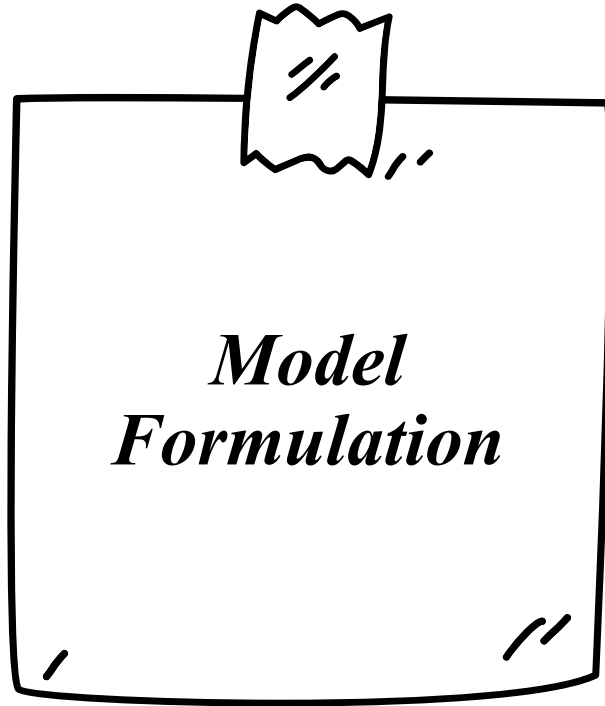
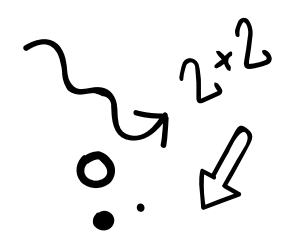
- Experimental neuronal *spike counts* are **highly skewed** and **long-tailed** in distribution, and so are the *synaptic strengths*

*Can the very large spike counts be explained by the very large synaptic strengths?*

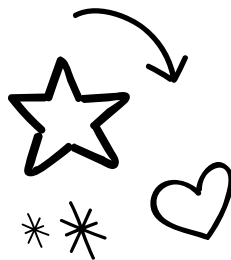
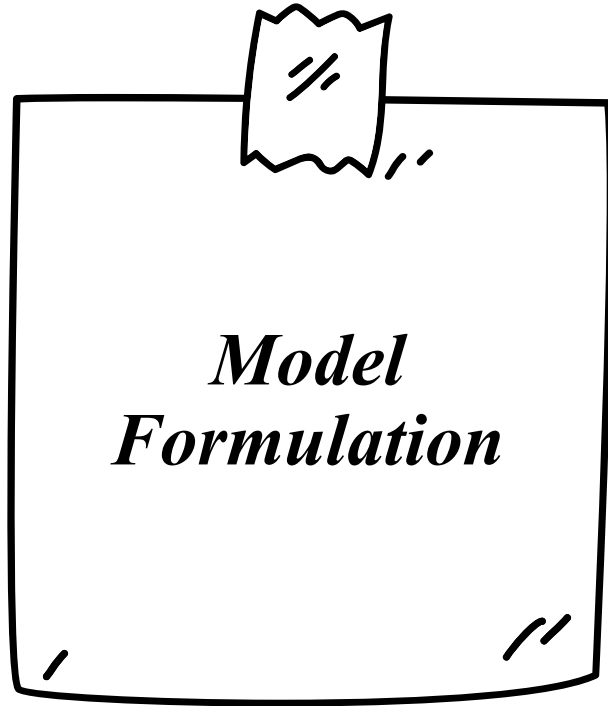
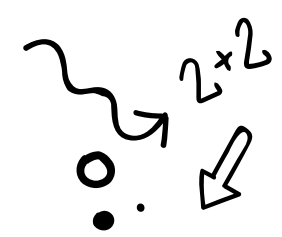




**Synaptic Spiking Model**  
***Model Implementation***







# 3. Synaptic Spiking Model

- Every neuron is described by
  - (i) **membrane potential**  $v(t)$ , and
  - (ii) **recovery variable**  $u(t)$ , following

$$\frac{dv}{dt} = 0.04v^2 + v + 140 - u + I(t)$$
$$\frac{du}{dt} = a(bv - u),$$

where  $I(t)$  is the **synaptic current** term,  
with a *fire and reset* rule:

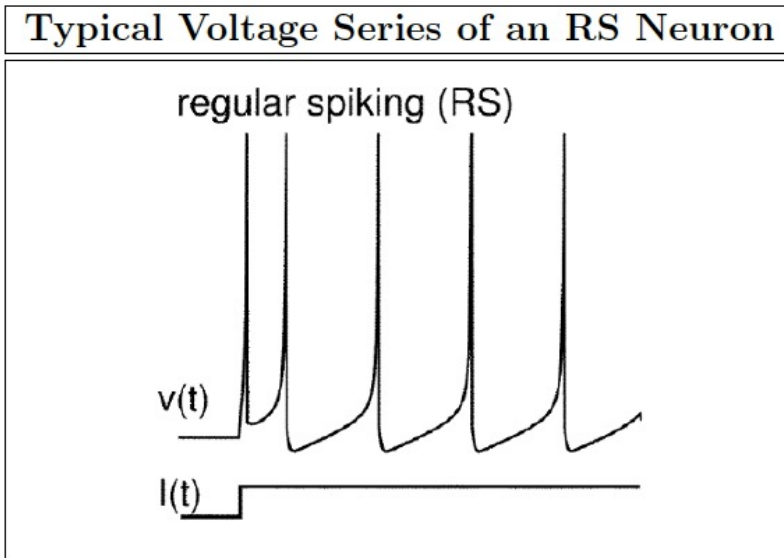
When  $v$  assumes  $v_{\text{peak}} = 30\text{eV}$ ,

$$v(t) \leftarrow c \text{ and } u(t) \leftarrow u(t) + d$$

### 3. Synaptic Spiking Model

$$\begin{cases} \frac{dv}{dt} = 0.04v^2 + v + 140 - u + I(t) \\ \frac{du}{dt} = a(bv - u), \\ v(t) \leftarrow c \text{ and } u(t) \leftarrow u(t) + d \end{cases}$$

- Parameters  $a, b, c, d$  are specific to a neuron type (require calibration)
- *e.g.* Regular spiking neuron:  $a = 0.02, b = 0.2, c = -65, d = 8$



### 3. Synaptic Spiking Model

$$\begin{cases} \frac{d\textcolor{red}{v}}{dt} = 0.04v^2 + v + 140 - u + I(t) \\ \frac{d\textcolor{green}{u}}{dt} = a(bv - u), \\ v(t) \leftarrow c \text{ and } u(t) \leftarrow u(t) + d \end{cases}$$

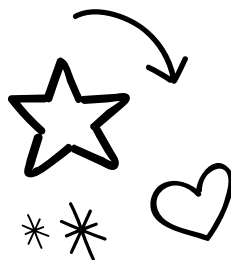
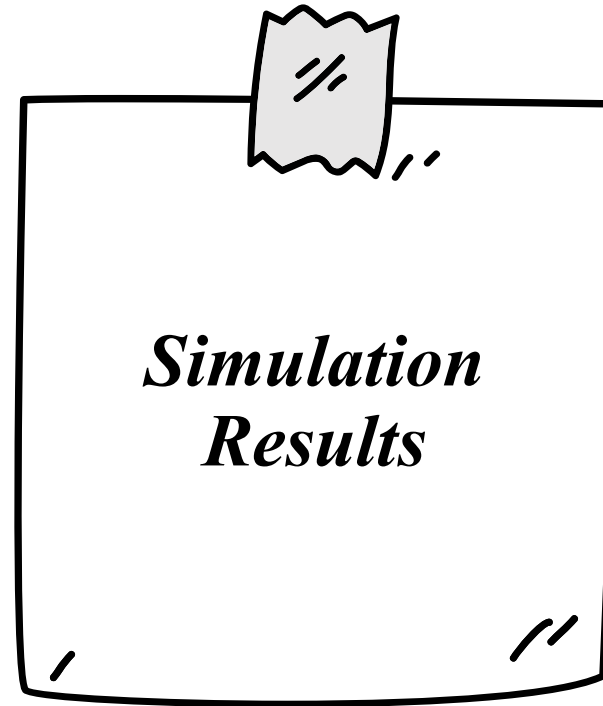
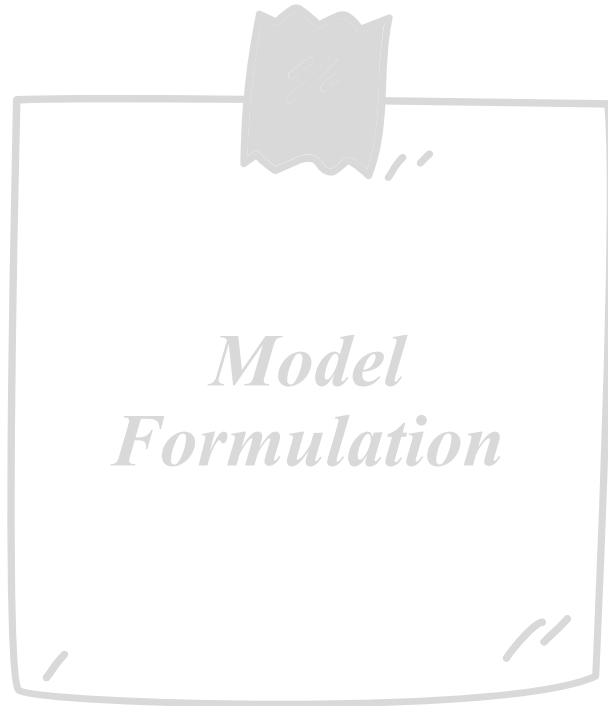
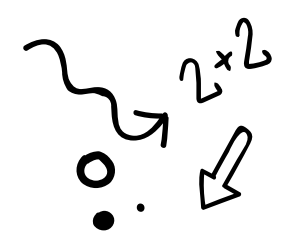
- For neuron  $i$ ,  
**conductance** is incorporated in  $I_i(t)$ :

$$I_i(t) = \mathbf{G}^{\text{exc}}(t)(V_E - v_i(t)) + \mathbf{G}^{\text{inh}}(t)(V_I - v_i(t)) + \eta_i$$

- Time evolution of  $\mathbf{G}^{\text{exc/inh}}$  is analytically given by:

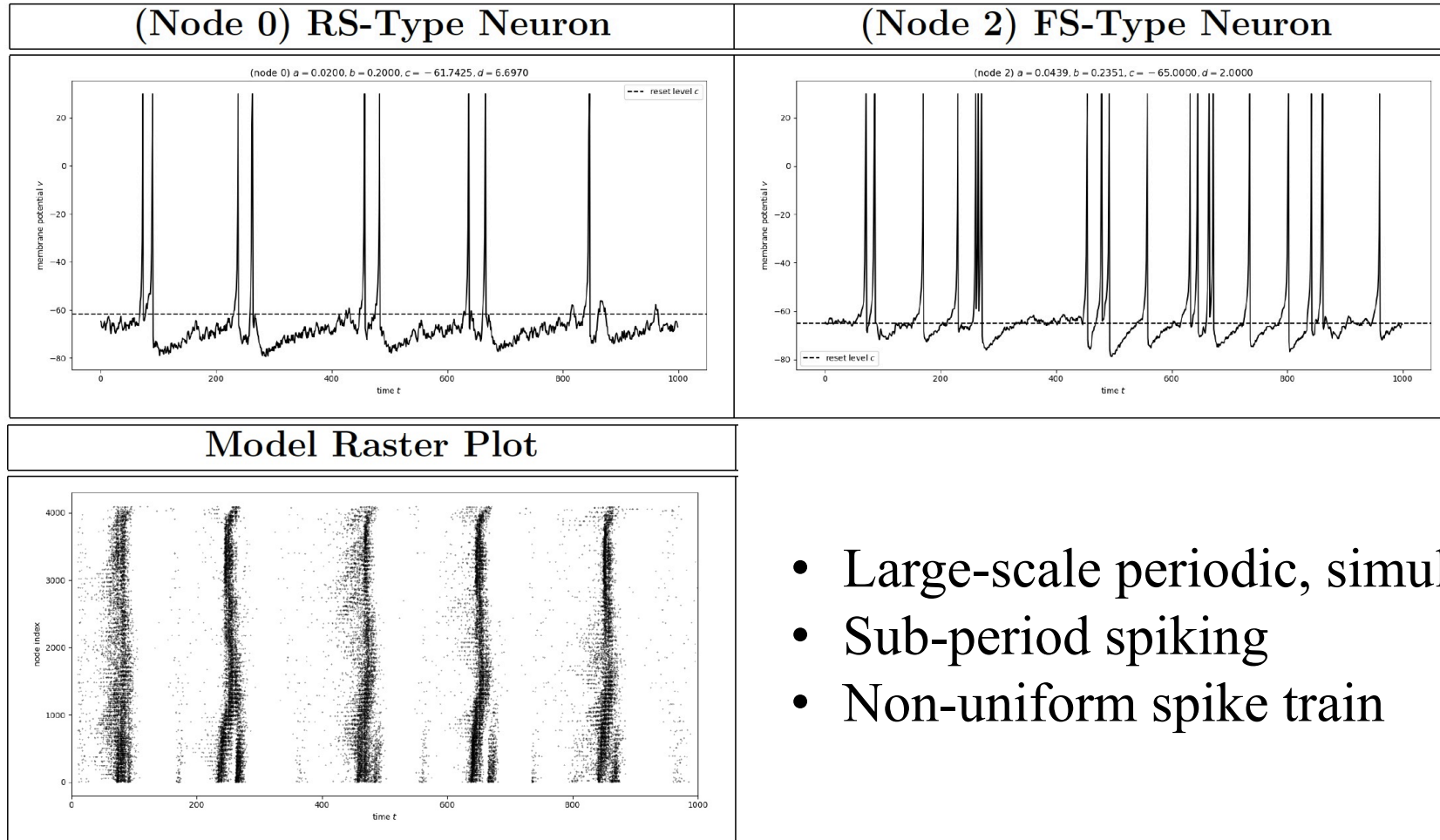
$$\begin{aligned} \mathbf{G}_i^{\text{exc}} &= \beta \sum_{\{j: g_{ij} > 0\}} \left( g_{ij} \sum_k \exp\left(-\frac{t-t_{j,k}}{\tau_{\text{exc}}}\right) \Theta(t - t_{j,k}) \right) \\ \mathbf{G}_i^{\text{inh}} &= \beta \sum_{\{j: g_{ij} < 0\}} \left( g_{ij} \sum_k \exp\left(-\frac{t-t_{j,k}}{\tau_{\text{inh}}}\right) \Theta(t - t_{j,k}) \right) \end{aligned}$$

- where  $V_E, V_I, \tau_{\text{exc}}, \tau_{\text{inh}}, \beta$  are parameters
- Conductance  $\mathbf{G}^{\text{exc/inh}}$  summarize the *historical* spikes of the *connecting* exc./inh. neurons with impacts scaled by *coupling strength*  $g_{ij}$
- In turn, conductance affects the current  $I$  neuron  $i$  experiences



# 3. Synaptic Spiking Model

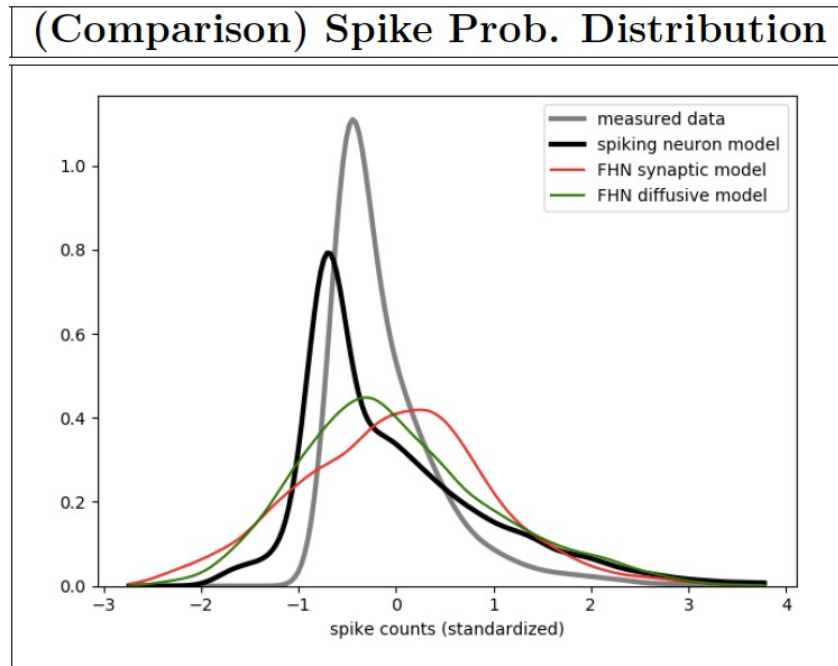
- We drive the dynamics using uniformly distributed  $\eta_i \sim \mathcal{U}[0, \delta]$
- Within the model, there are two neuron types: *Regular* & *Fast Spiking*



- Large-scale periodic, simultaneous spiking
- Sub-period spiking
- Non-uniform spike train

# 3. Synaptic Spiking Model

- The model succeeds in producing a *long right tail*, with spike counts spreading over a wide range [0,409]
- Synaptic spiking model exhibits more realistic dynamics than previous models
- Spike count distribution of different models:





# **What Explain the Spikes?**

## ***Analysis & Discussion***



## 4. What Explain the Spikes?

- **Reference networks** *vary* network features of interest while *preserving* the rest, and are constructed through artificial manipulation of the reconstructed  $\mathbf{G}$
- Effects of the varied features on the dynamics are studied
- Main results from **reference network analysis** – *causal* relation
  - The reference network that has *rows of  $\mathbf{G}$  shuffled*, thus (i) keeping the *long-tailed distribution of  $k_{\text{in}}, s_{\text{in}}$*  and (ii) making *distribution of  $k_{\text{out}}, s_{\text{out}}$  bell-shaped*, preserves the distribution of spike counts
  - Other reference networks with *bell-shaped  $k_{\text{in}}, s_{\text{in}}$*  or *long-tailed  $k_{\text{in}}$*  distort the spike count distribution
  - Only  $s_{\text{in}}$  remains as the important driving factor of the spiking dynamics
  - **Conclusion.** Long-tailed  $s_{\text{in}}$  leads to long-tailed spike counts

# Conclusion

- The synaptic spiking model successfully generates realistic neuronal spikes with a long tail, with a better performance than previous models
- **Reference network analysis.** The long-tailed incoming synaptic strength  $s_{in}$  leads to the long-tailed spike counts
- This echoes with the conclusion in my FYP part I

*Can the very large spike counts be explained by the very large synaptic strengths?*

*- Yes, in the context of the synaptic spiking model.*

*In particular, it's the very large incoming synaptic strengths  
that have an important effect on spike counts.*

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