

Active dendrites stochastic neuronal model

Leonardo L. Gollo

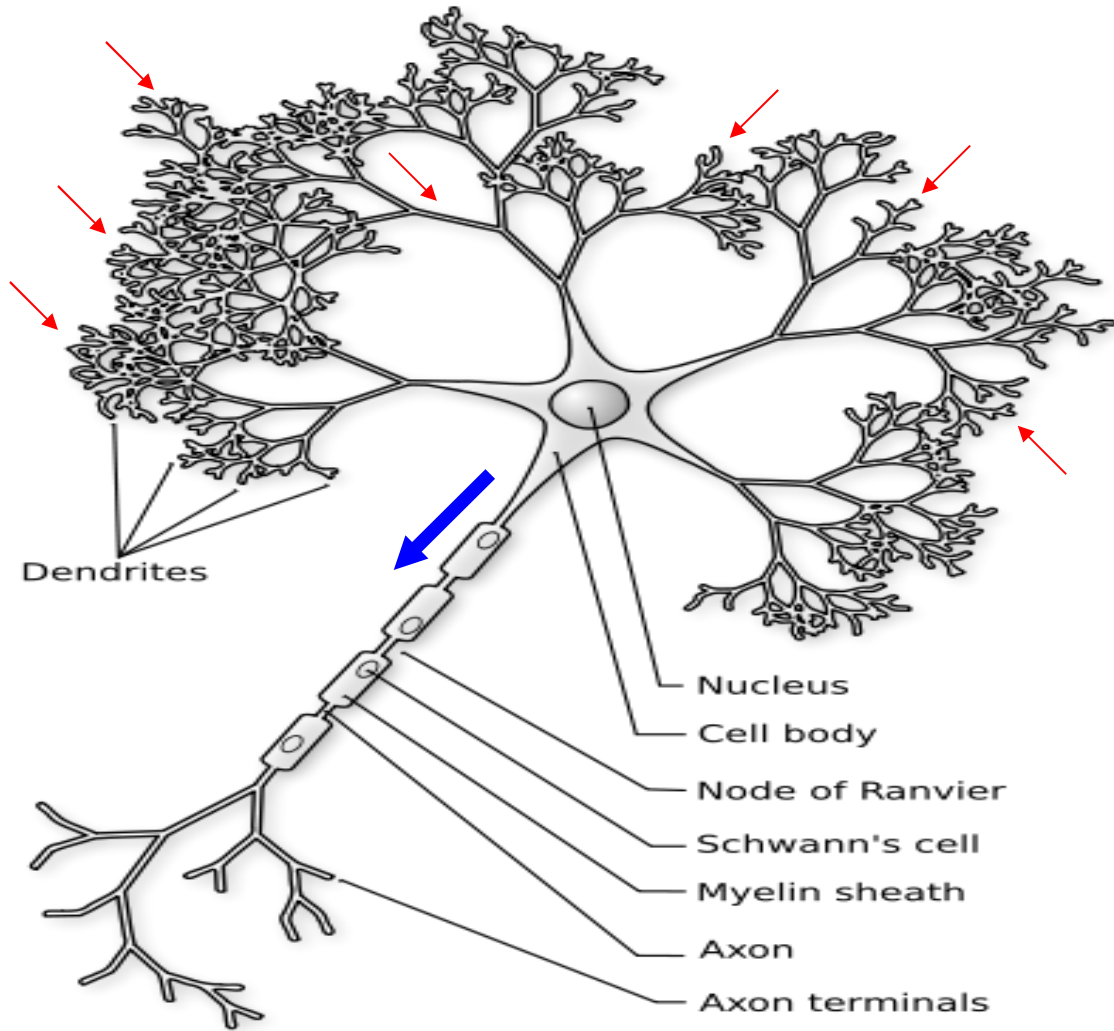
Mauro Copelli , Osame Kinouchi



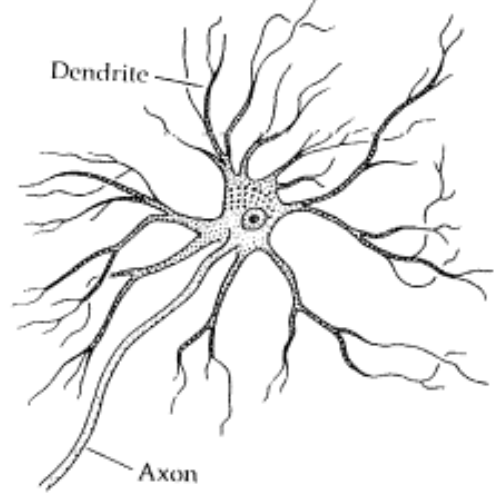
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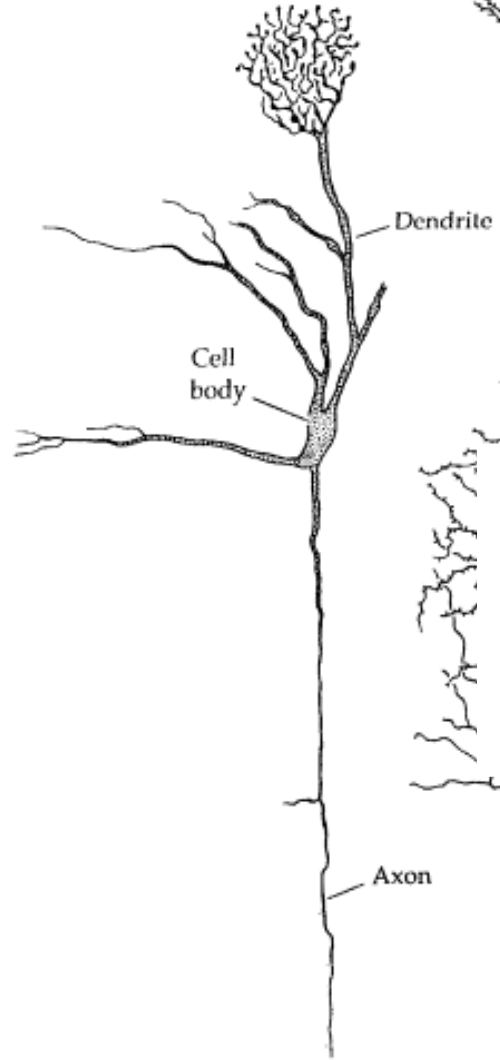




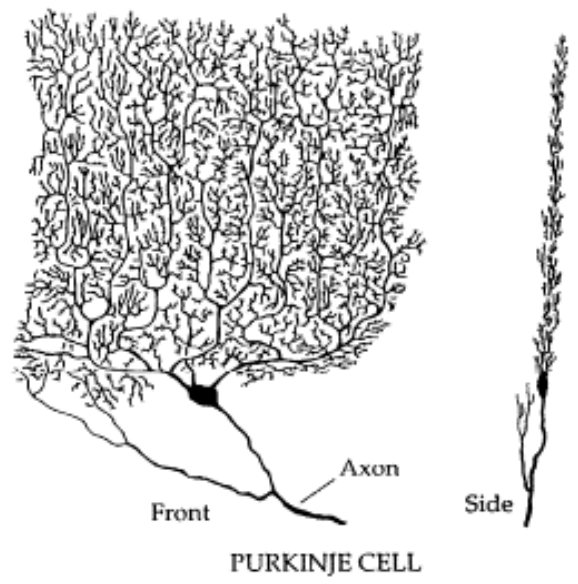
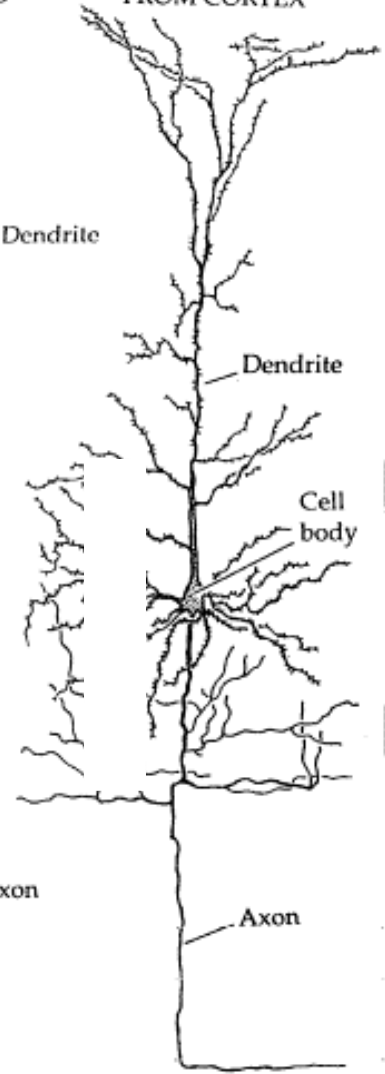
MOTOR NEURON FROM SPINAL CORD

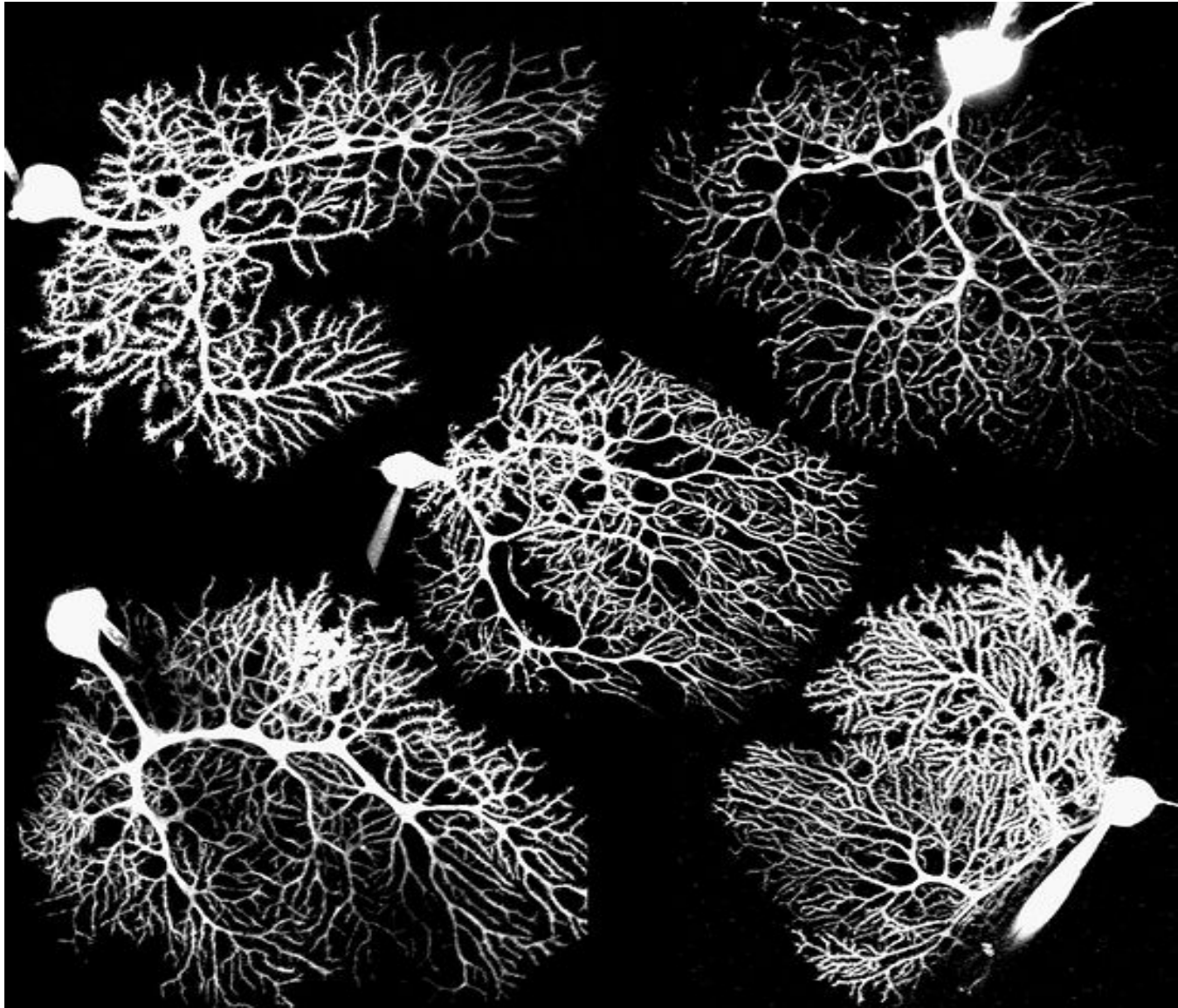


MITRAL CELL FROM OLFACTORY BULB

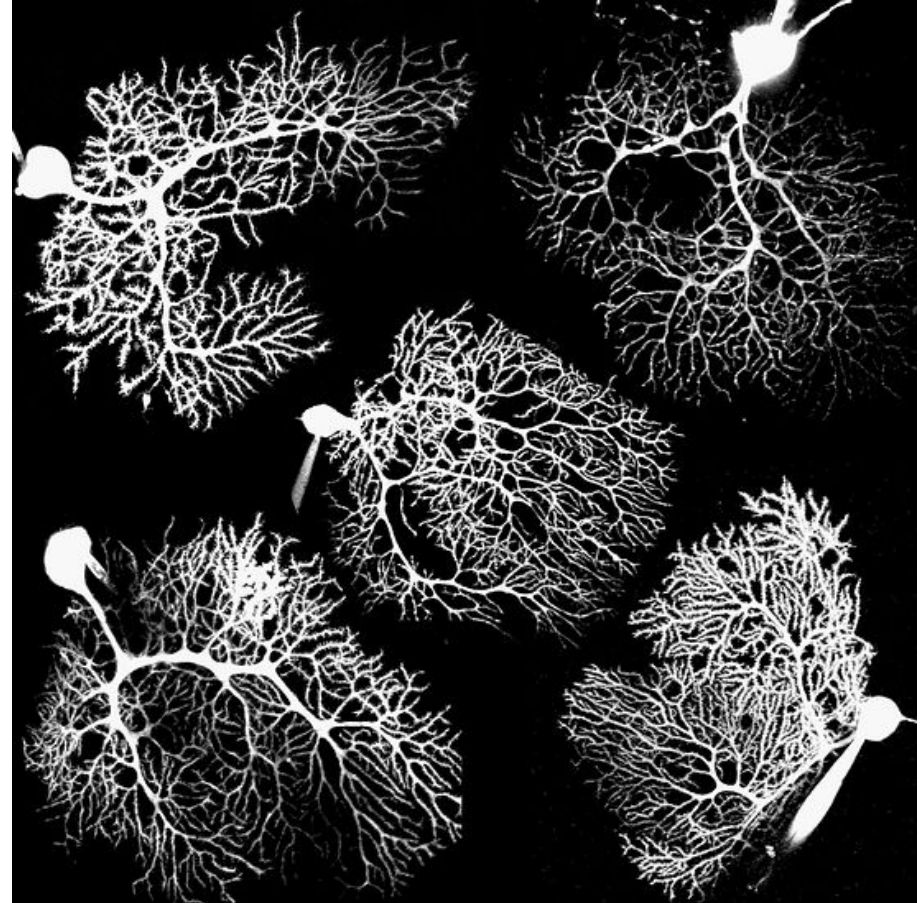


PYRAMIDAL CELL FROM CORTEX



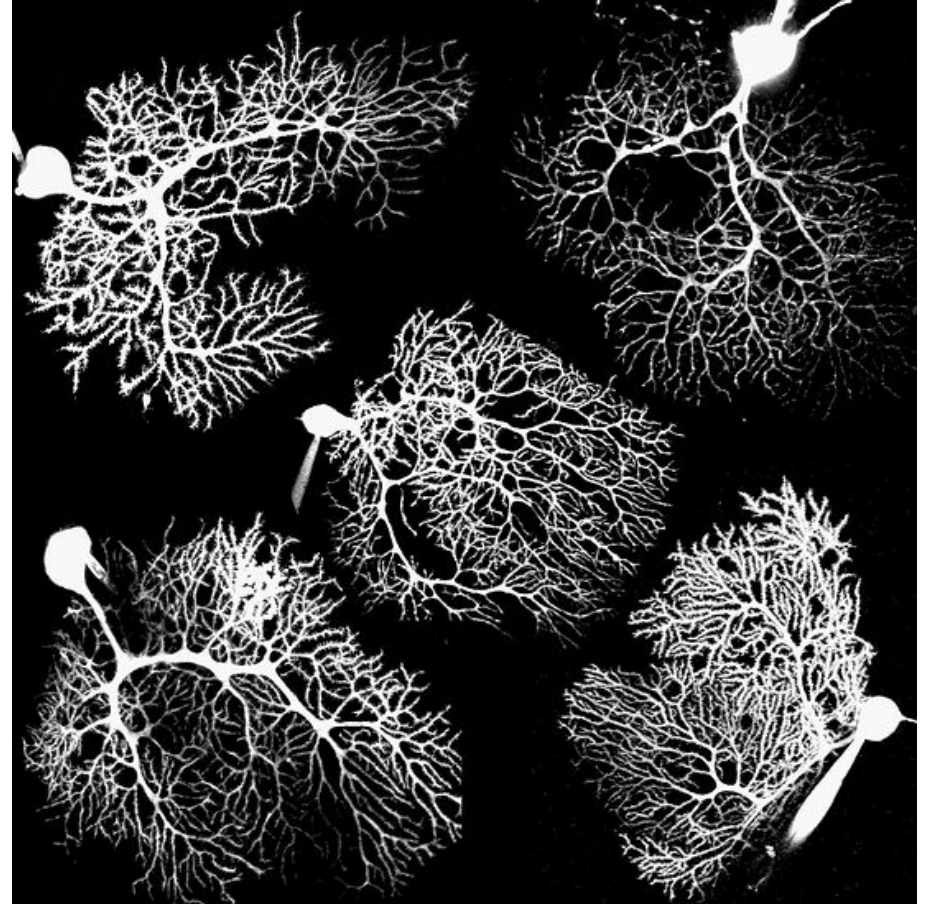


- Voltage summation
- Coincidence detectors
- Biological logic gates
- Learn modulation



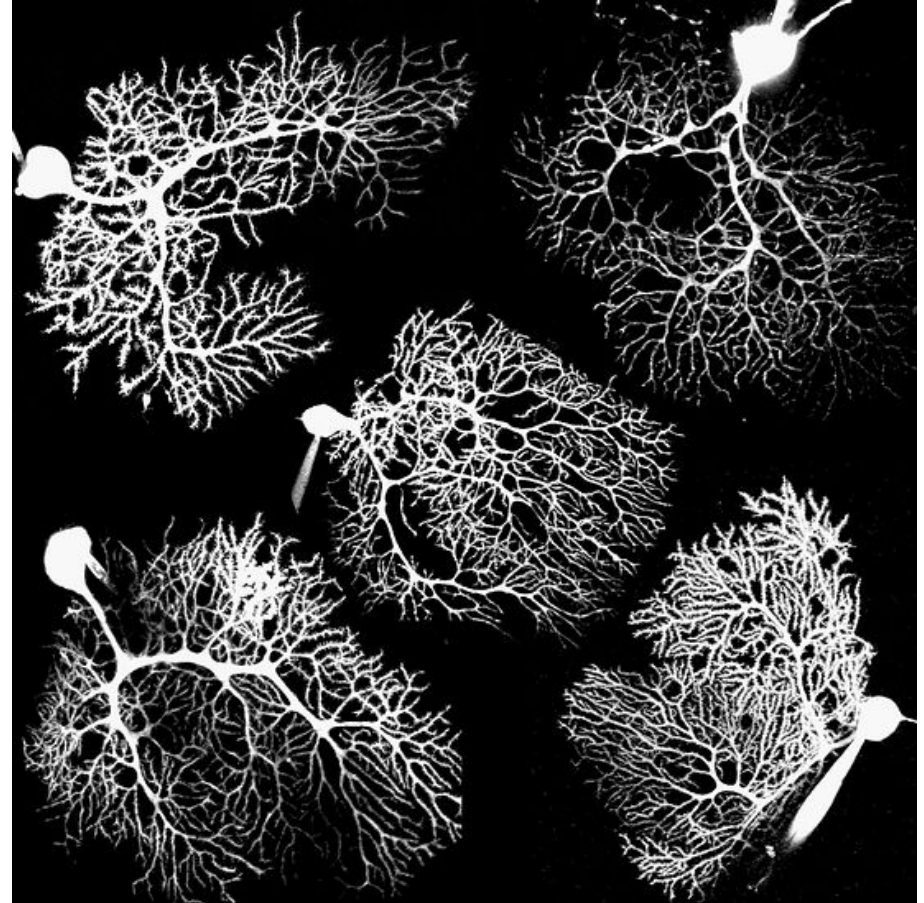
1. improbable fine tuning of biological parameters
2. not robust over morphology variability

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- Coincidence detectors
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2. not robust over morphology variability

- Voltage summation
- Coincidence detectors
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1. improbable fine tuning of biological parameters
2. not robust over morphology variability

Eccles works (1958)

- active conductances
- dendritic spike

Ultimate wish: theory for active dendrites

Eccles works (1958)

- active conductances
- dendritic spike

Ultimate wish: **theory** for active dendrites

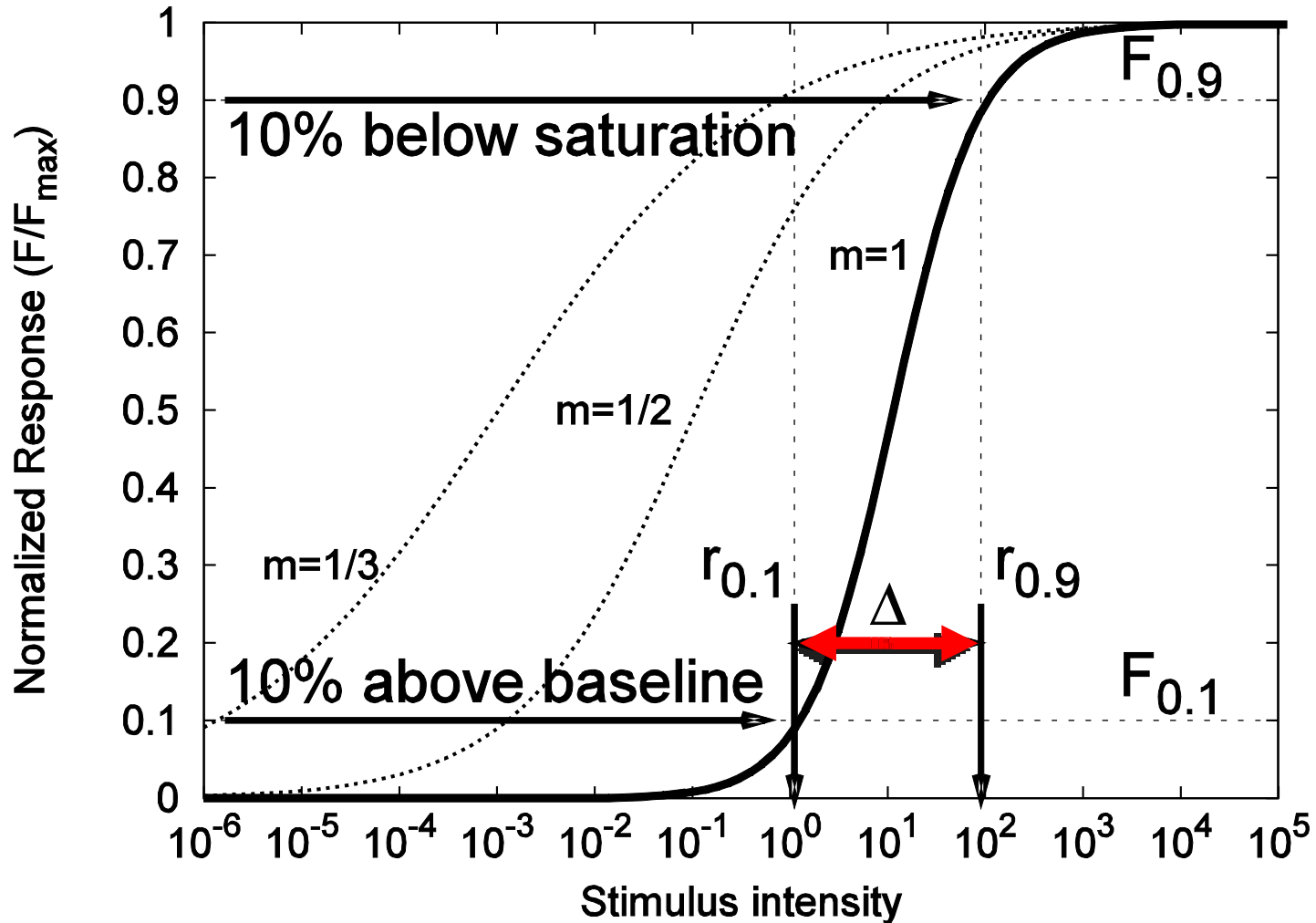
- Sensory stimulus intensity problem
- Stochastic model
- Mathematical formulation

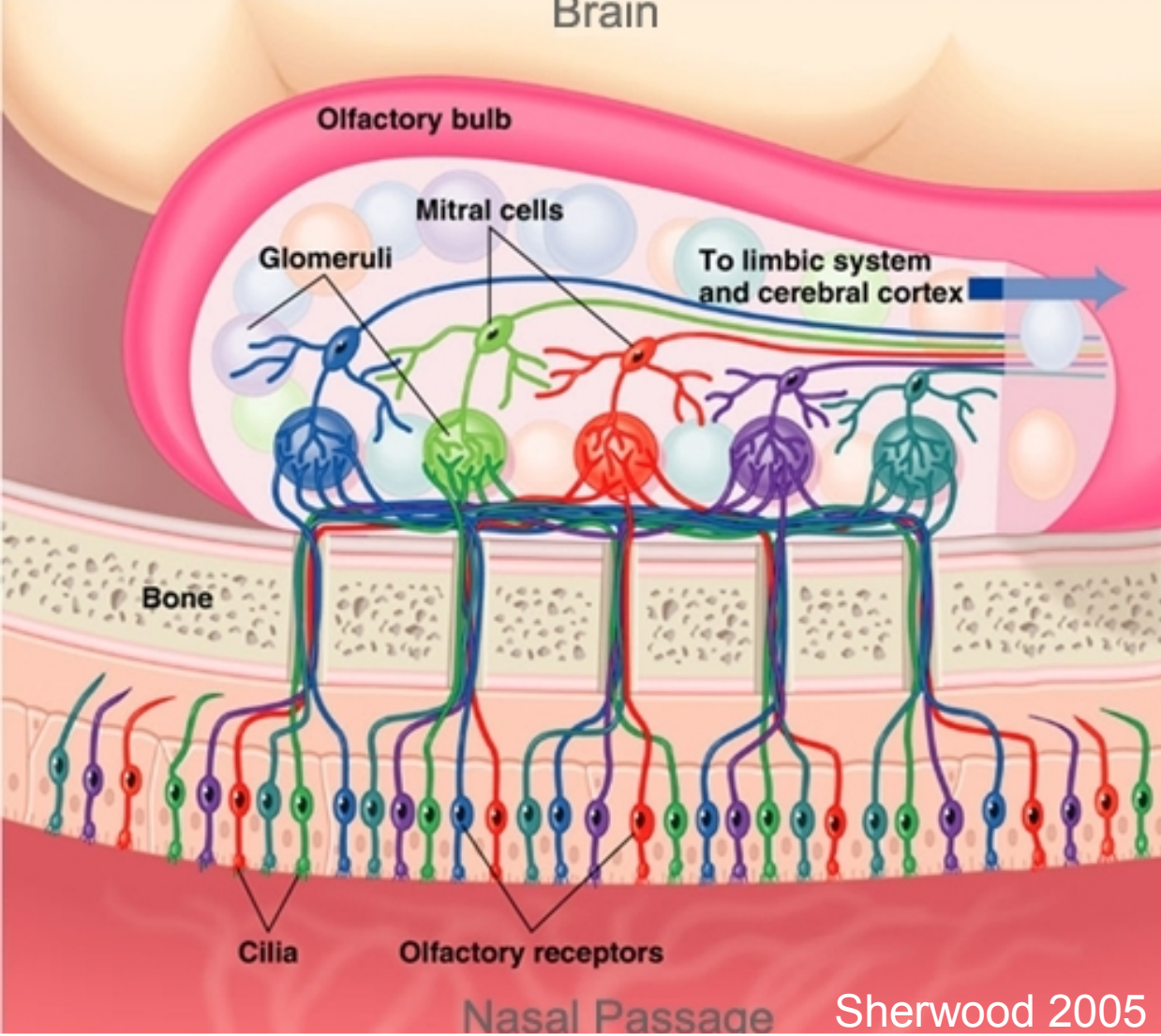
- **Sensory stimulus intensity problem**
- **Stochastic model**
- **Mathematical formulation**

$$\Delta = 10 \log_{10} \left(\frac{r_{0.9}}{r_{0.1}} \right)$$

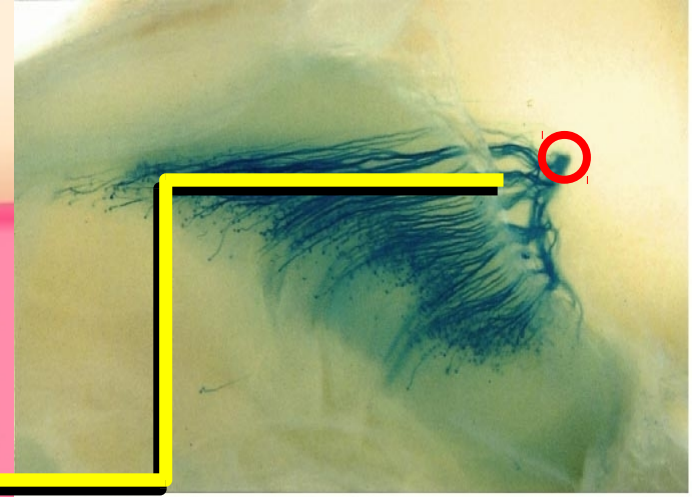
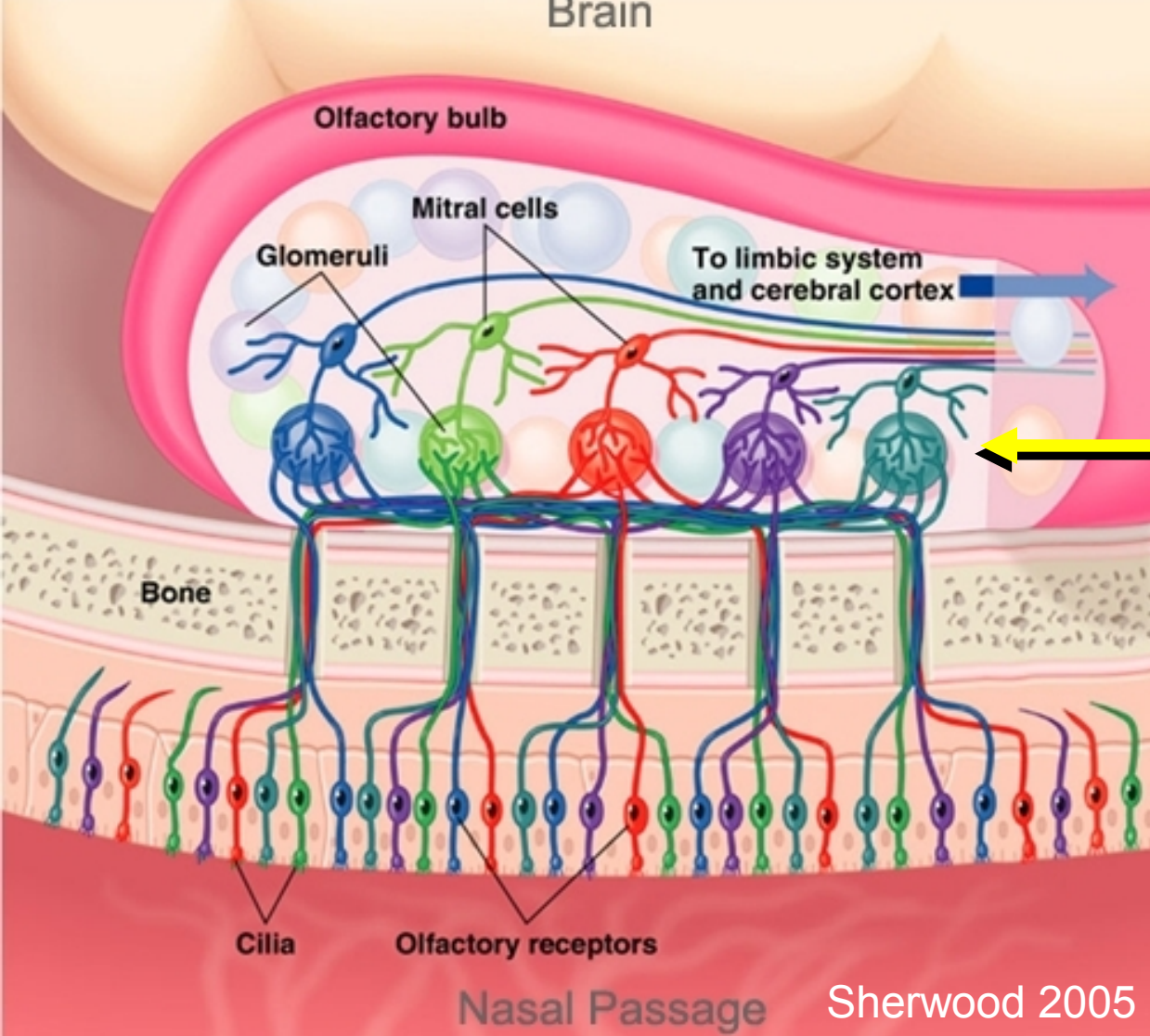
$$\Delta = 10 \log_{10} \left(\frac{r_{0.9}}{r_{0.1}} \right)$$

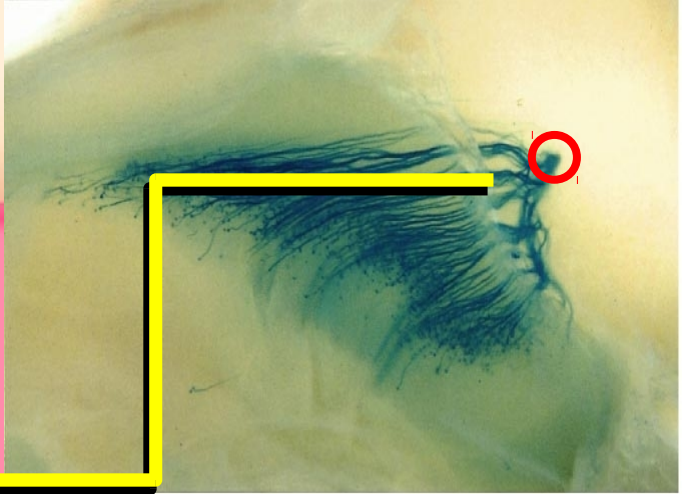
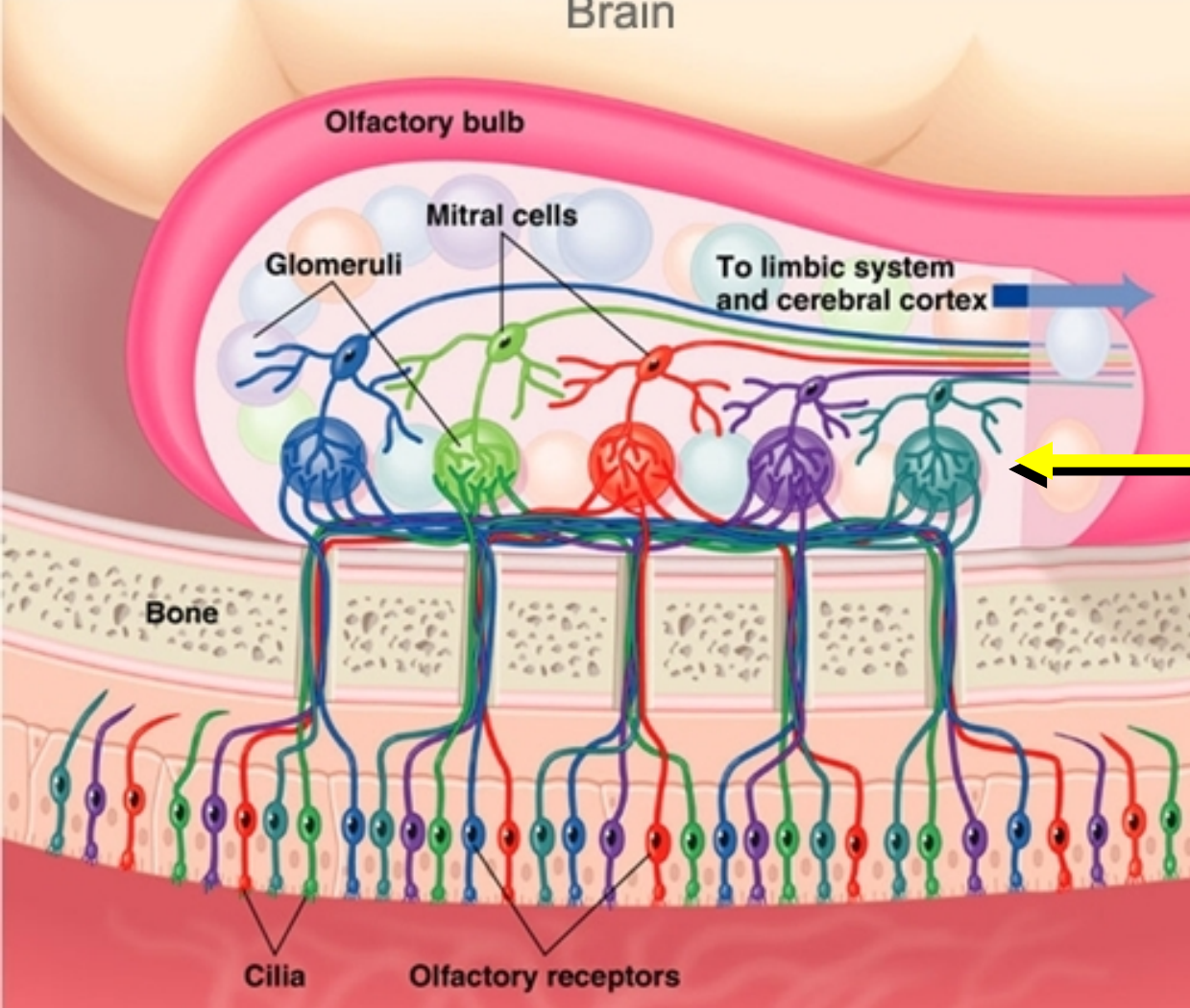
$$F_x = x(F_{max} - F_0) + F_0$$



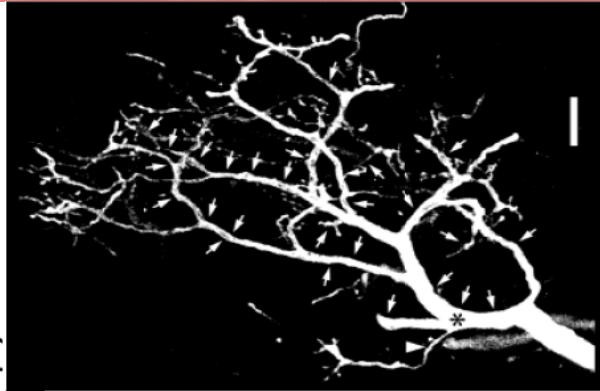


Sherwood 2005

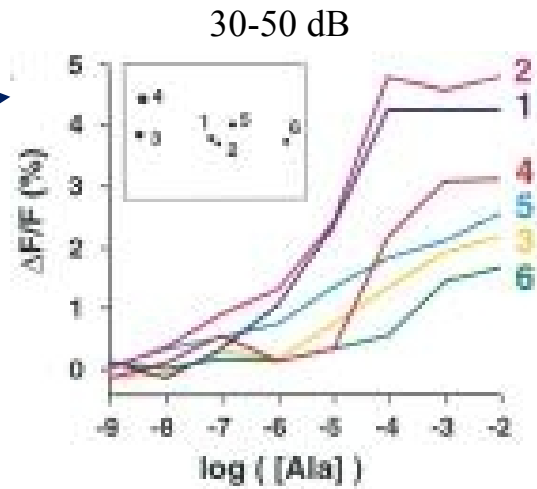
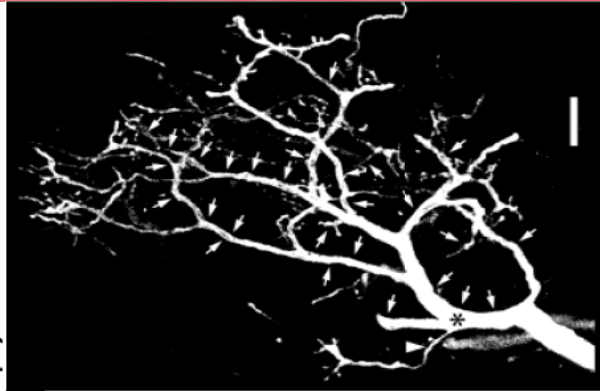
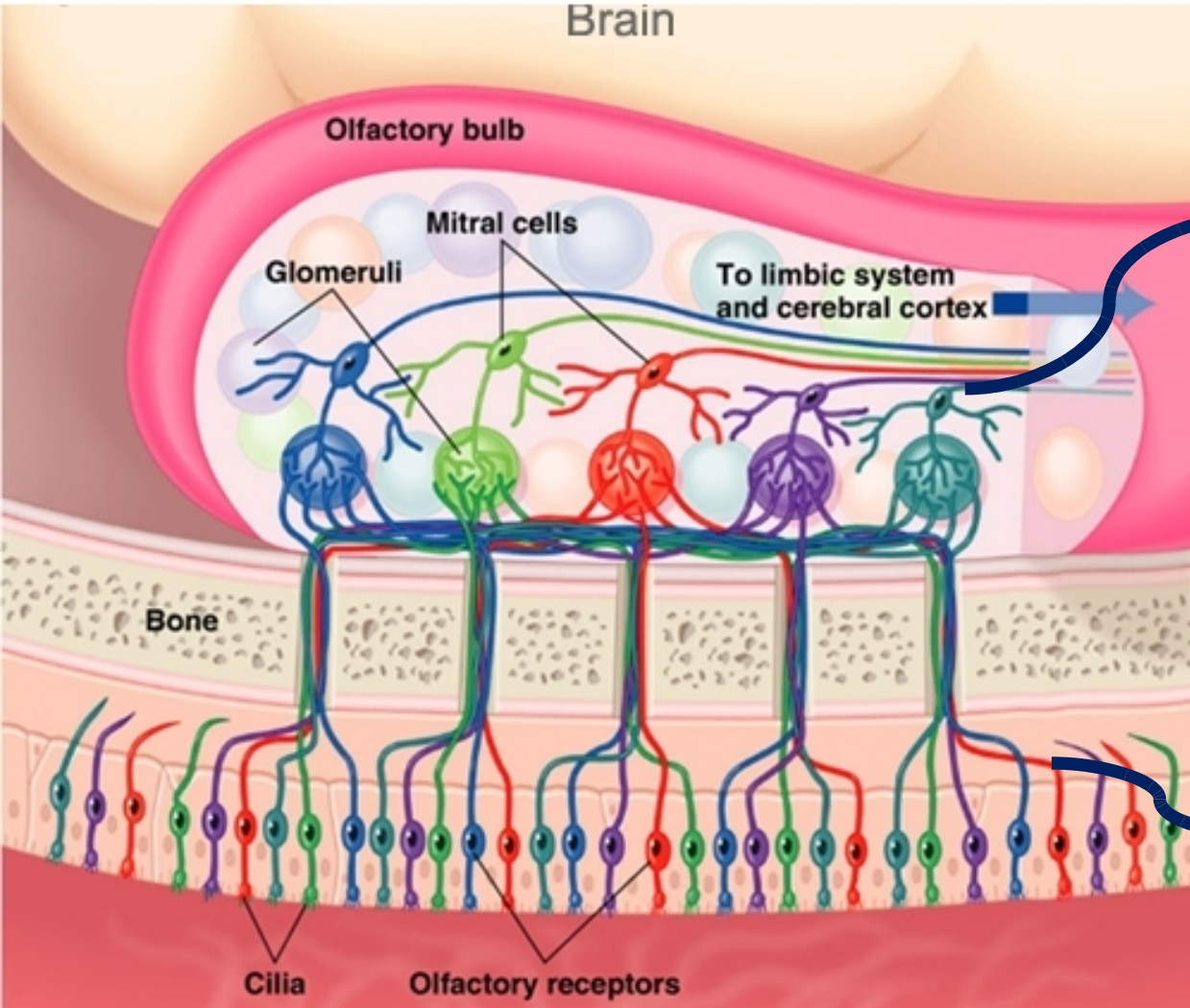




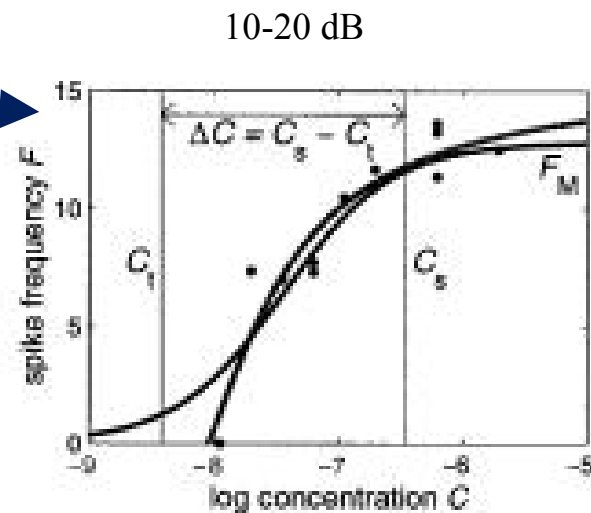
Squire et al. 2003



Kosaka et al. 2001



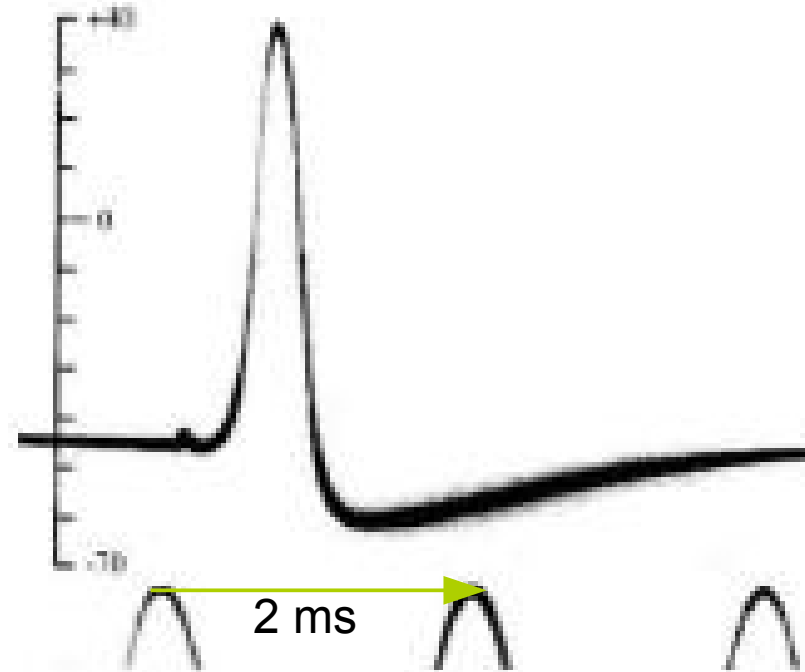
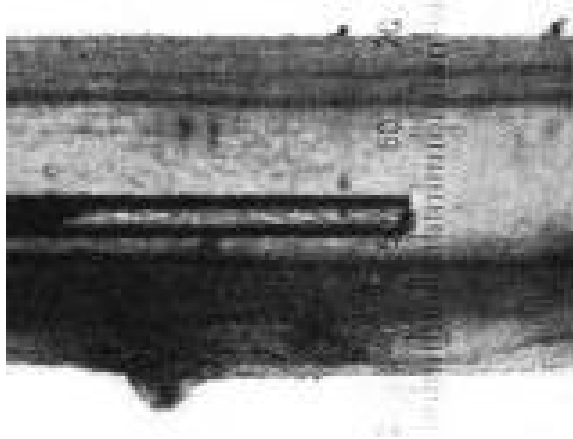
Friedrich et al 1997



J.P.Rospars et al. 2000

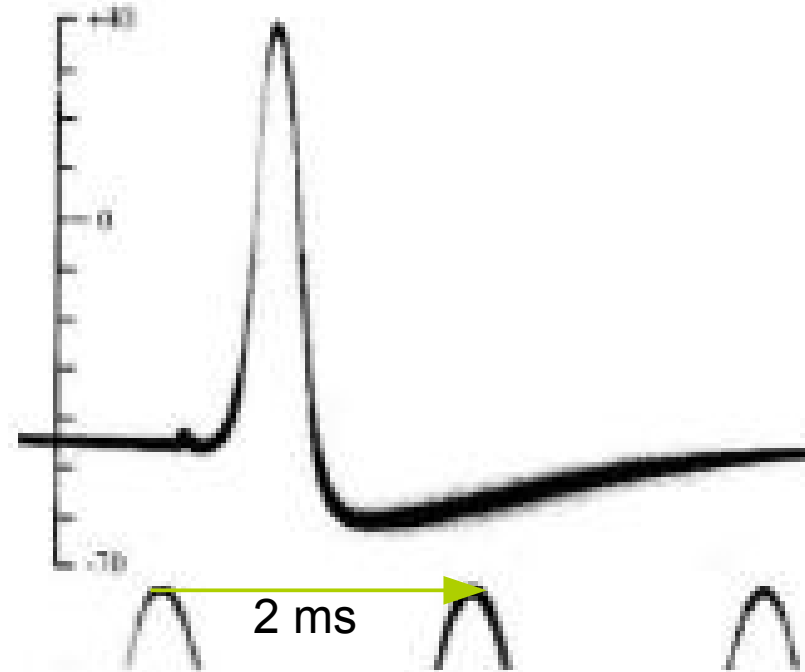
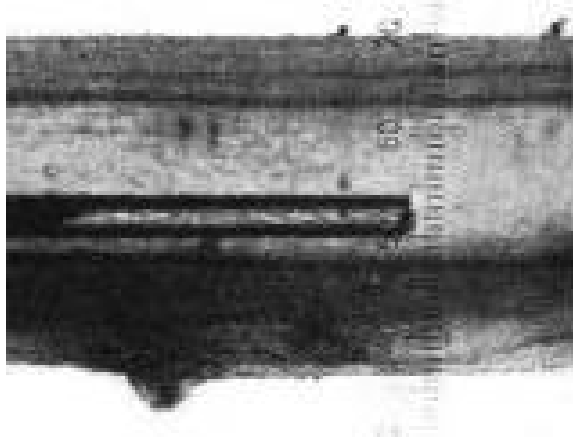
- Sensory stimulus intensity problem
- **Stochastic model**
- **Mathematical formulation**

Hodgkin – Huxley (1939)



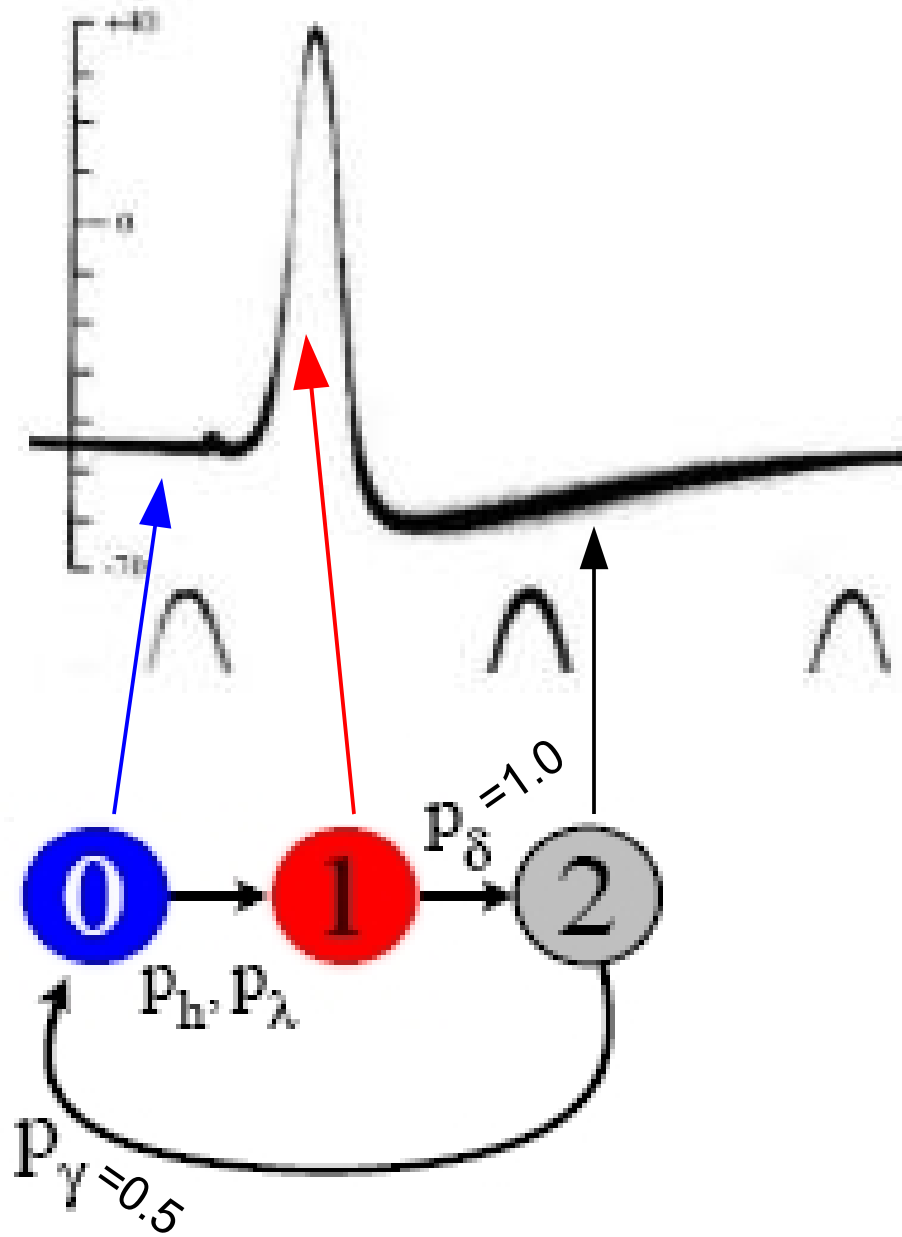
- Active membranes
 - coupled non-linear differential equations
 - electric potential and ionic conductances

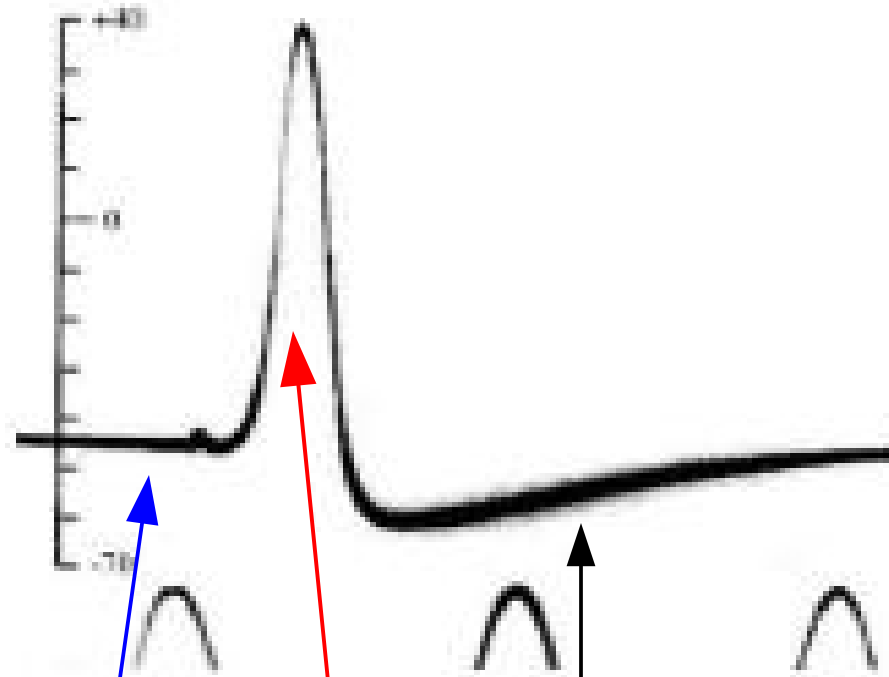
Hodgkin – Huxley (1939)



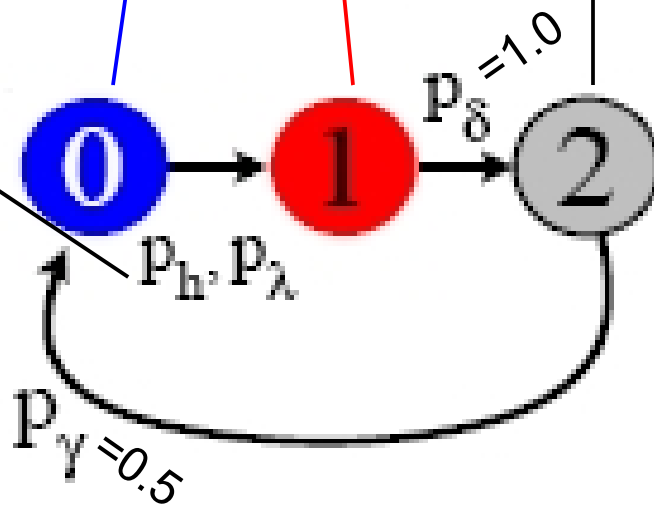
- Active membranes
 - coupled non-linear differential equations
 - electric potential and ionic conductances
- Detailed compartmental modelling

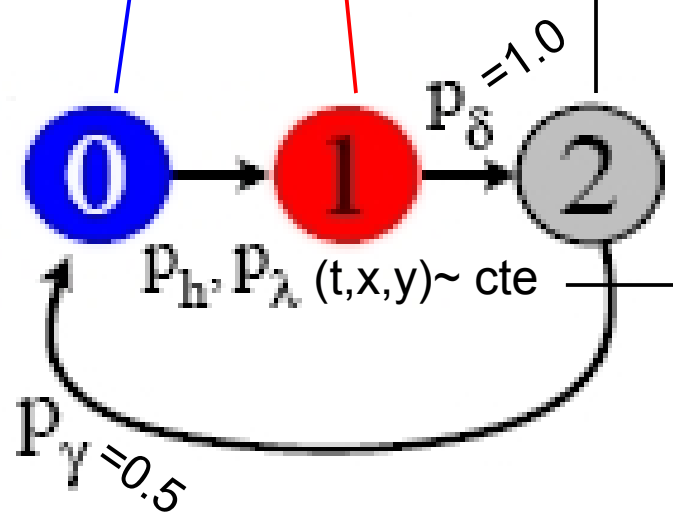
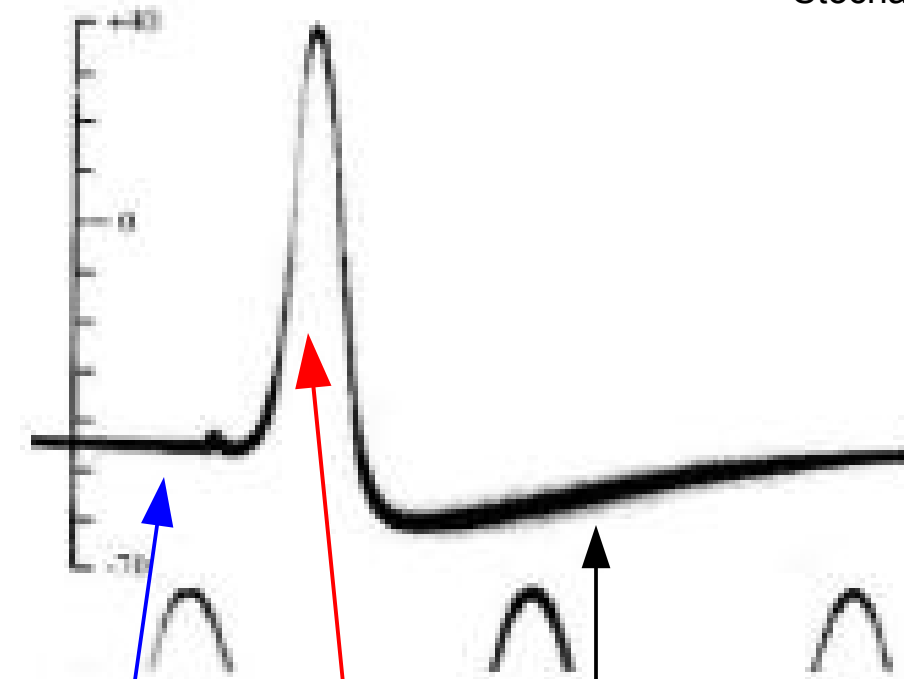
- Spatially extended excitable system
- Simple non-linear dynamics
- Collective behavior



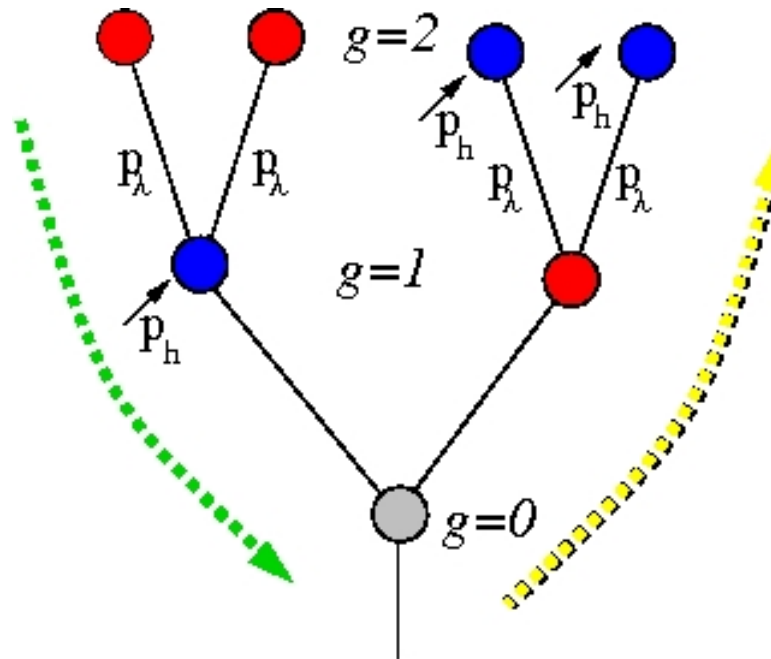
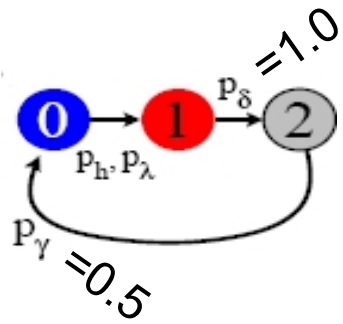


External driving

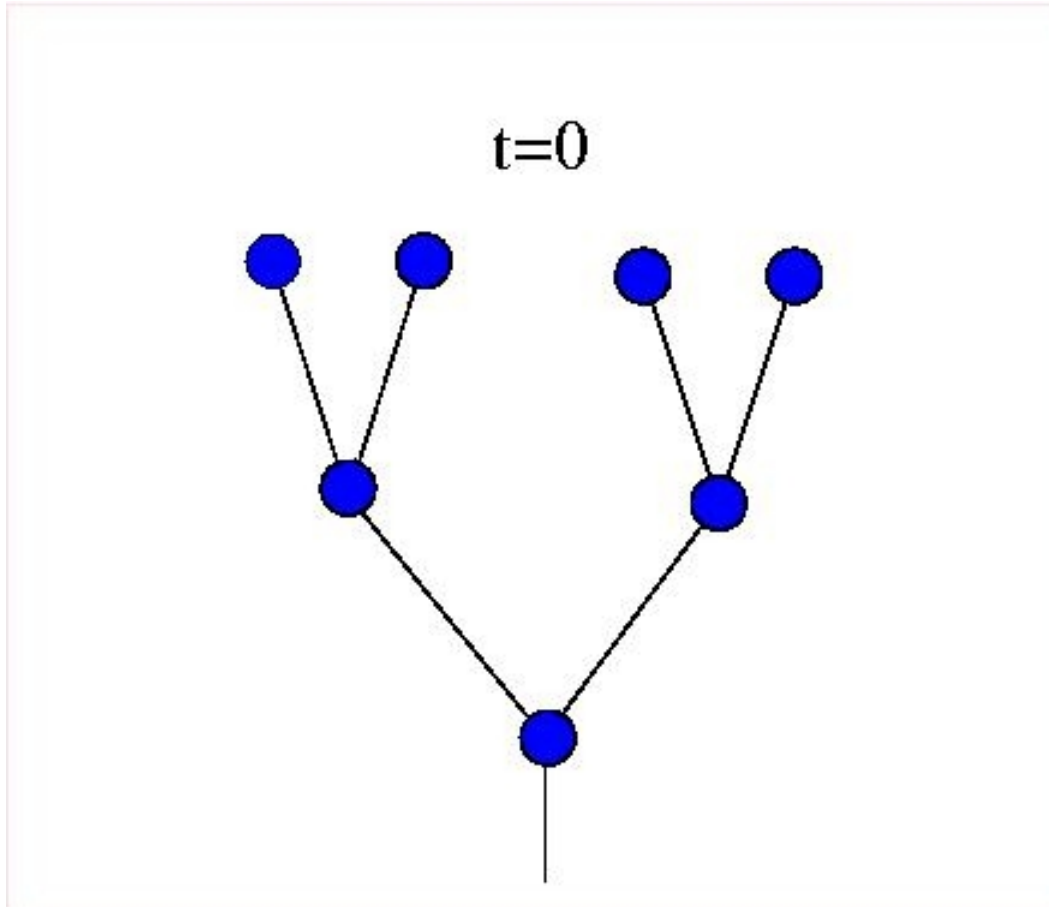


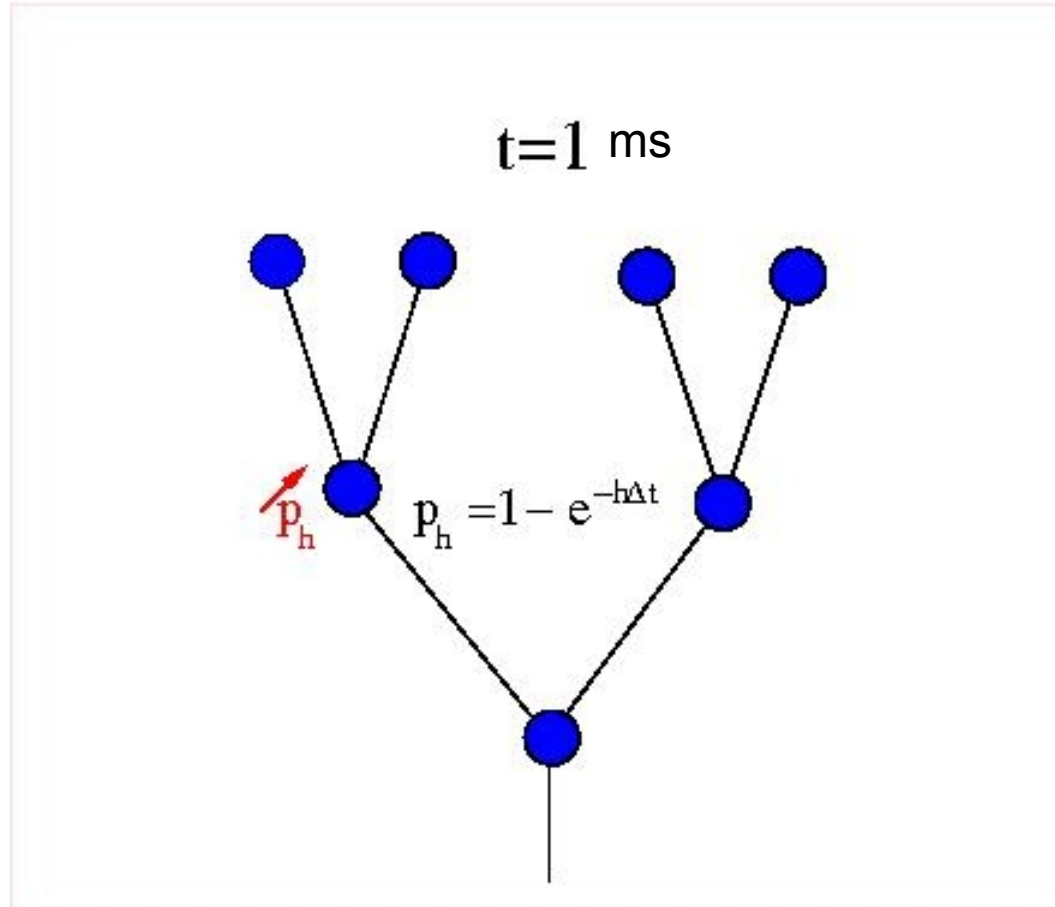


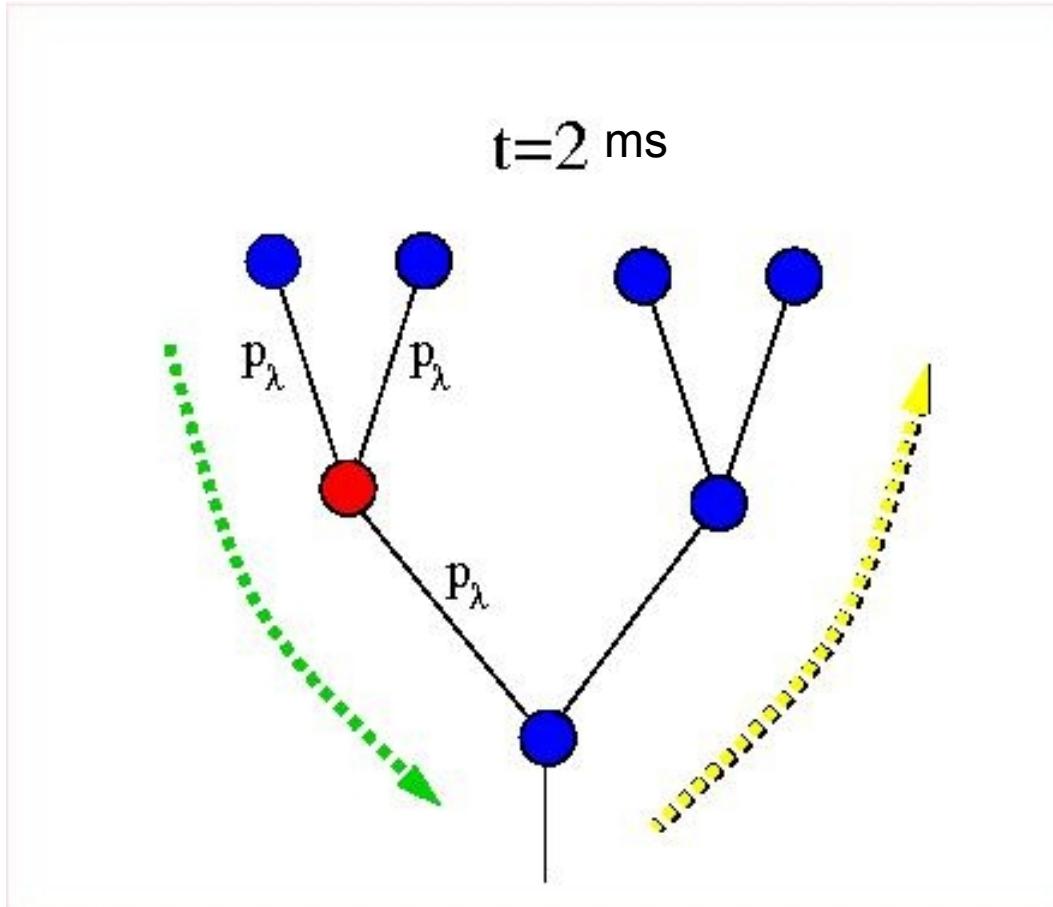
Coupling parameter

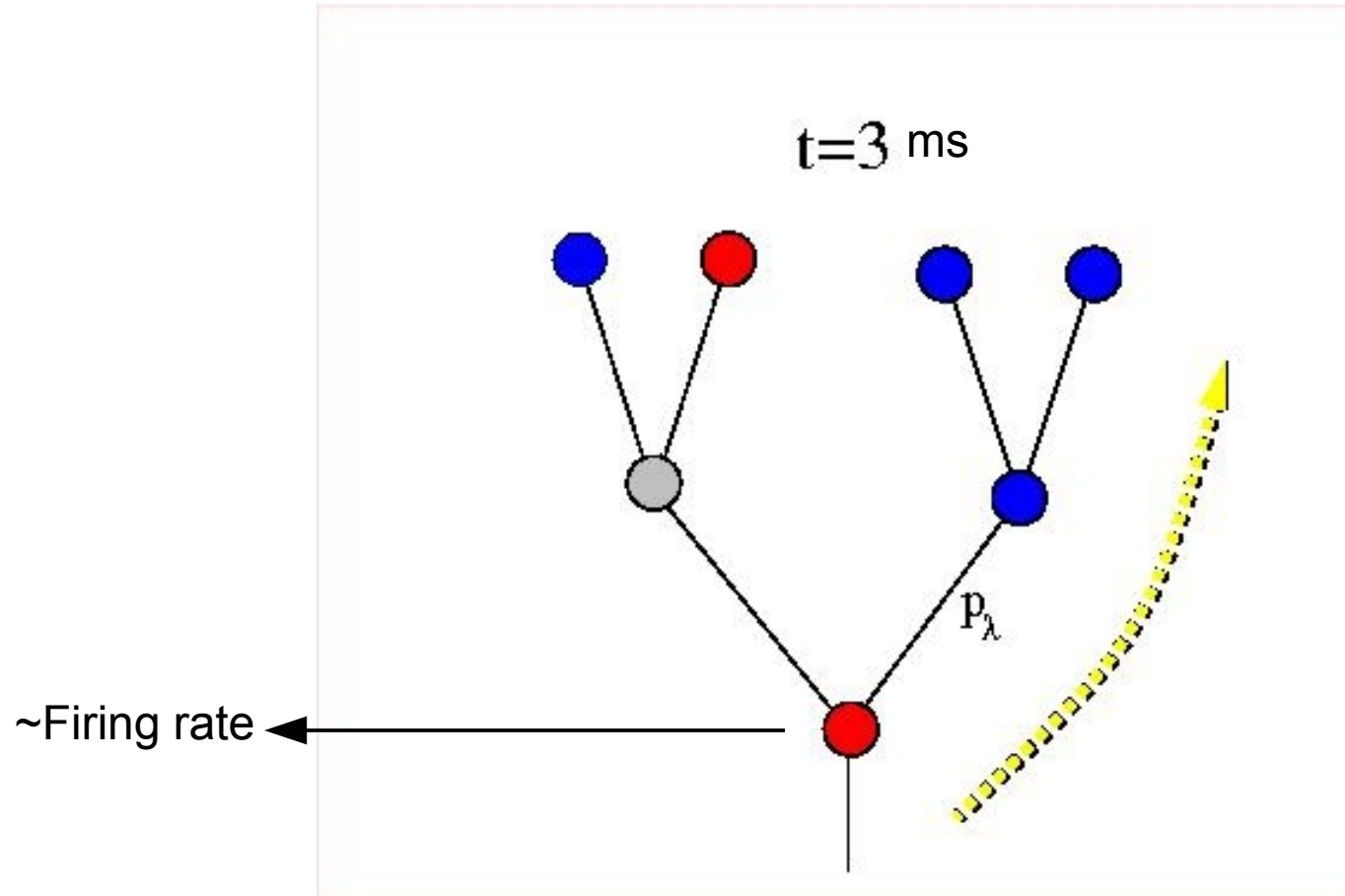


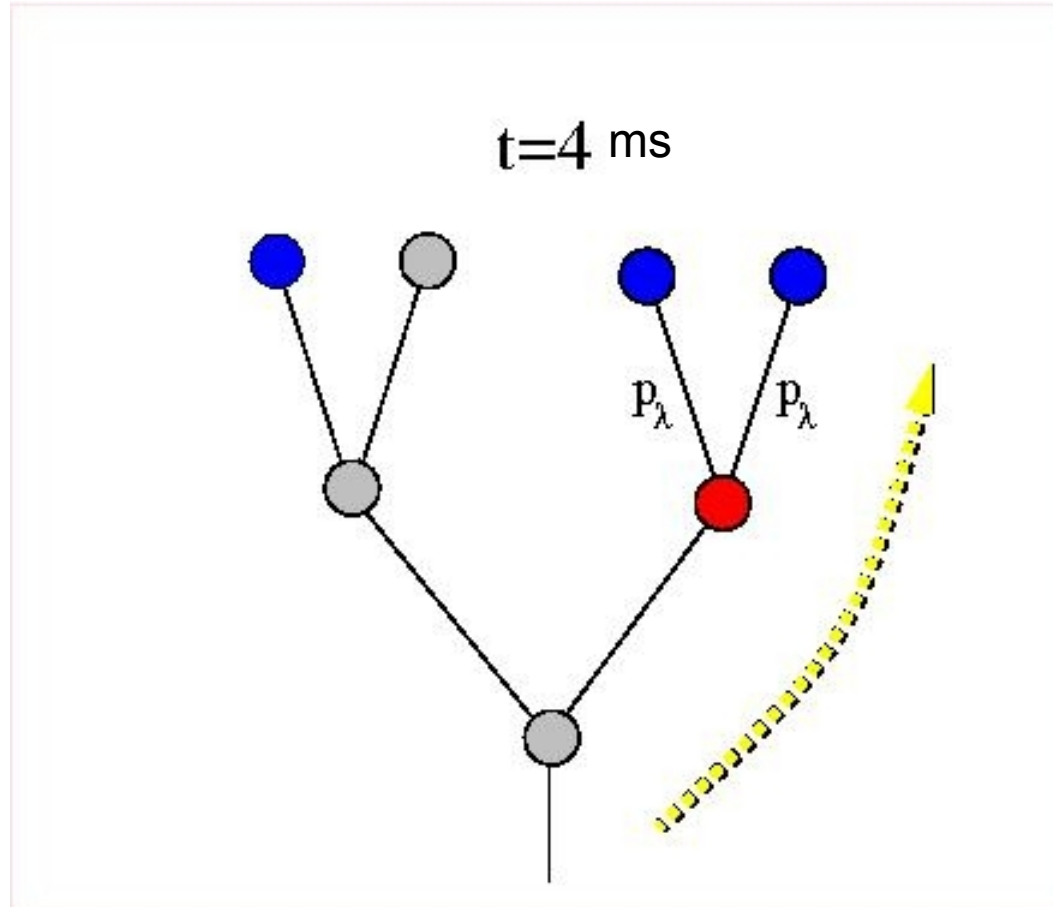
Example:

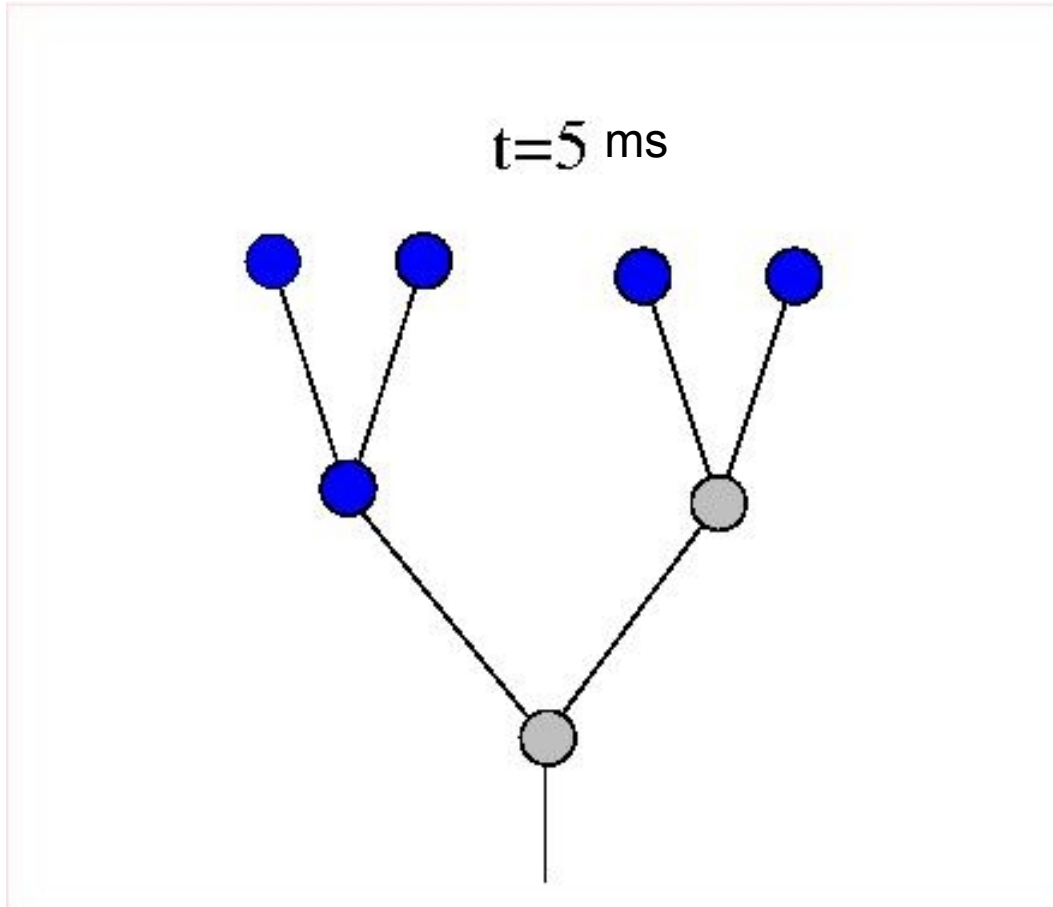


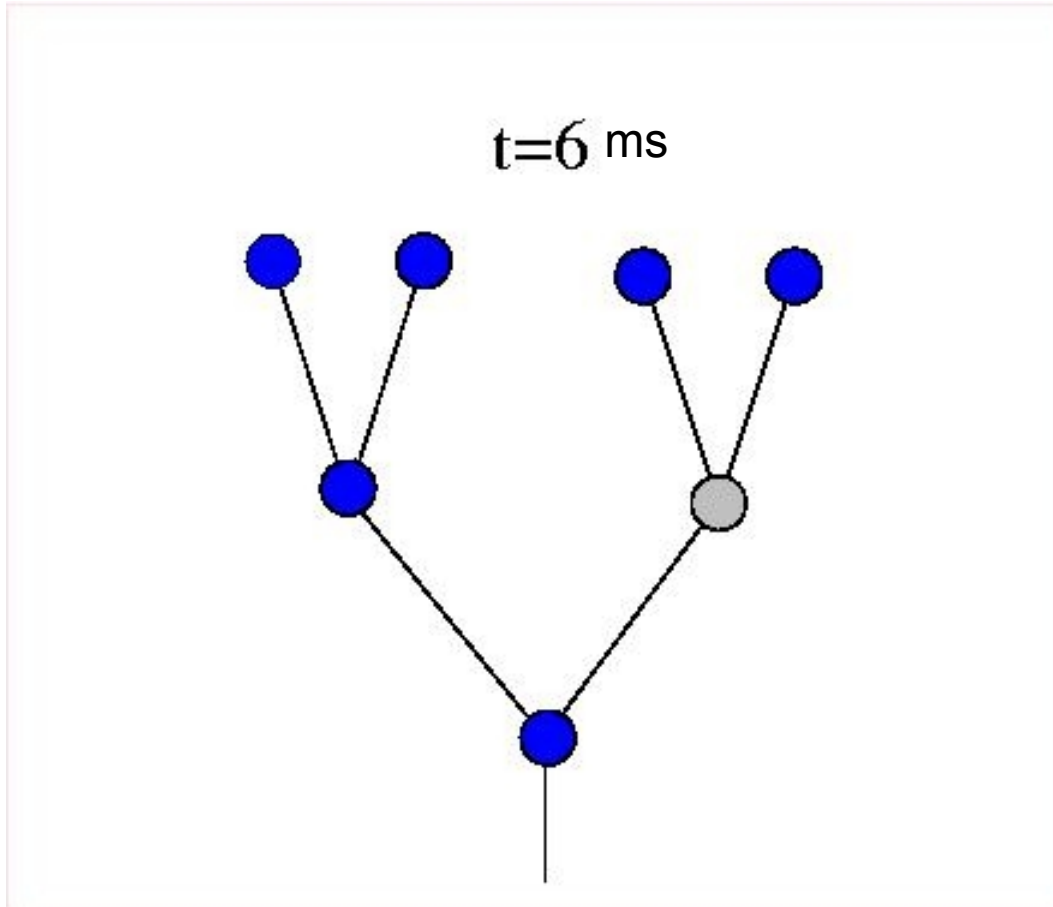


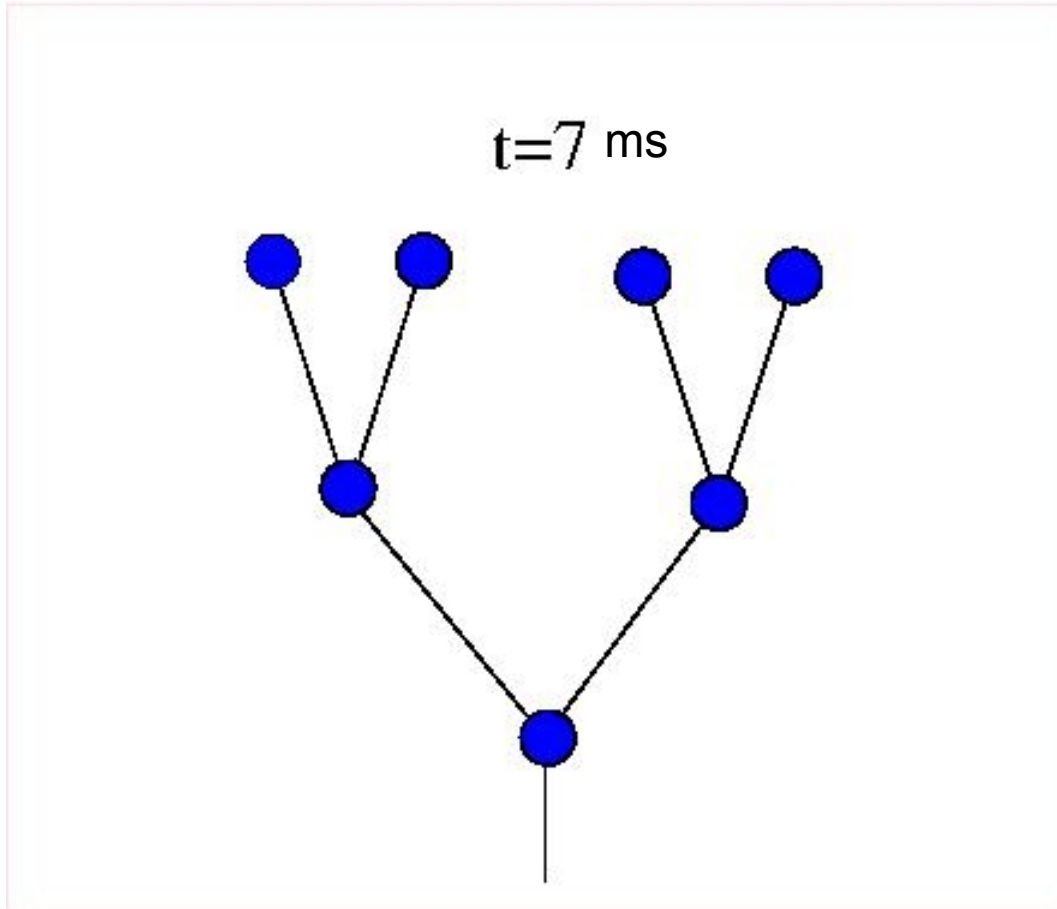


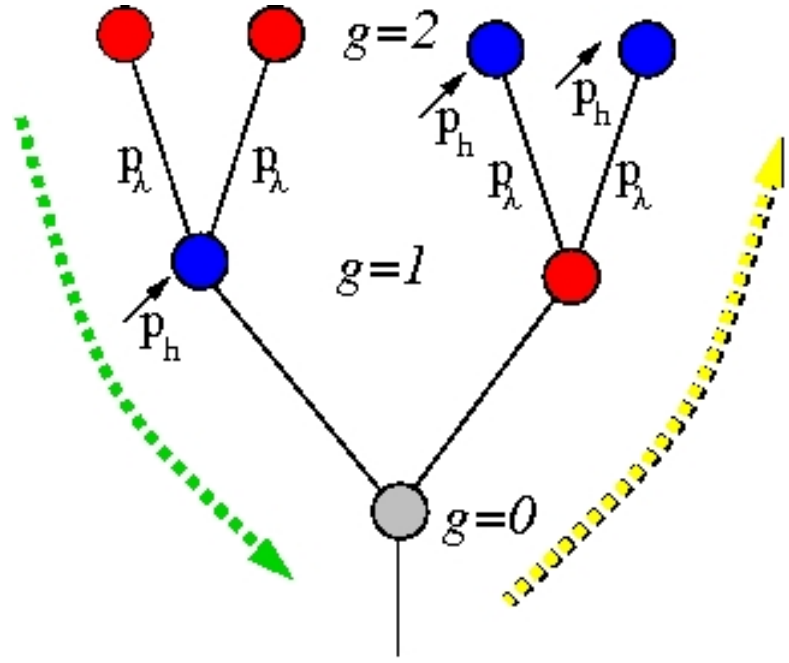




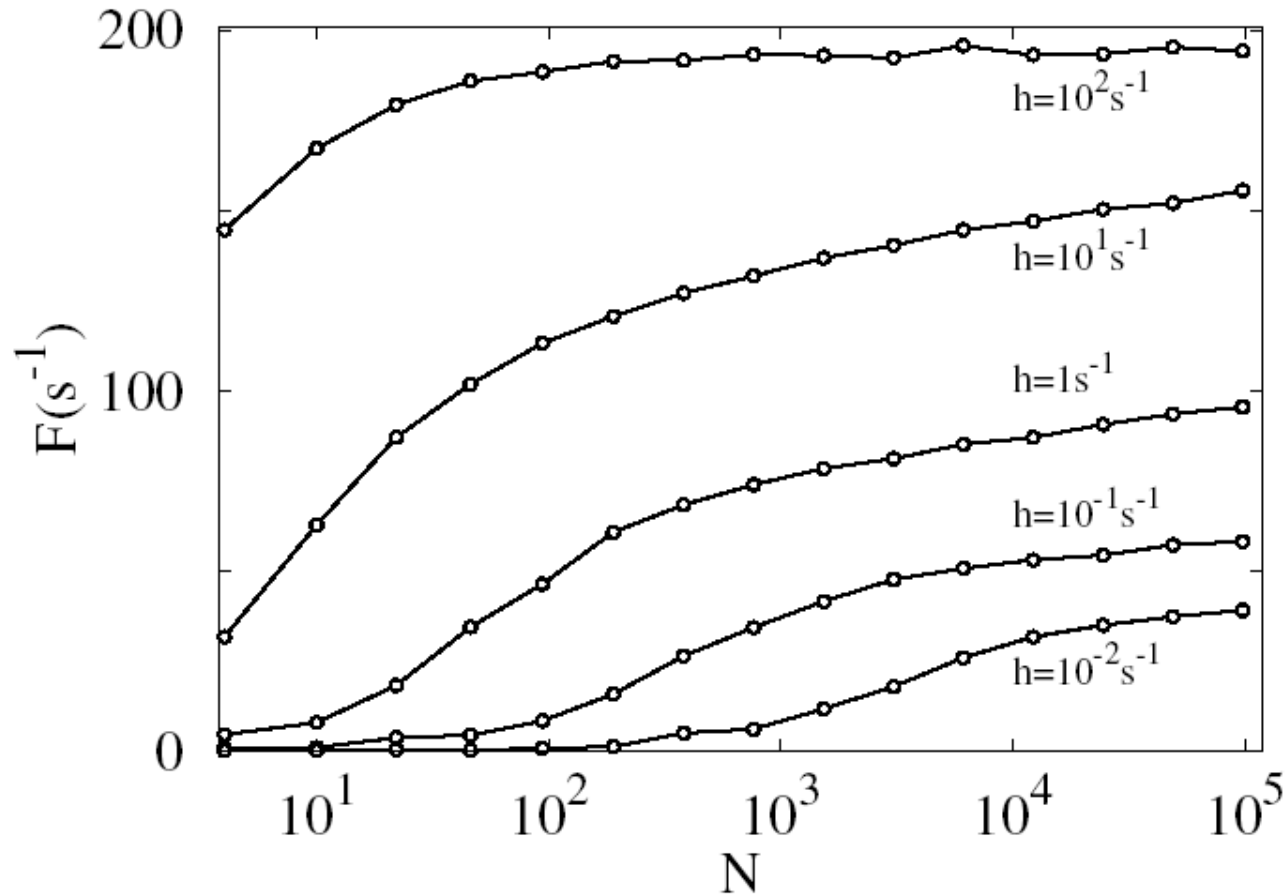






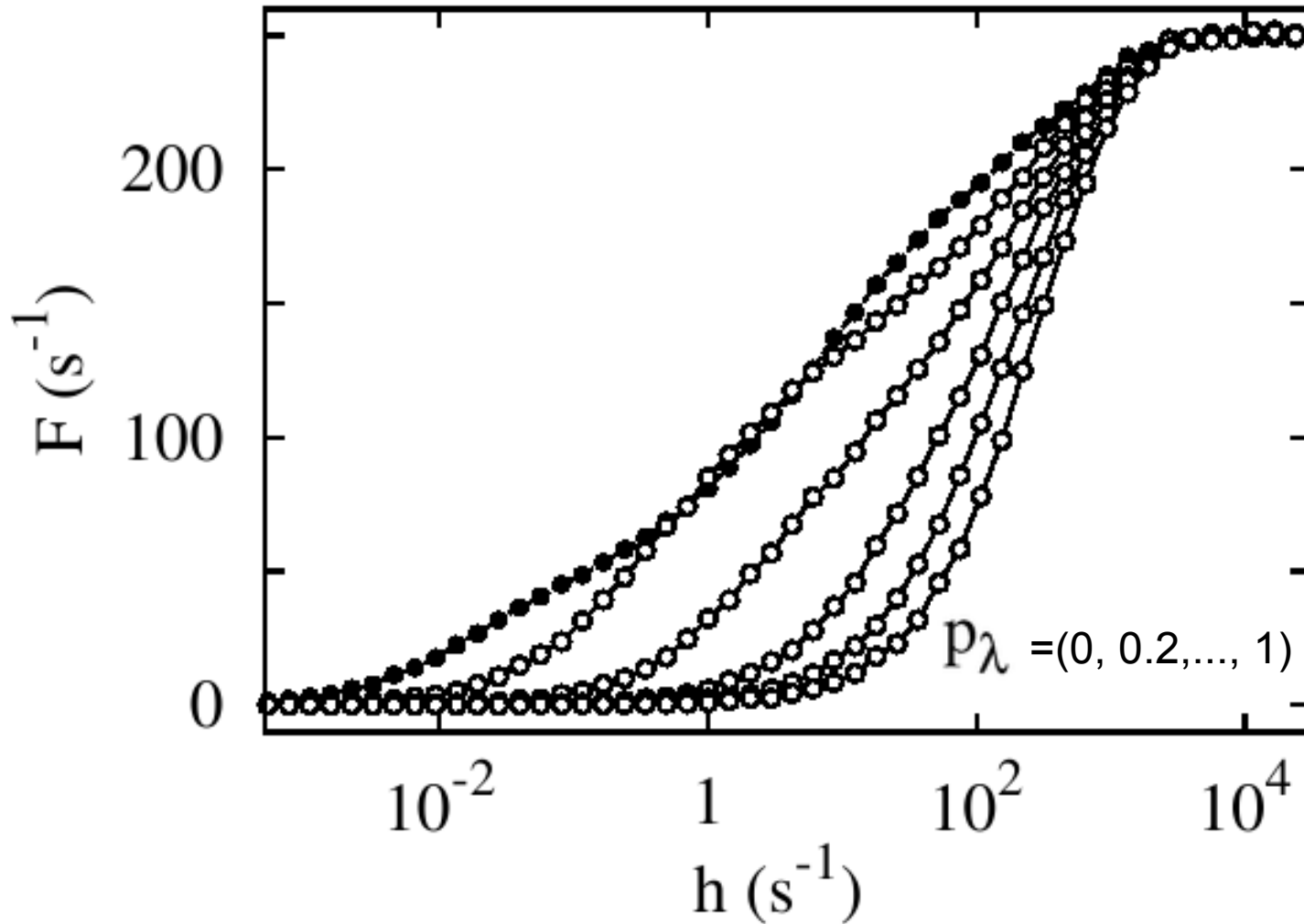


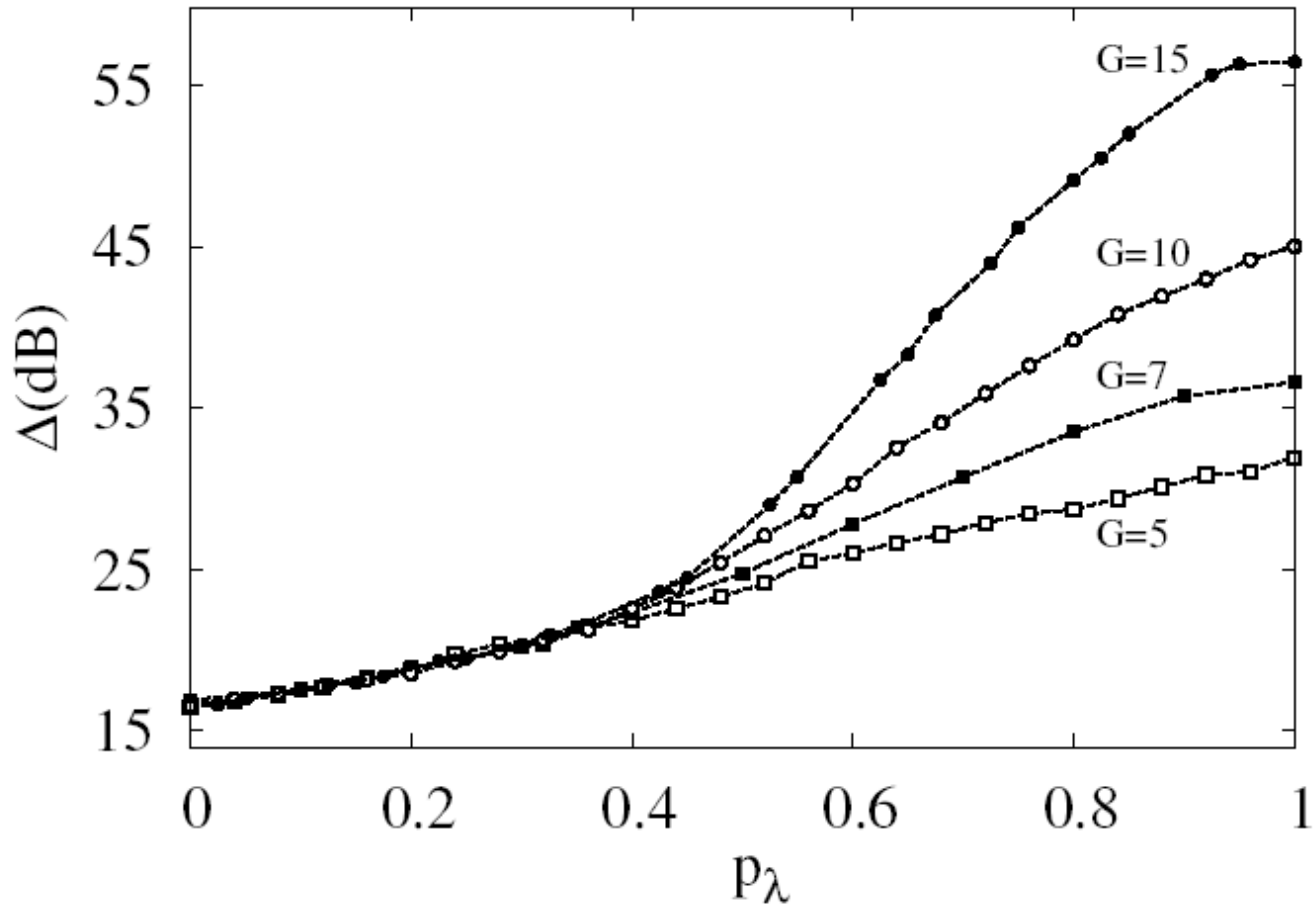
Does the output depend on the number of branchlets?

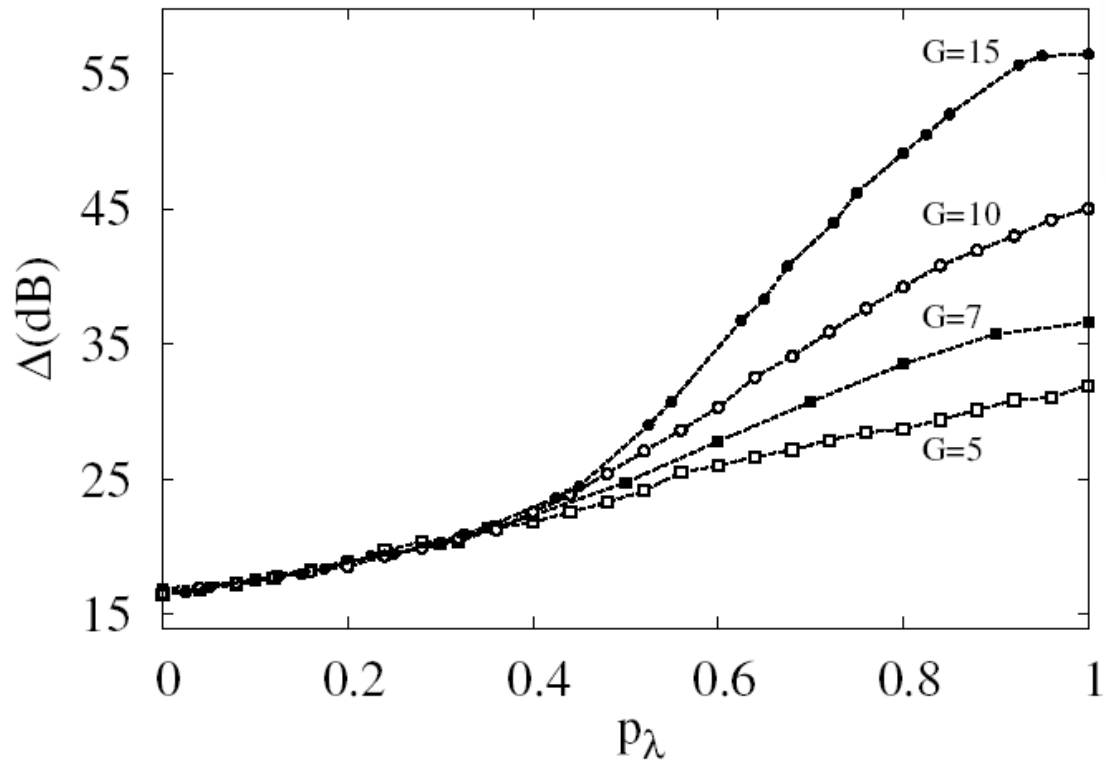
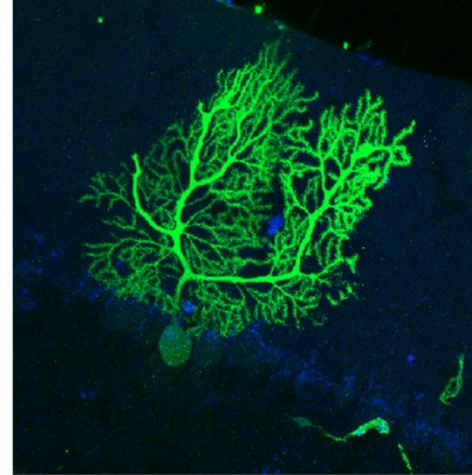


G=10
 $P\lambda=1.0$

- Family of response functions $G=10$

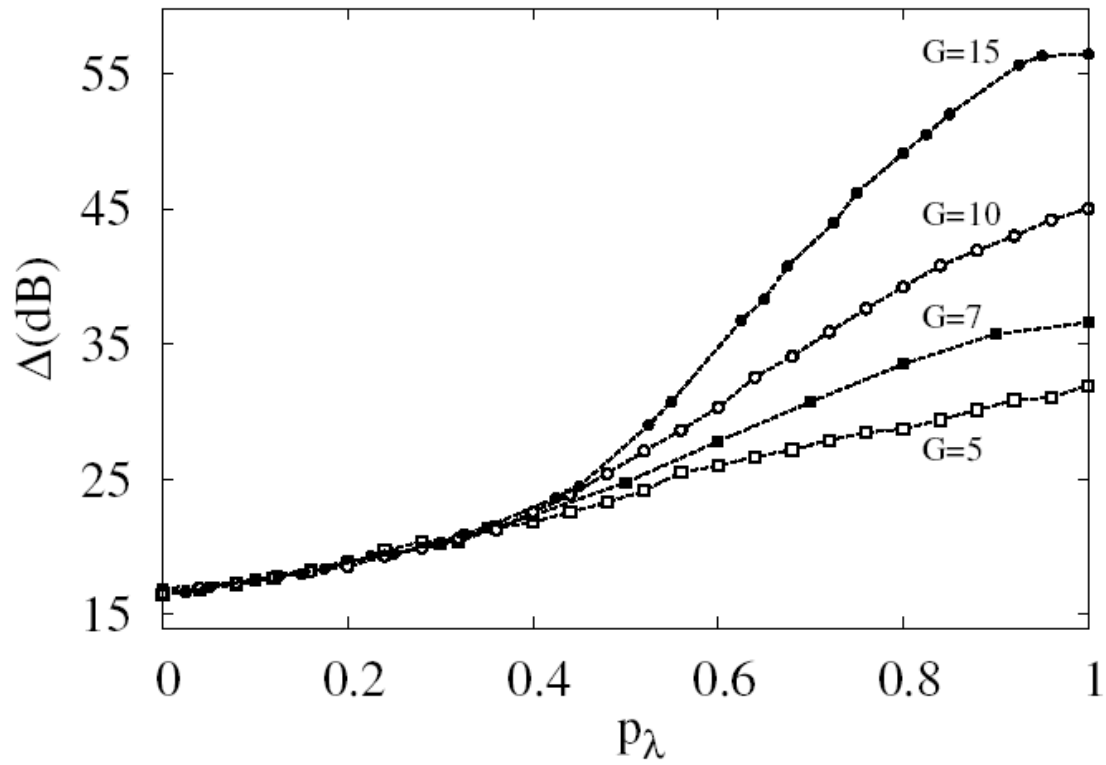






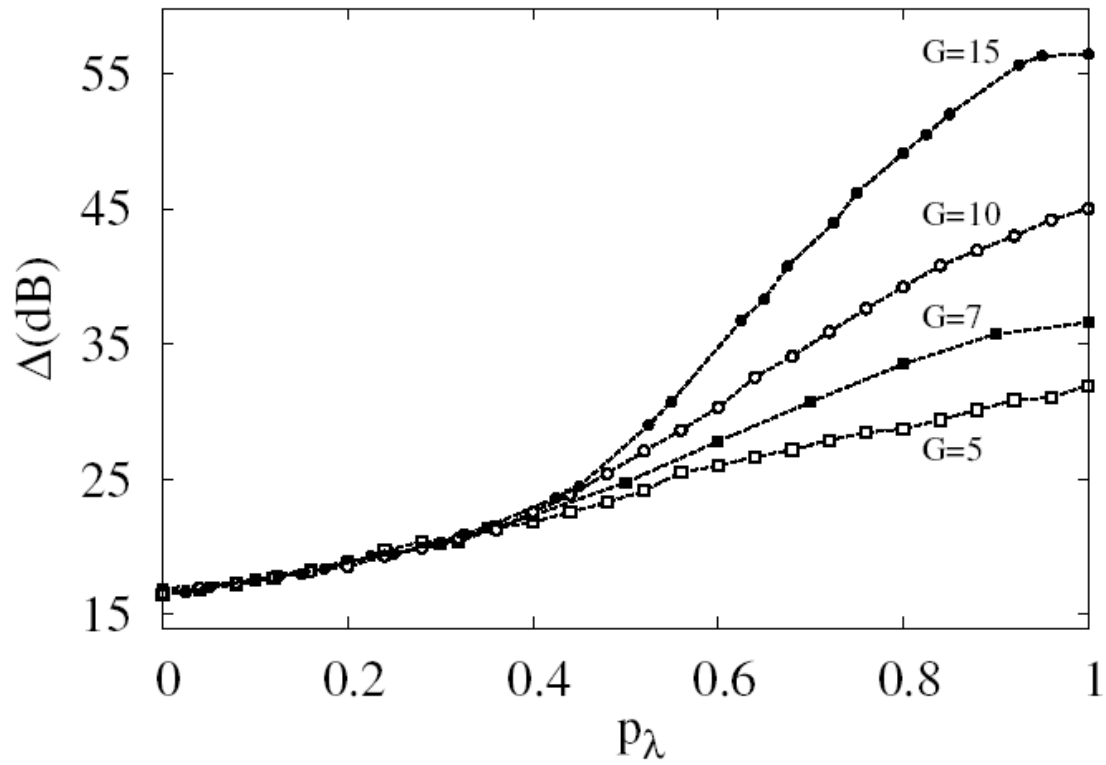
Purkinje cell Conjecture:

- play crucial role in fine motor control in cerebellum



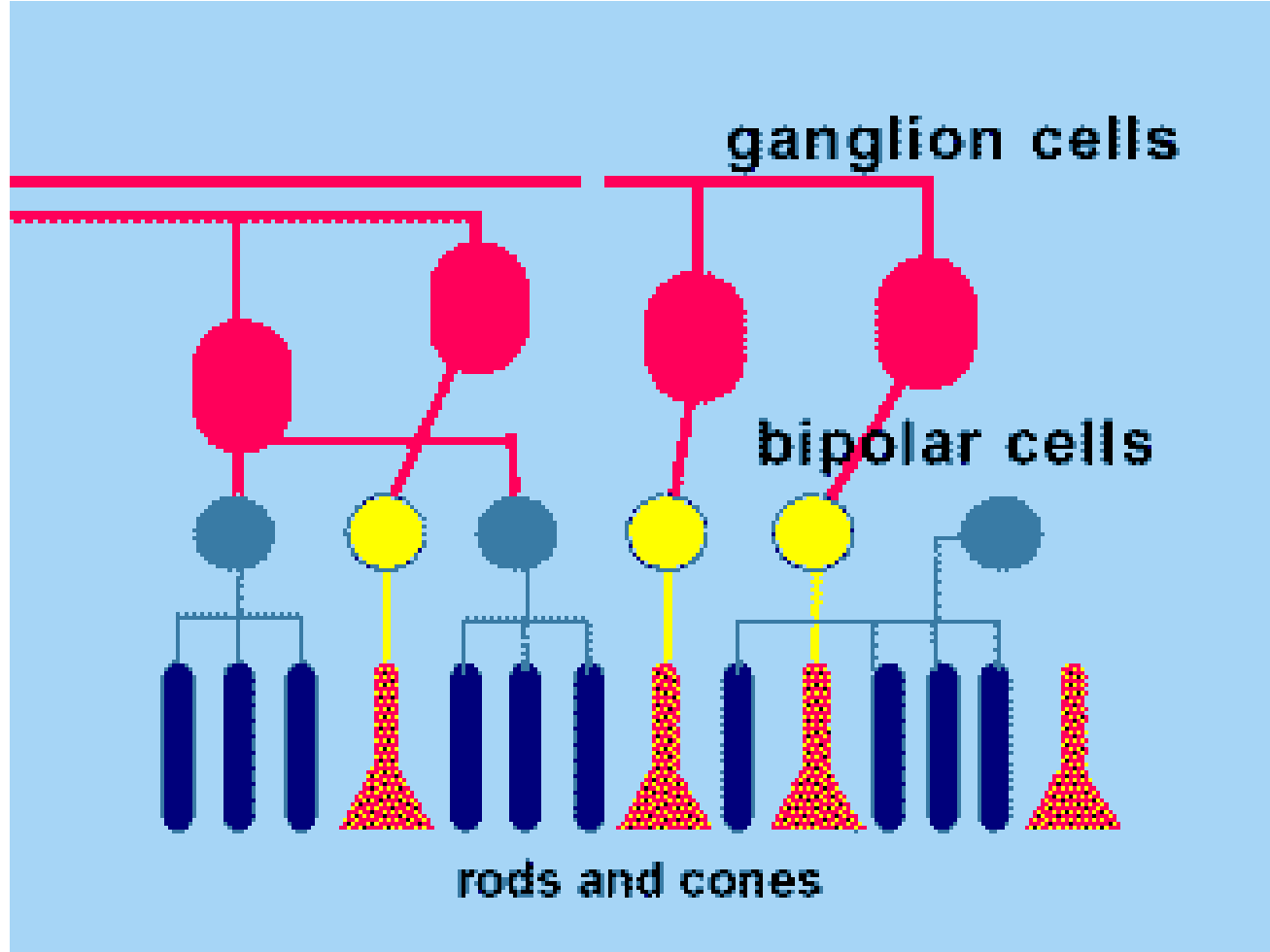
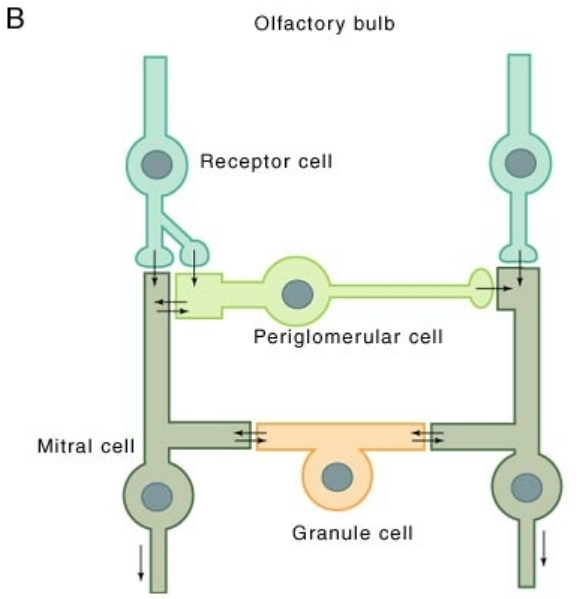
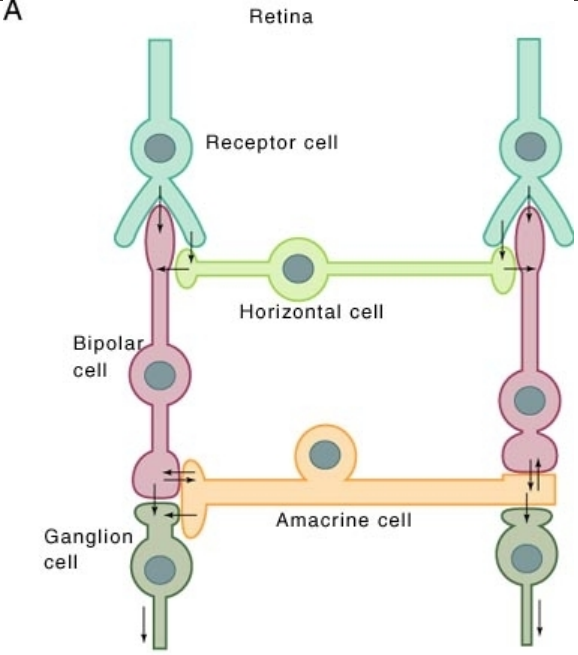
Predictions:

1. larger trees implies larger dynamic range



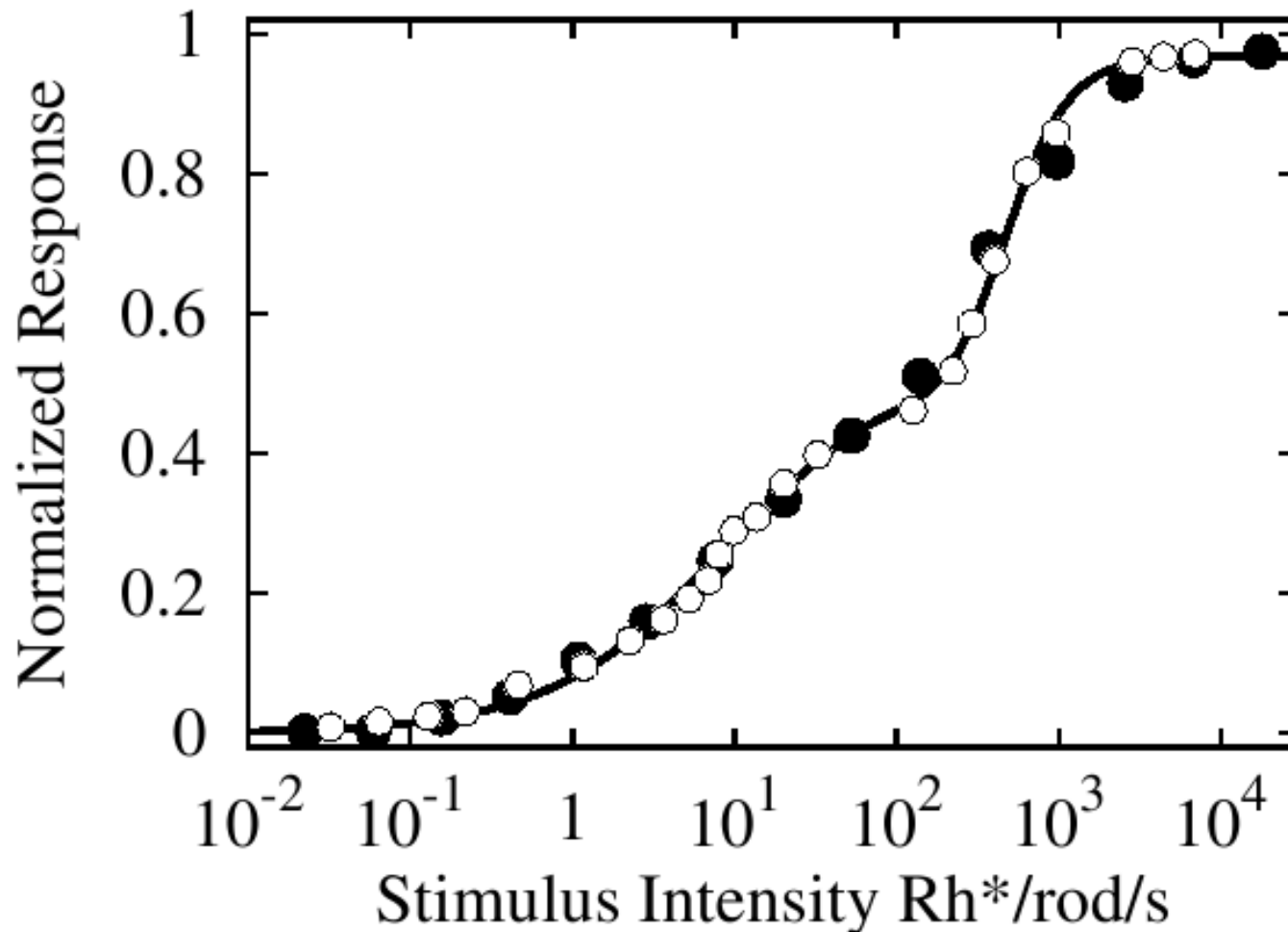
Predictions:

2. to block active conductances should decrease dynamic range



Shepherd 1998

- First model to obtain double sigmoid response function



- Large dendrites → low stimulus intensity

- Large dendrites -> low stimulus intensity
- Double sigmoid

- Large dendrites -> low stimulus intensity
- Double sigmoid
- dynamic range
 - i. Larger and more active trees distinguish better

- Large dendrites -> low stimulus intensity
- Double sigmoid
- dynamic range
 - i. Larger and more active trees distinguish better
 - ii. Blocking active conductances decreases dynamic range

- Large dendrites -> low stimulus intensity
- Double sigmoid
- **dynamic range**
 - i. Larger and more active trees distinguish better
 - ii. Blocking active conductances decreases dynamic range
- Backpropagation (plasticity, memory, learn) an exaptation

New propose for active dendrites

Robust

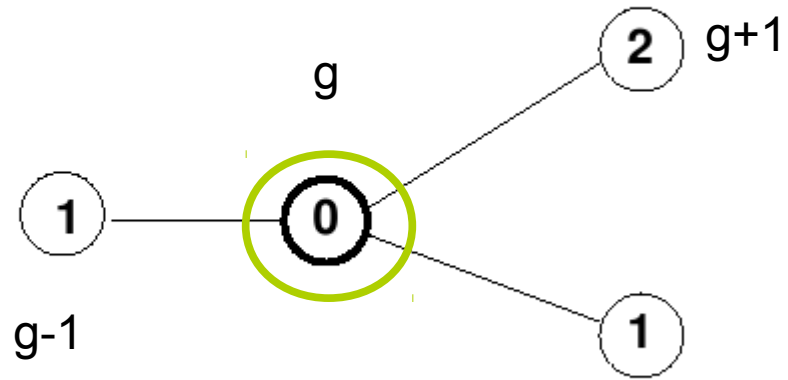
New propose for active dendrites

Robust

General properties of excitable media

- Sensory stimulus intensity problem
- Stochastic model
- **Mathematical formulation**

$$P^g(1; 0; 2, 1) \doteq$$



$$P_{t+1}^g(; 1;) = P_t^g(; 0;) p_h$$

$$+(1 - p_\delta) P_t^g(; 1;) , \quad (1)$$

$$P_{t+1}^g(; 0;) = 1 - P_{t+1}^g(; 1;) - P_{t+1}^g(; 2;) , \quad (2)$$

$$P_{t+1}^g(; 2;) = p_\delta P_t^g(; 1;) + (1 - p_\gamma) P_t^g(; 2;) , \quad (3)$$

$$\begin{aligned}
 P_{t+1}^g(; 1;) &= P_t^g(; 0;) \\
 &\quad - (1 - p_h) \sum_{i=0}^{z-1} \left[p_\lambda^i \binom{z-1}{i} (-1)^i P_t^g(; 0; 1^{(i)}) \right. \\
 &\quad \left. - \beta p_\lambda^{i+1} \binom{z-1}{i} (-1)^i P_t^g(1; 0; 1^{(i)}) \right] \\
 &\quad + (1 - p_\delta) P_t^g(; 1;), \tag{1}
 \end{aligned}$$

$$P_{t+1}^g(; 0;) = 1 - P_{t+1}^g(; 1;) - P_{t+1}^g(; 2;), \tag{2}$$

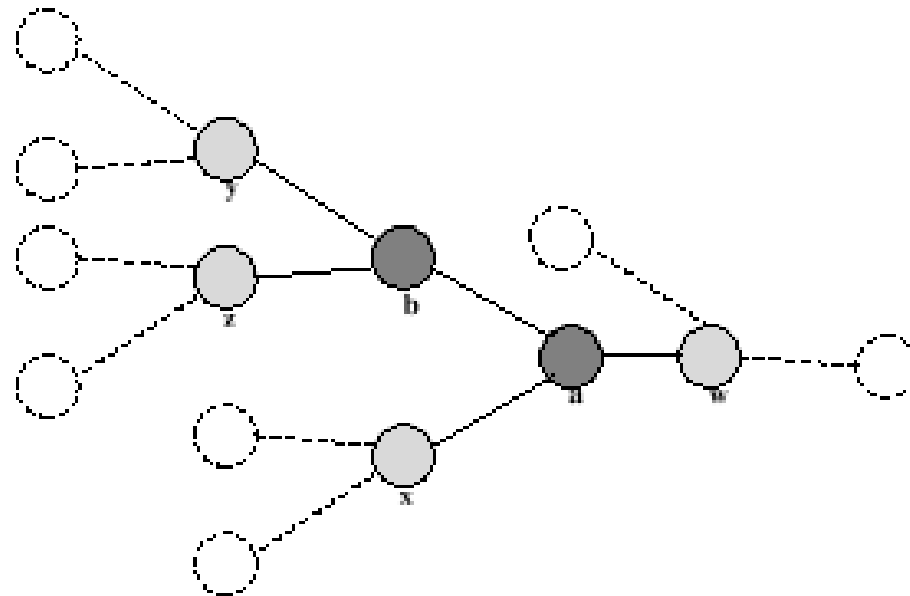
$$P_{t+1}^g(; 2;) = p_\delta P_t^g(; 1;) + (1 - p_\gamma) P_t^g(; 2;), \tag{3}$$

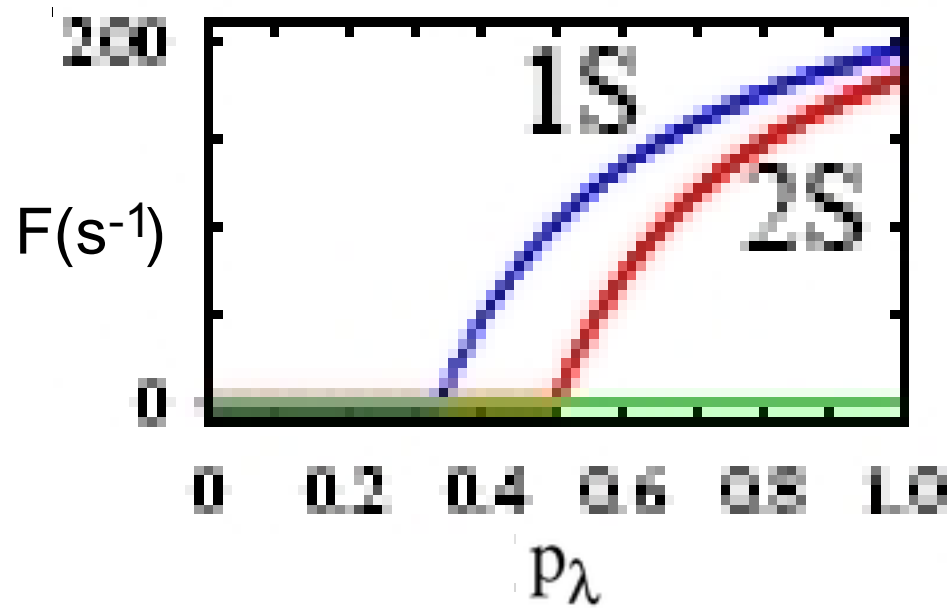
$$P_t(j_1 | j_2, \dots, j_m) \approx P_t(j_1),$$

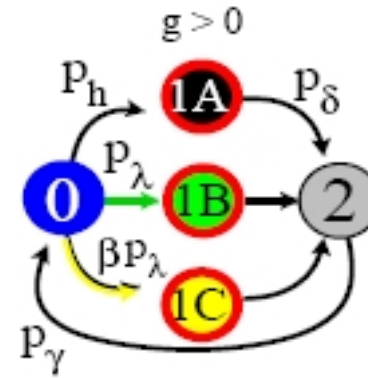
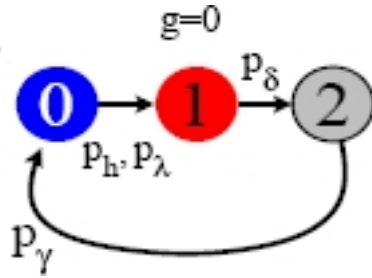
$$\implies P_t(j_1; j_2, \dots, j_{m-1}, j_m) \approx \prod_{i=1}^m P_t(j_i).$$

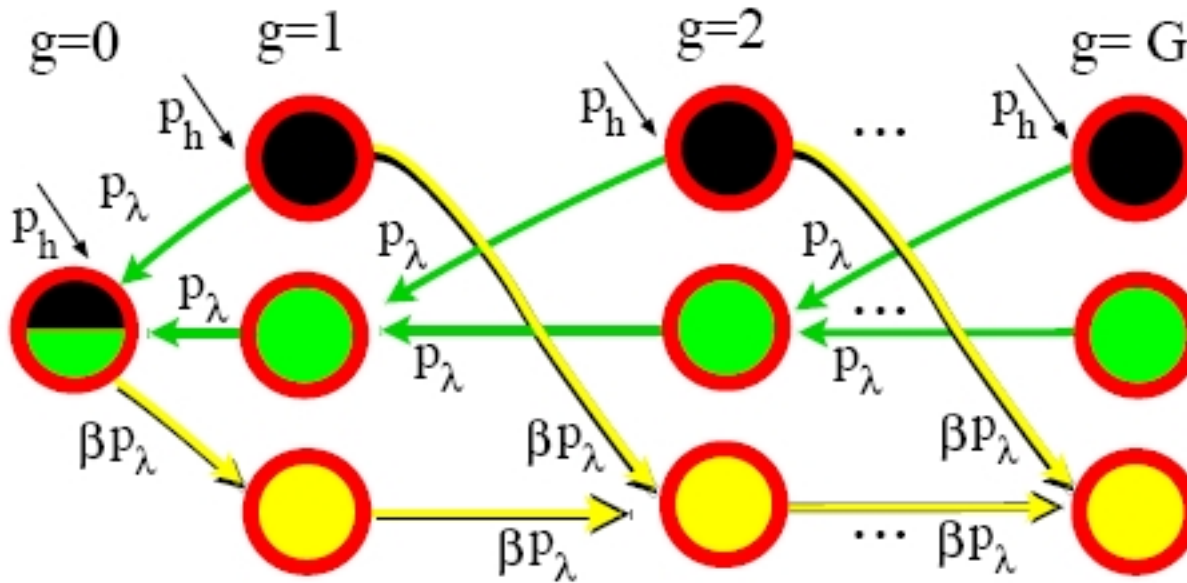
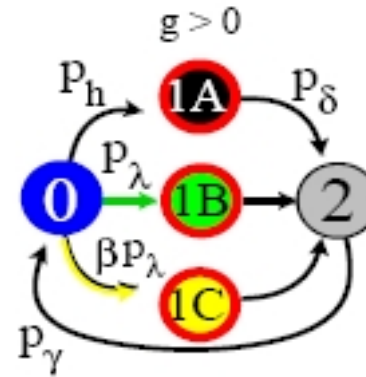
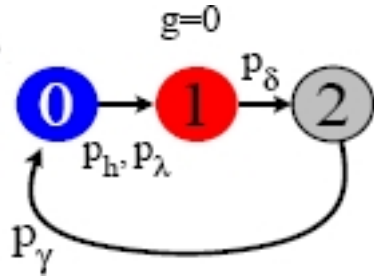
$$P_t(j_1 | j_2, \dots, j_m) \approx P_t(j_1 | j_2),$$

$$\implies P_t(j_1; j_2, \dots, j_{m-1}, j_m) \approx \frac{P_t(j_1, j_2) P_t(j_2, j_3) \dots P_t(j_{m-1}, j_m)}{P_t(j_2) \dots P_t(j_{m-1})}$$

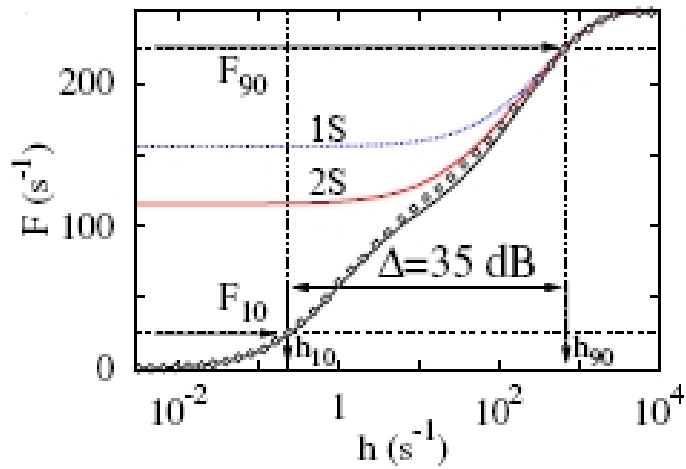


$h=0$ 

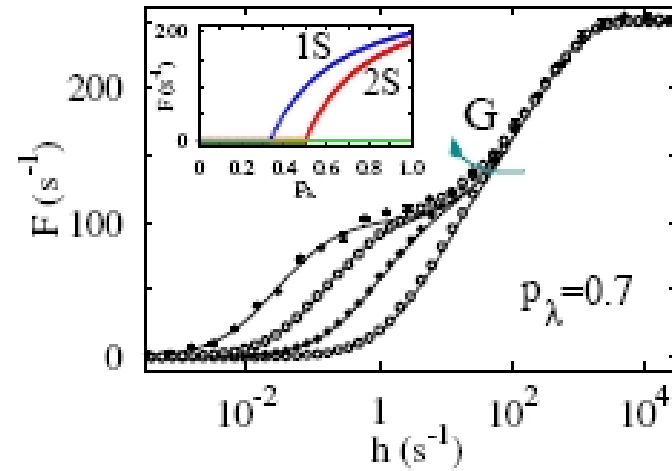
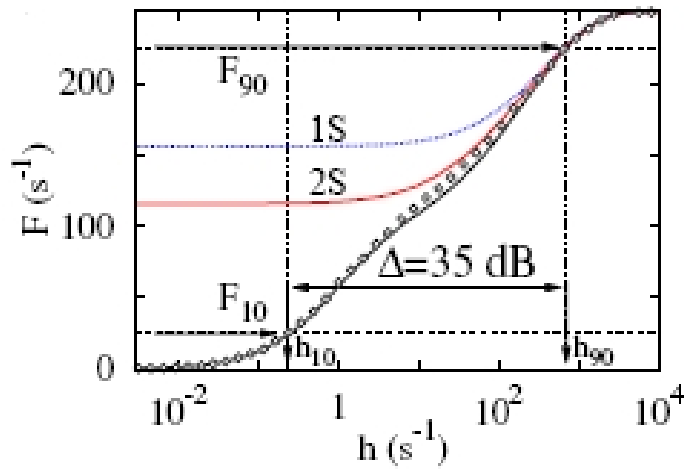




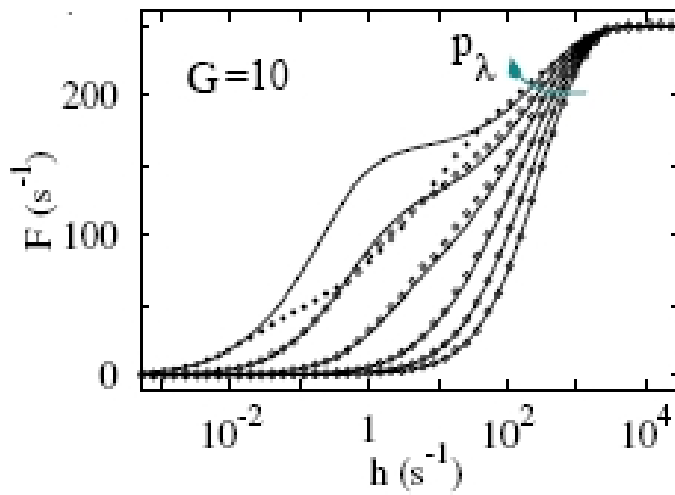
Gollo, Copelli (in prep.)



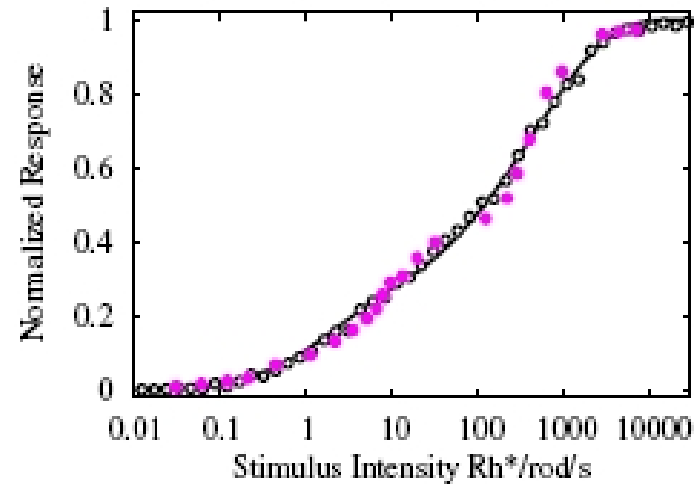
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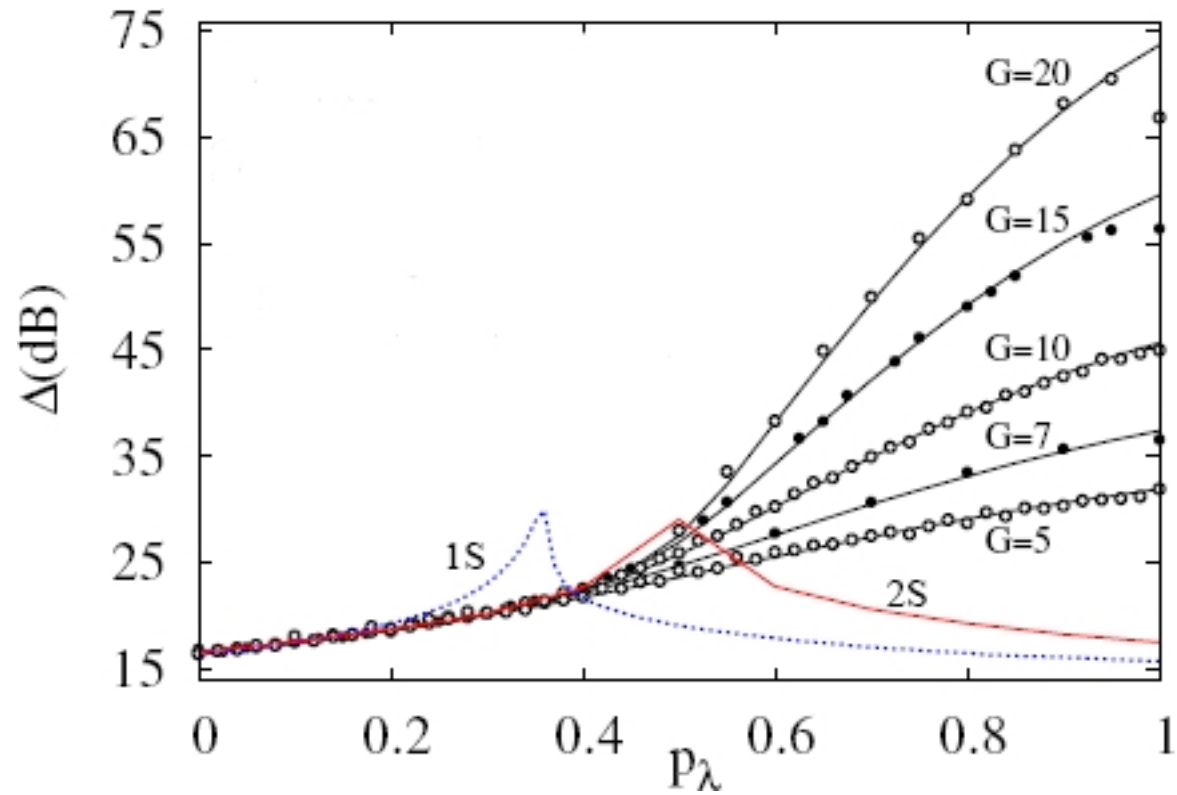
Gollo, Copelli (in prep.)



Deans et al. Neuron 2002



Gollo, Copelli (in prep.)



Gollo, Copelli (in prep.)

Final remark : EW

Captures essential dynamical aspects

Good agreement: simulations and experimental data



Thank you!

