Week 9 – part 1 : Models and data

ÉCOLE POLYTECHNIQUE
FÉDÉRALE DE LAUSANNE

Biological Modeling of Neural Networks:

Week 9 – Coding and Decoding

Wulfram Gerstner

EPFL, Lausanne, Switzerland

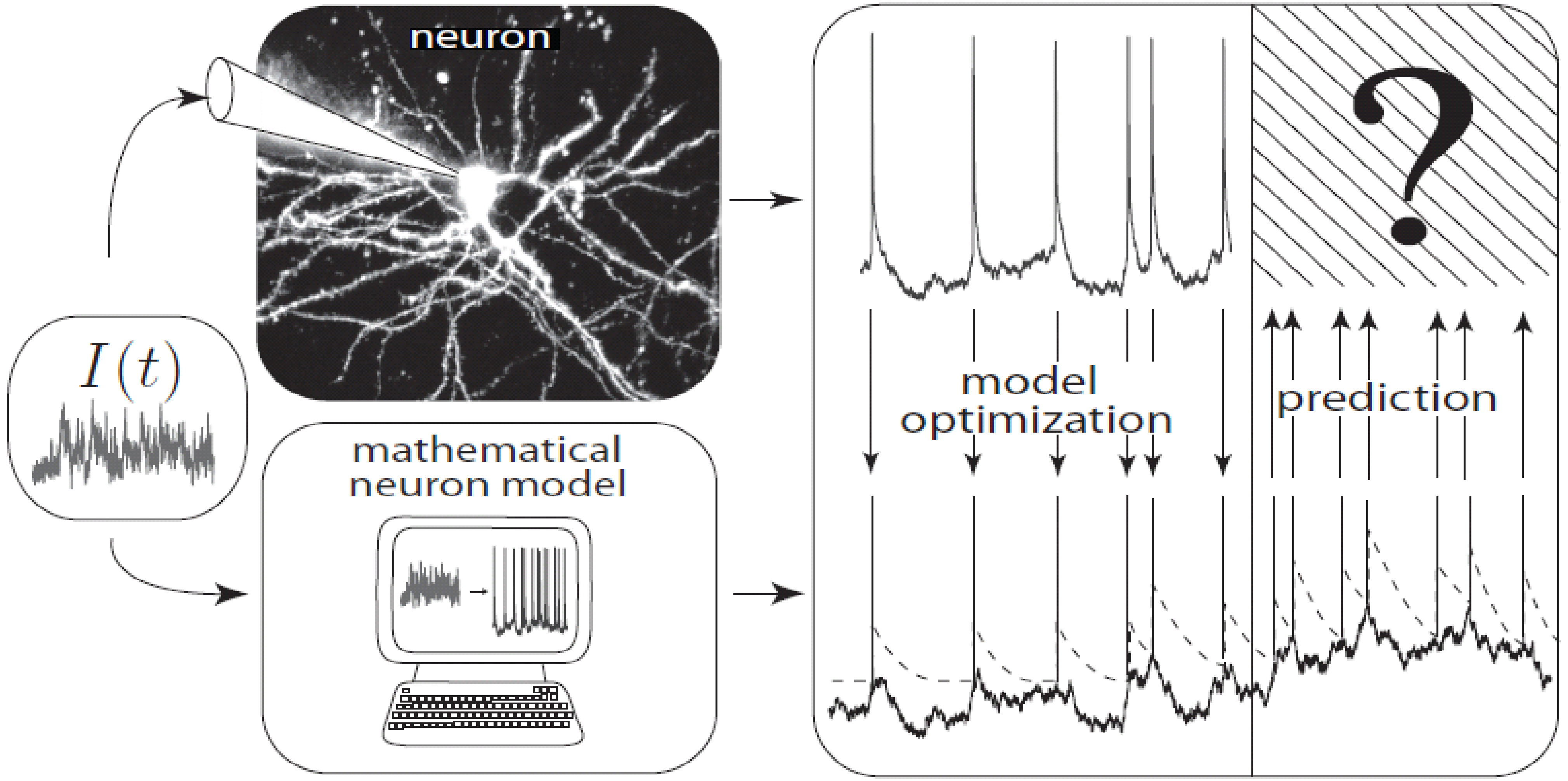
9.1 What is a good neuron model?
- Models and data

9.4 Generalized Linear Model
- Adding noise to the SRM

9.6. Modeling in vitro data
- how long lasts the effect of a spike?

9.7 Systems neuroscience
- reverse correlations
- helping humans

Neuronal Dynamics – 9.1 Neuron Models and Data

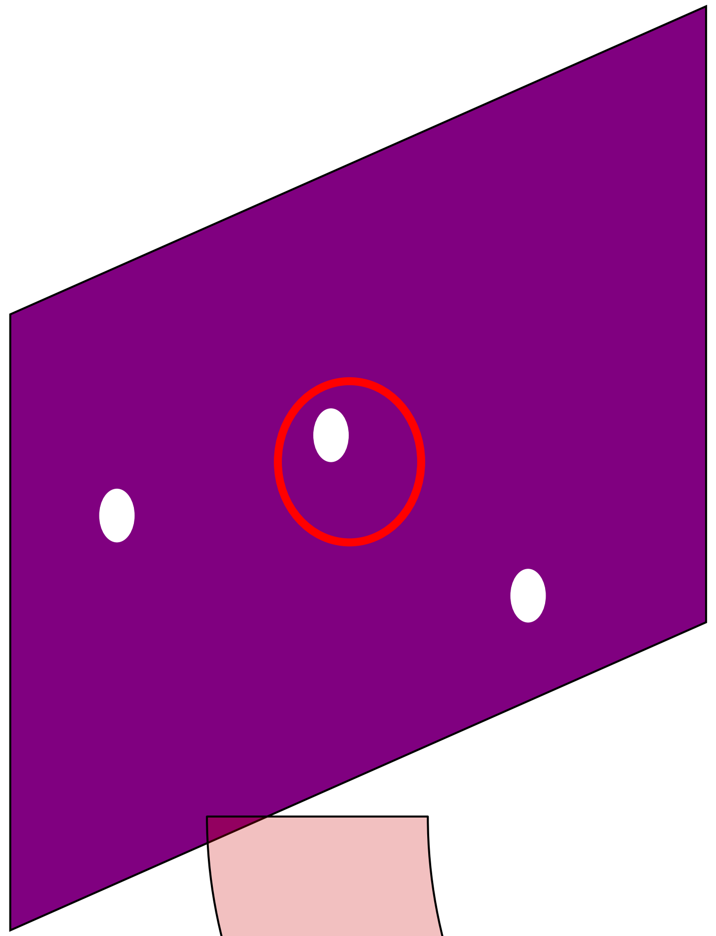


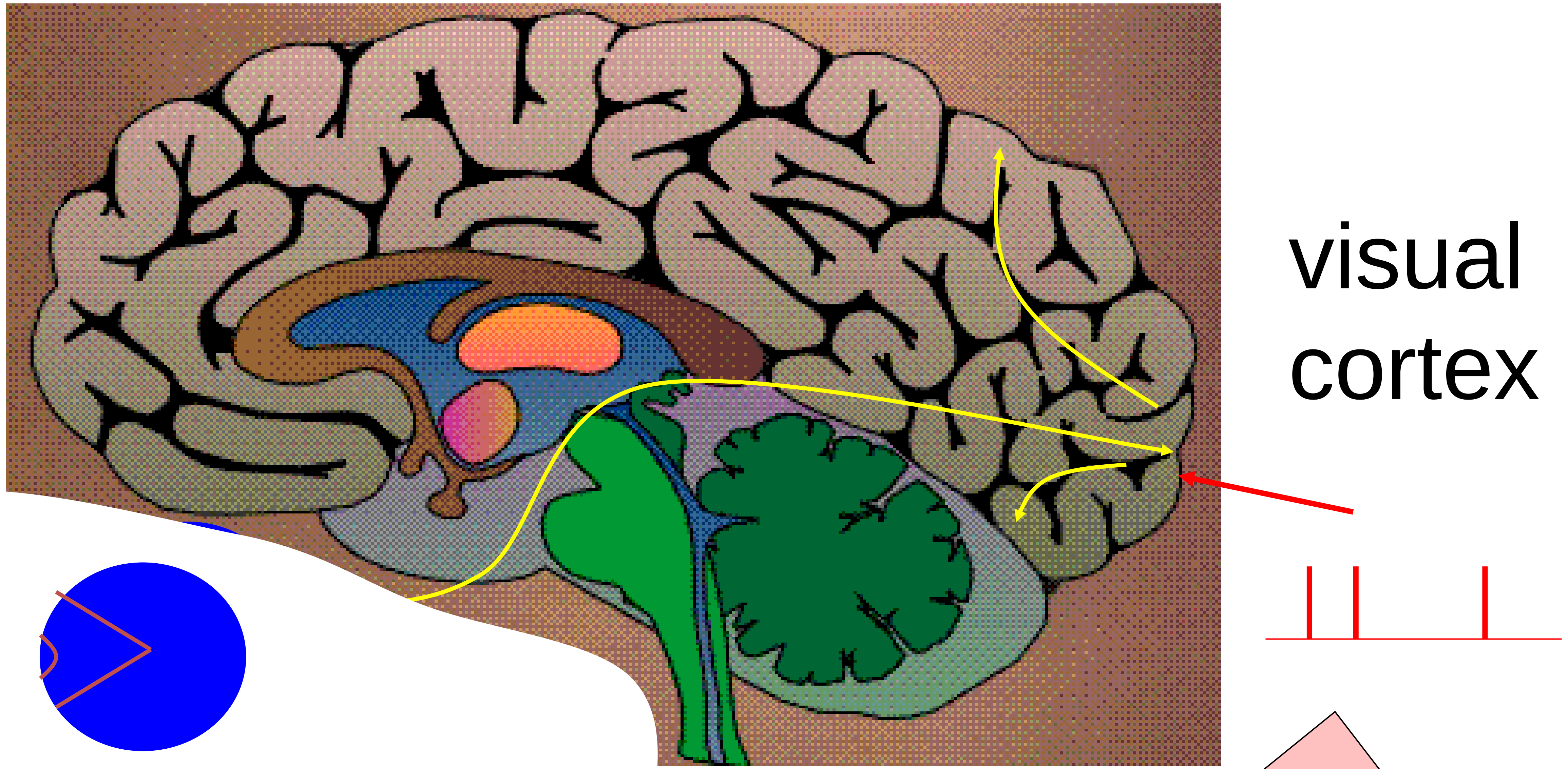
Intracellular recordings

-What is a good neuron model?
-Estimate parameters of models?
-How does a neuron encode?
-Decoding: what do we learn from a spike train?

Neuronal Dynamics – 9.1 intro: Systems neuroscience, in vivo

Now: extracellular recordings



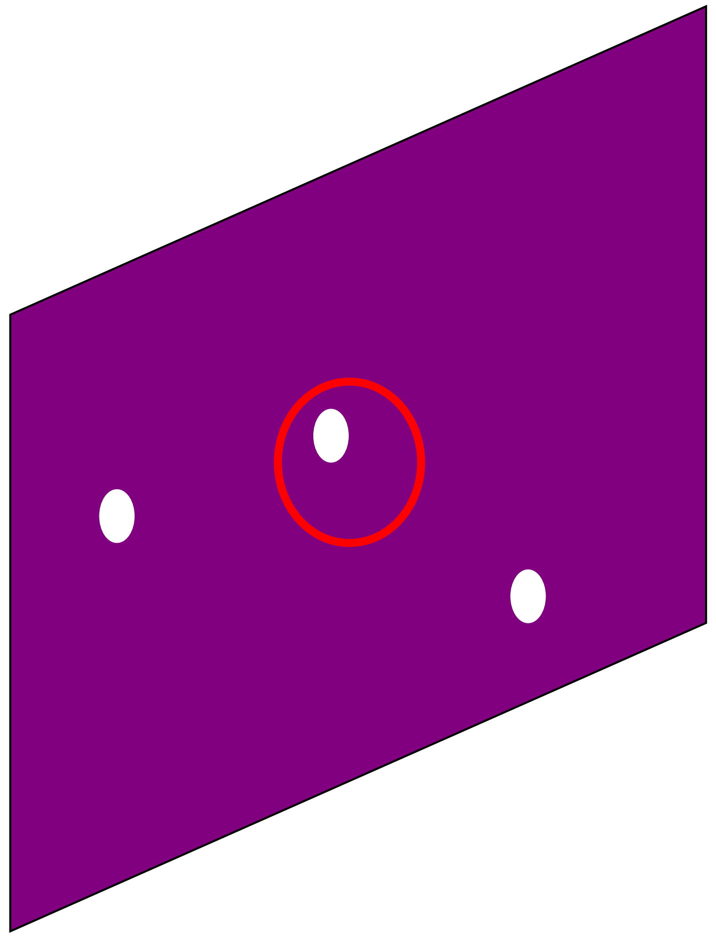


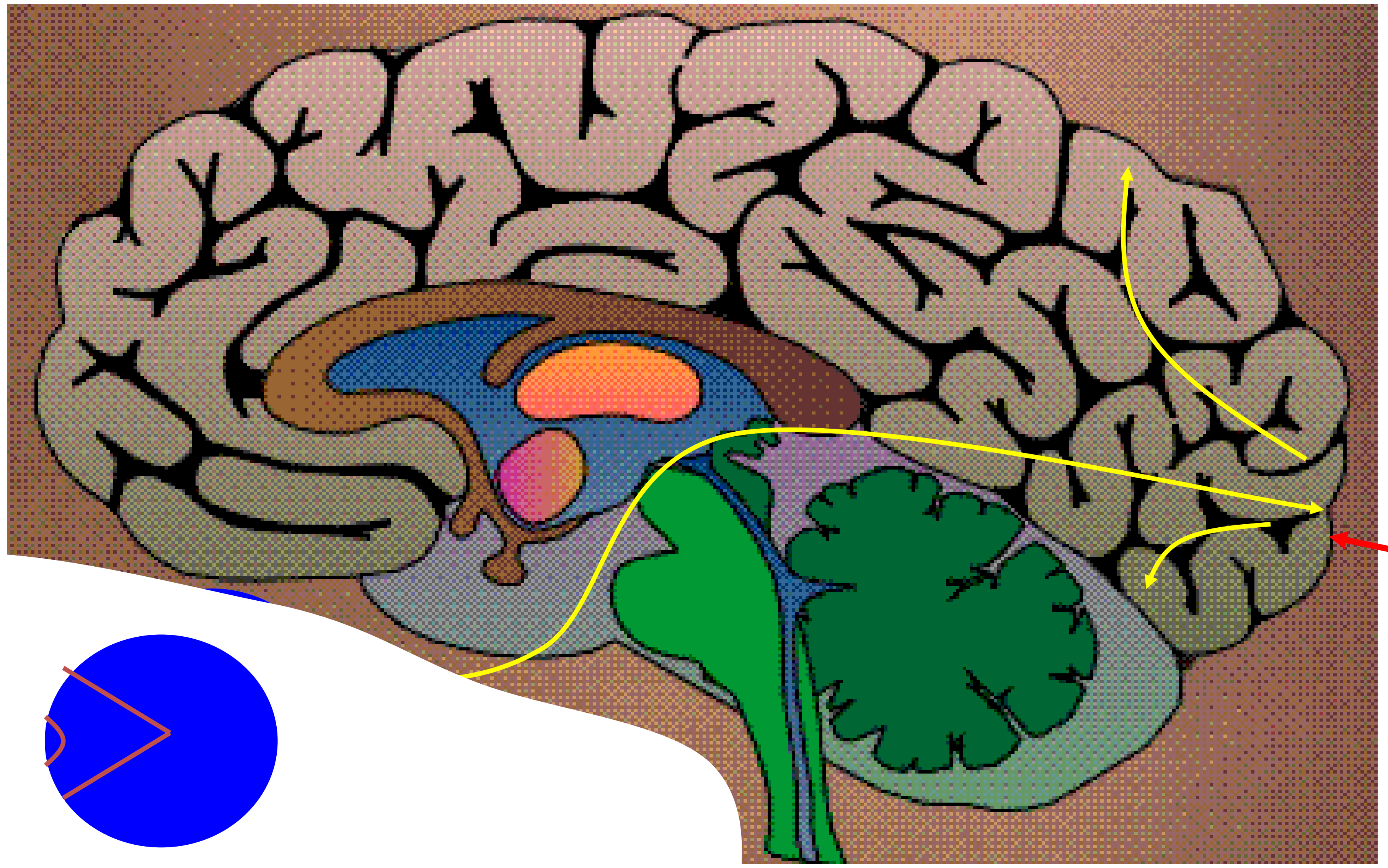
-What is a good ‘processing’ model?
-Estimate parameters of models?
-How does a neuron encode?
-Decoding: what do we learn from a spike train?

Model of ‘Encoding’

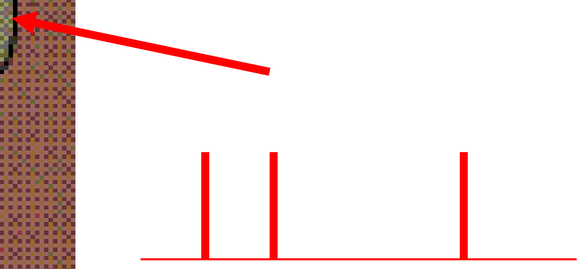
Neuronal Dynamics – 9.1 intro: Model of DECODING

Predict stimulus!





visual
cortex



Model of ‘Decoding’:

predict stimulus, given spike times

Week 9 – part 4 : Generalized linear model

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Biological Modeling of Neural Networks:

Week 9 – Coding and Decoding

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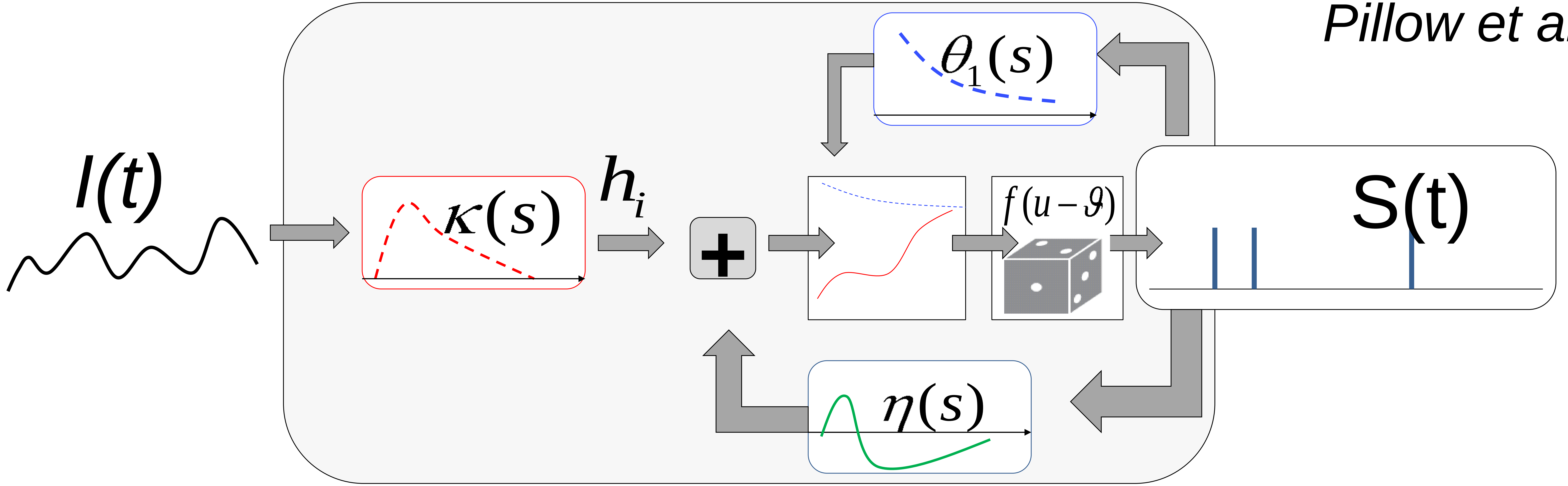
Spike Response Model (SRM)
Generalized Linear Model GLM

Gerstner et al., 1992,2000
Truccolo et al., 2005
Pillow et al. 2008



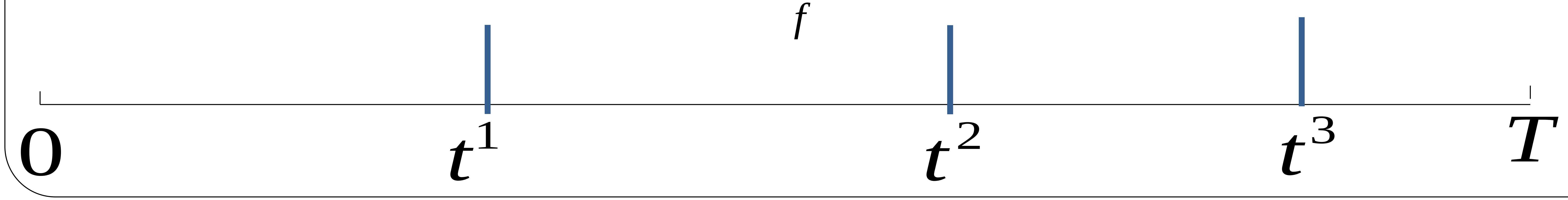
potential $u(t) = \int \eta(s)\, S(t-s)\,ds + \int_0^\infty \kappa(s)\, I(t-s)\,ds + u_{rest}$

threshold $\vartheta(t) = \theta_0 + \int \theta_1(s) S(t-s)\,ds$

firing intensity $\rho(t) = f(u(t) - \vartheta(t))$

Neuronal Dynamics – 9.4 Likelihood of a spike train

$$S(t) = \sum_f \delta(t - t^f)$$

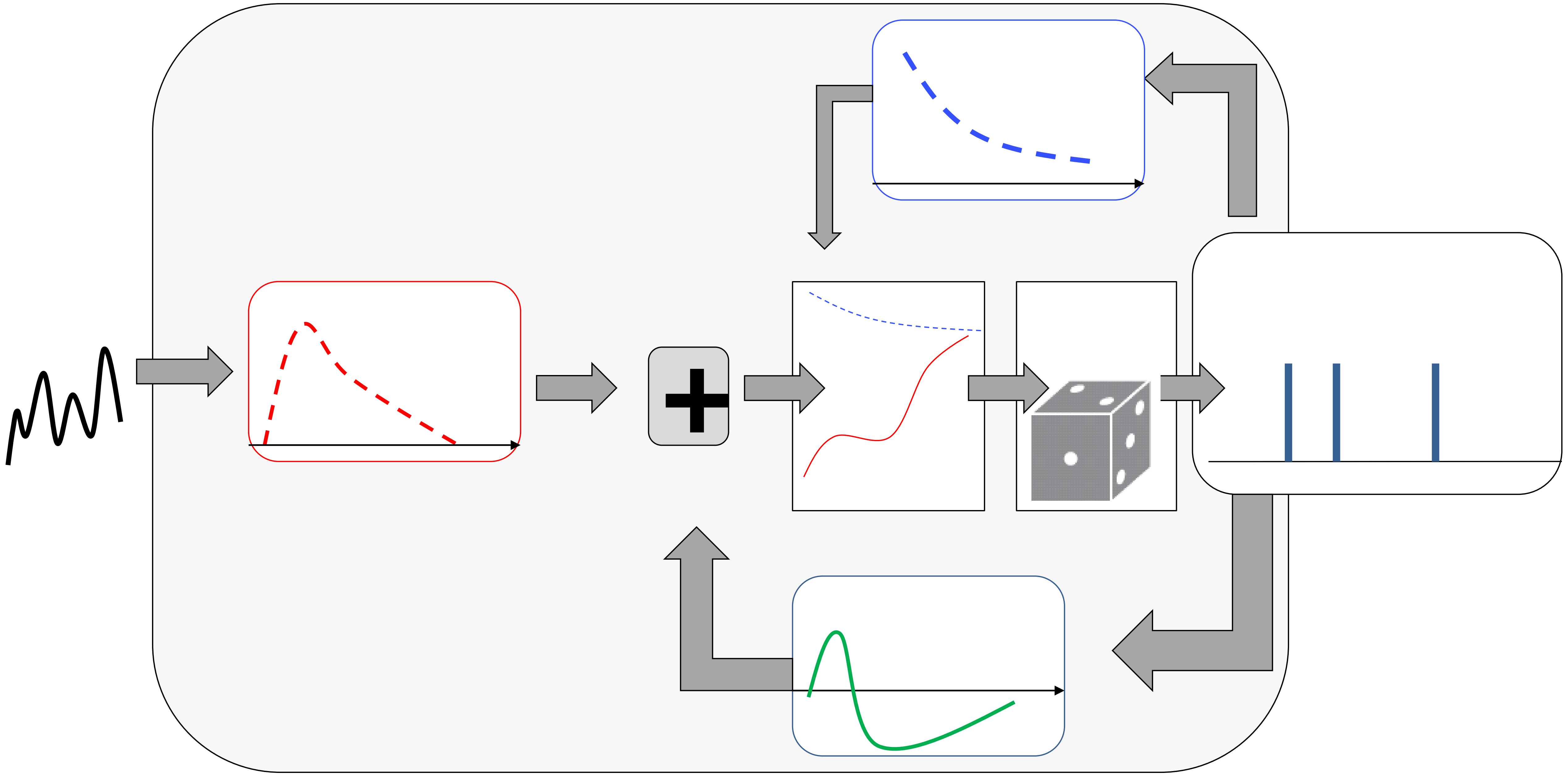


$$L(t^1,\ldots,t^N) = \exp\left(-\int_0^{t^1} \rho(t')dt'\right)\rho(t^1) \cdot \exp\left(-\int_{t^1}^{t^2} \rho(t')dt'\right)\rho(t^2)\ldots \cdot \exp\left(-\int_{t^N}^{T} \rho(t')dt'\right)$$

$$L(t^1,\ldots,t^N) = \exp\left(-\int_0^{T} \rho(t')dt'\right)\prod_f \rho(t^f)$$

$$\log L(t^1,\ldots,t^N) = -\int_0^{T} \rho(t')dt' + \sum_f \log \rho(t^f)$$

Neuronal Dynamics – 9.4 SRM with escape noise = GLM



-linear filters
-escape rate
→likelihood of observed spike train

→parameter optimization of neuron model

Week 9 – part 6 : Modeling in vitro data

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Week 9 –

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- for one neuron

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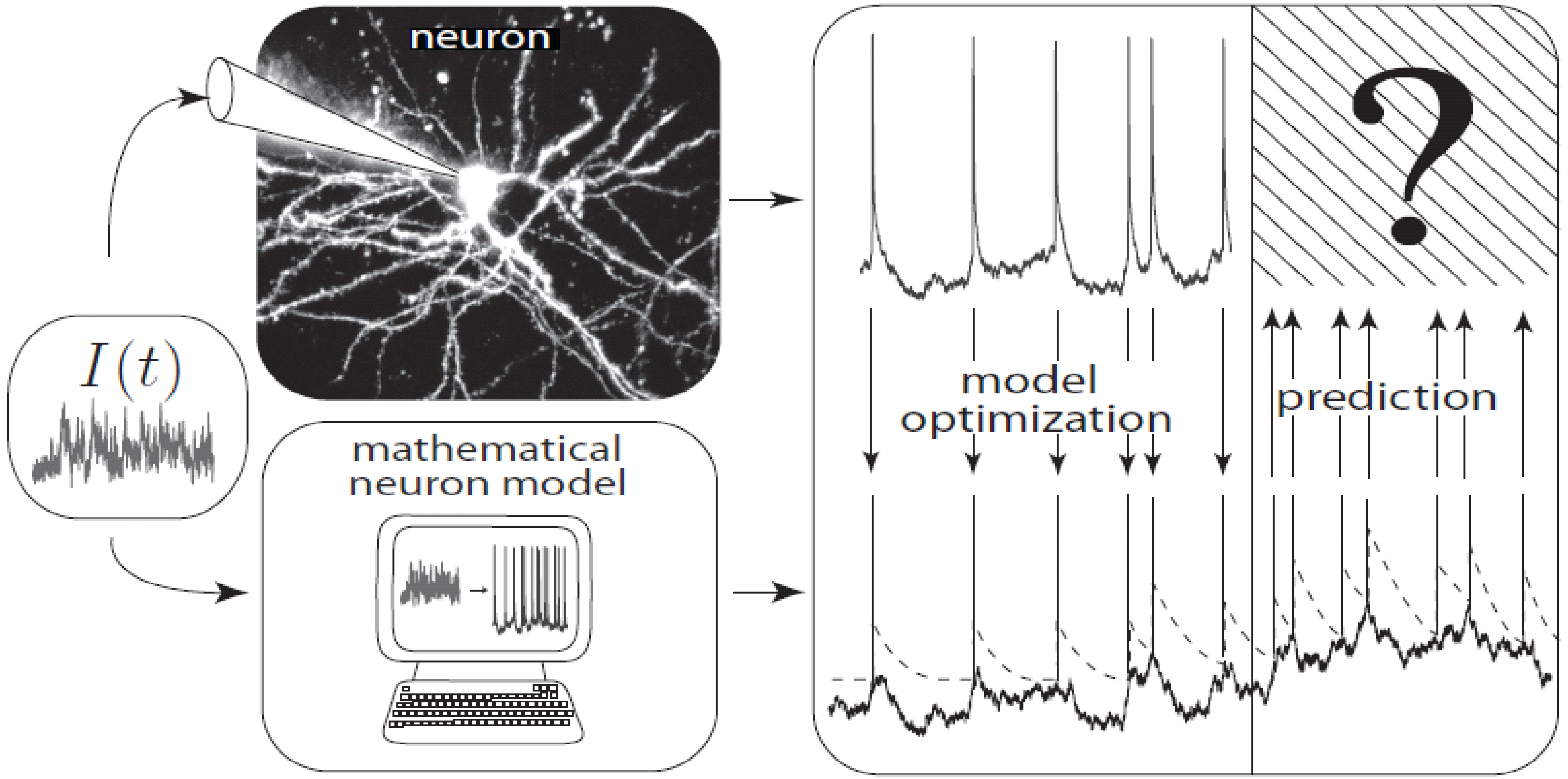
comparison model-data



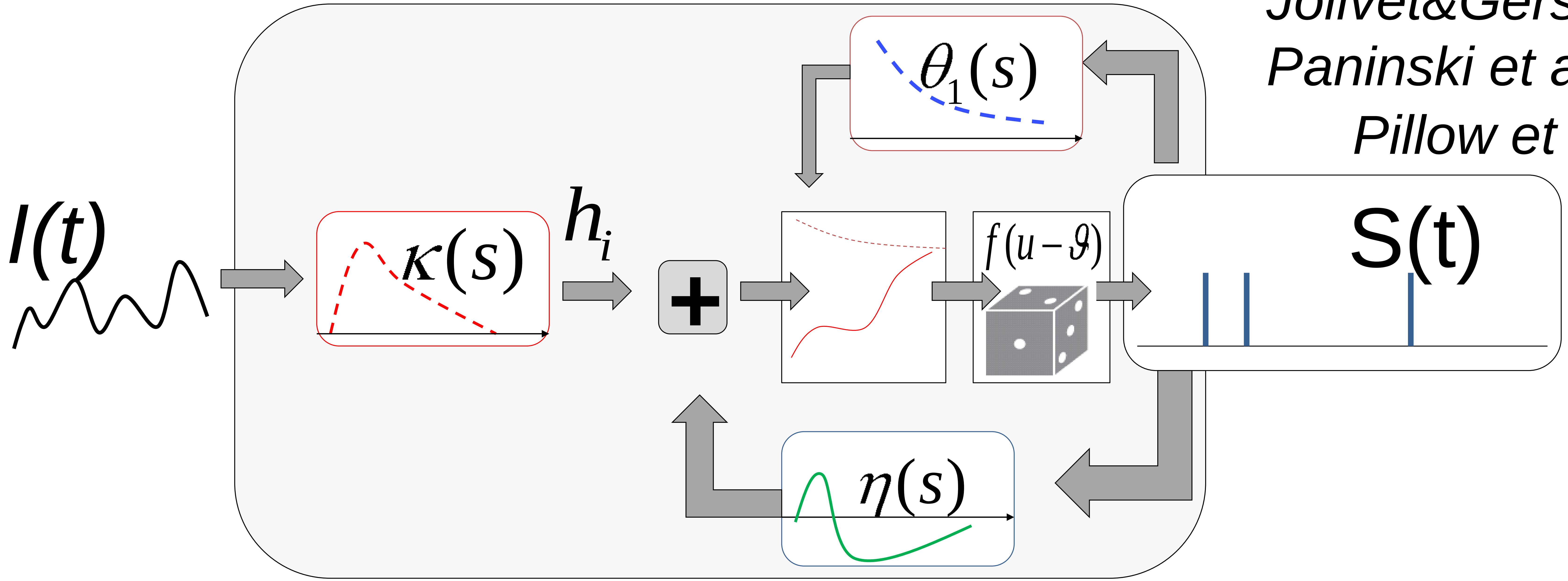
Predict

-Subthreshold voltage

-Spike times

Neuronal Dynamics – 9.6 GLM/SRM with escape noise

Jolivet&Gerstner, 2005
Paninski et al., 2004
Pillow et al. 2008



potential $u(t)=\int \eta(s)\,S(t-s)\,ds+\int_0^\infty \kappa(s)\,I(t-s)\,ds+u_{rest}$

threshold $\vartheta(t)=\theta_0+\int \theta_1(s)S(t-s)\,ds$

firing intensity $\rho(t)=f(u(t)-\vartheta(t))$

Neuronal Dynamics – 9.6 GLM/SRM predict subthreshold voltage

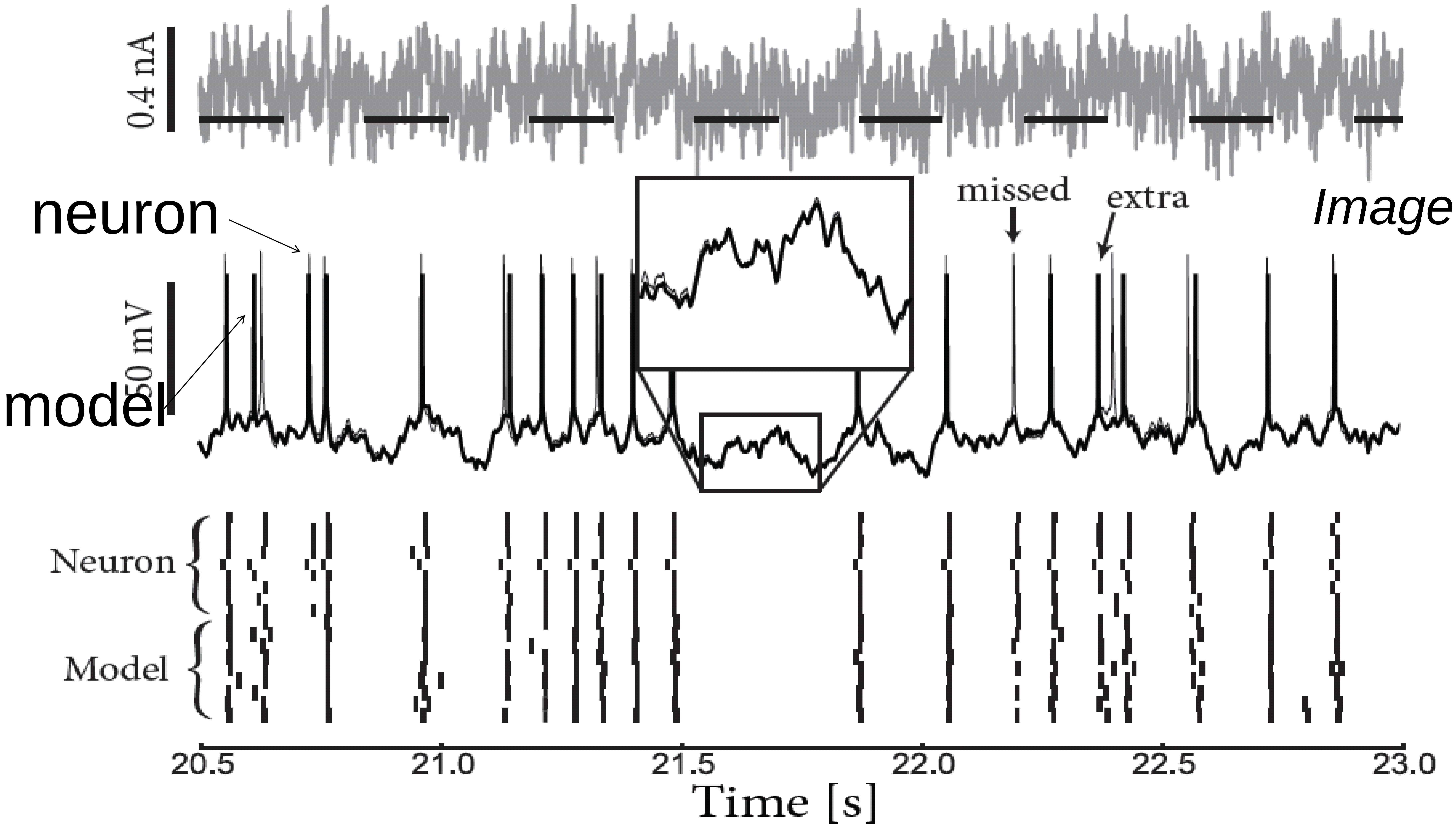
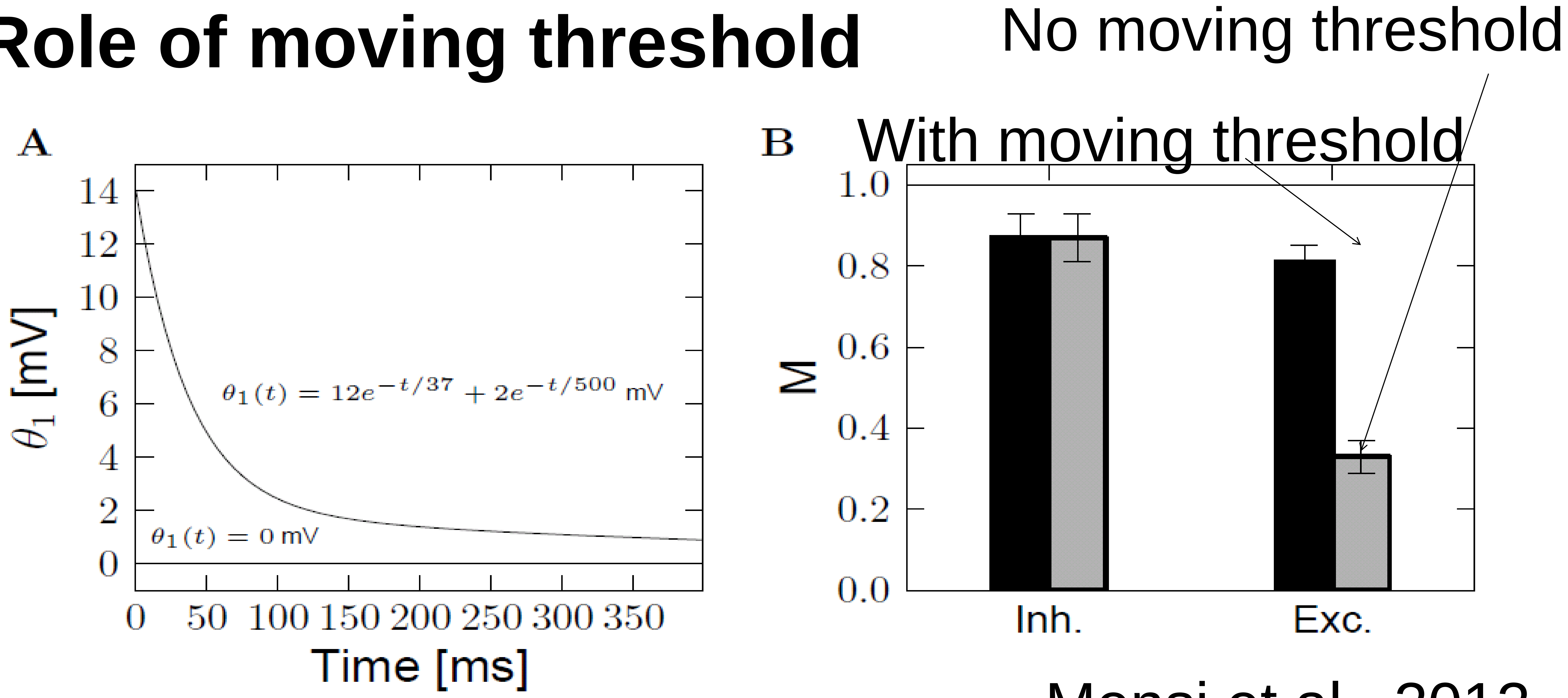


Image:Mensi et al.

Role of moving threshold



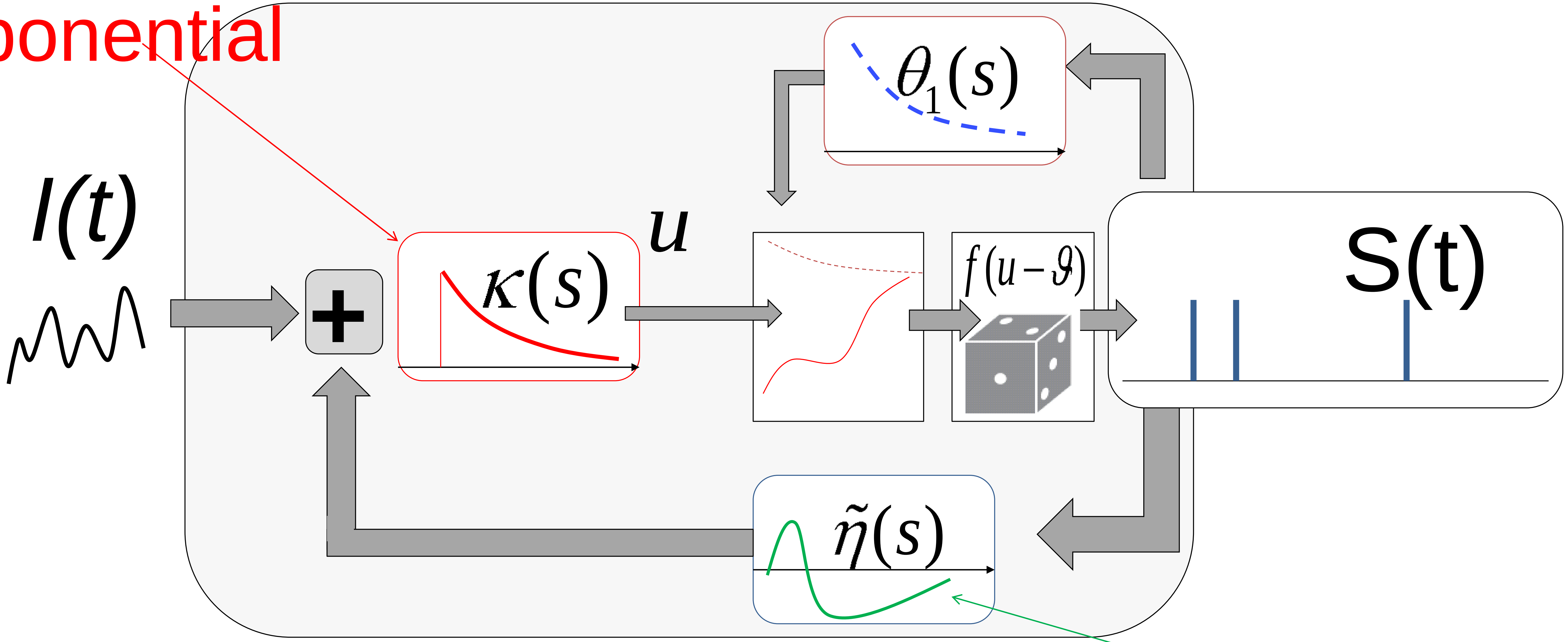
Mensi et al., 2012

Change in model formulation:

What are the units of …. ?

'soft-threshold adaptive IF model'

exponential



adaptation current

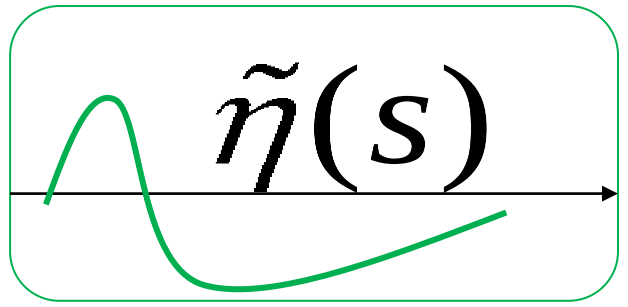
potential $$C\frac{d}{dt}u\ \ t\ = \int \underline{\tilde{\eta}\ \ s}\ S(t-s)ds \quad +I(t)$$

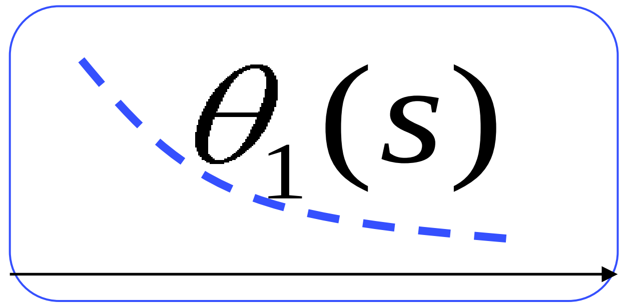
threshold $$\vartheta(t) = \theta_0 + \int \underline{\theta_1(s)} S(t-s)ds$$

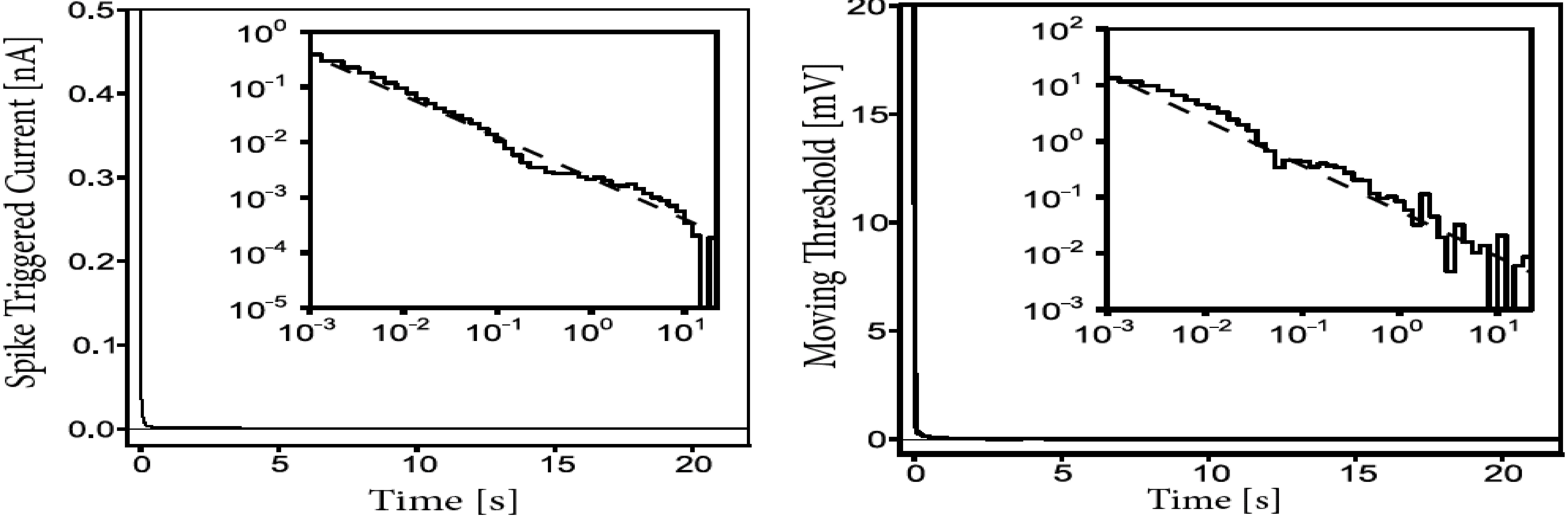
firing intensity $$\rho(t) = f(u(t) - \vartheta(t))$$

Time scale of filters?

→ **Power law**







Pozzorini et al. 2013

A single spike has a measurable effect more than 10 seconds later!

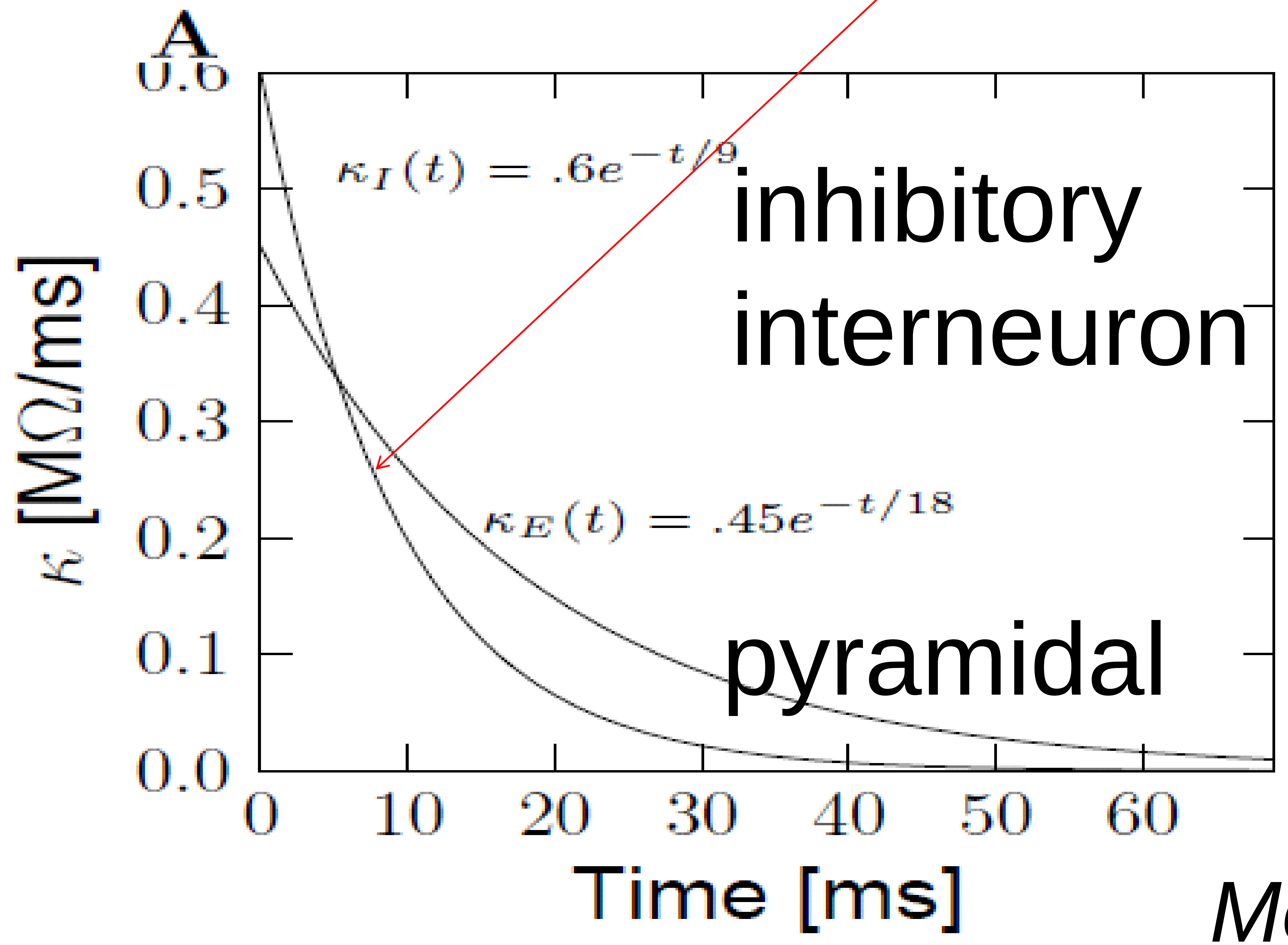
Neuronal Dynamics – 9.6 Extracted parameters: voltage

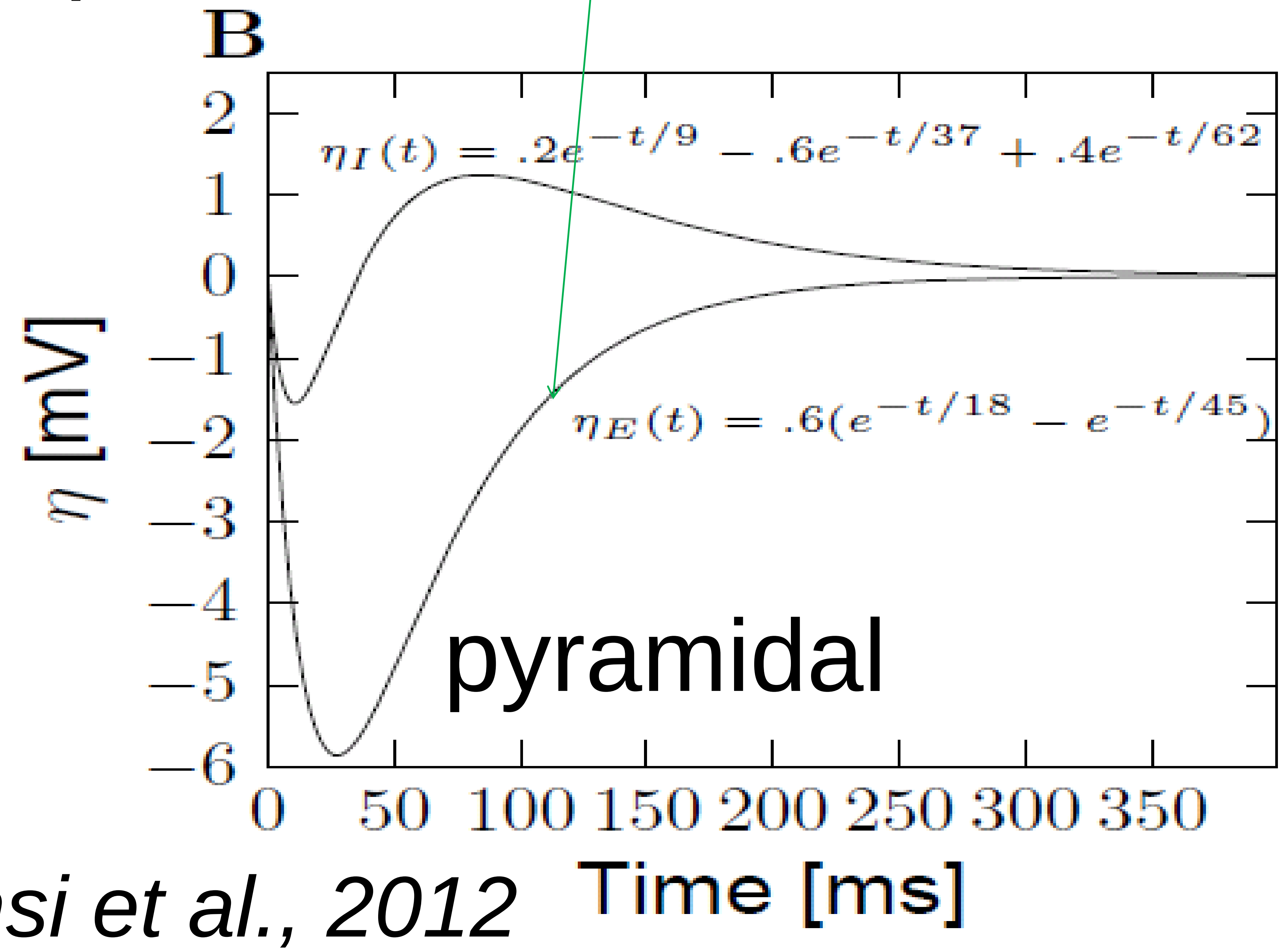
Subthreshold potential

$$u(t) = \int_0^\infty \underline{\kappa(s)}\, I(t-s)\,ds + u_{rest} + \int \underline{\eta(s)}\, S(t-s)\,ds$$

known input

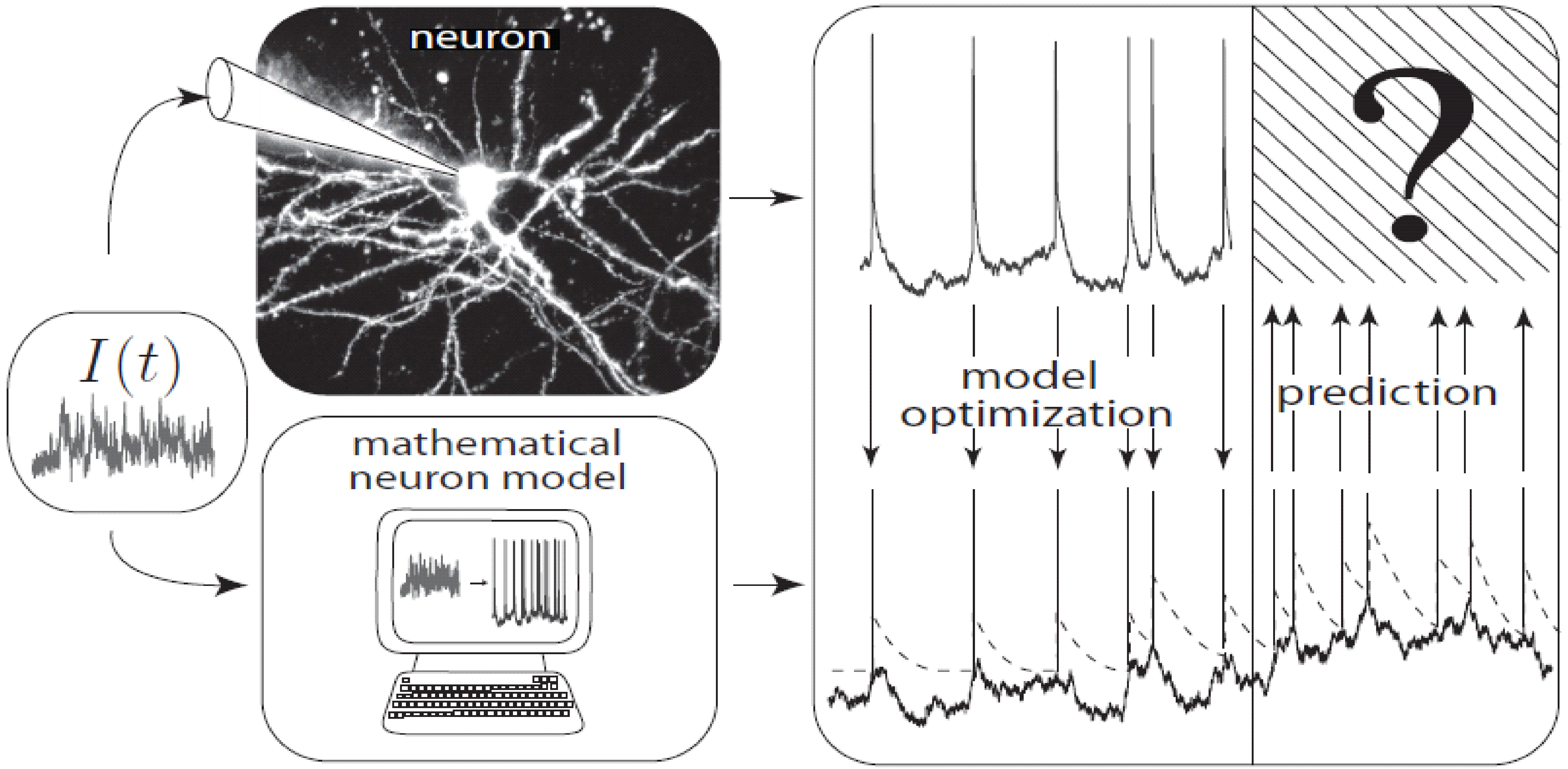
known spike train





Mensi et al., 2012

Neuronal Dynamics – 9.6 Models and Data



-Predict spike times
-Predict subthreshold voltage
-Easy to interpret (not a ‘black box’)
-Variety of phenomena
-Systematic: ‘optimize’ parameters

BUT so far limited to in vitro

Week 9 – part 7 : Models and data

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Biological Modeling of Neural Networks:

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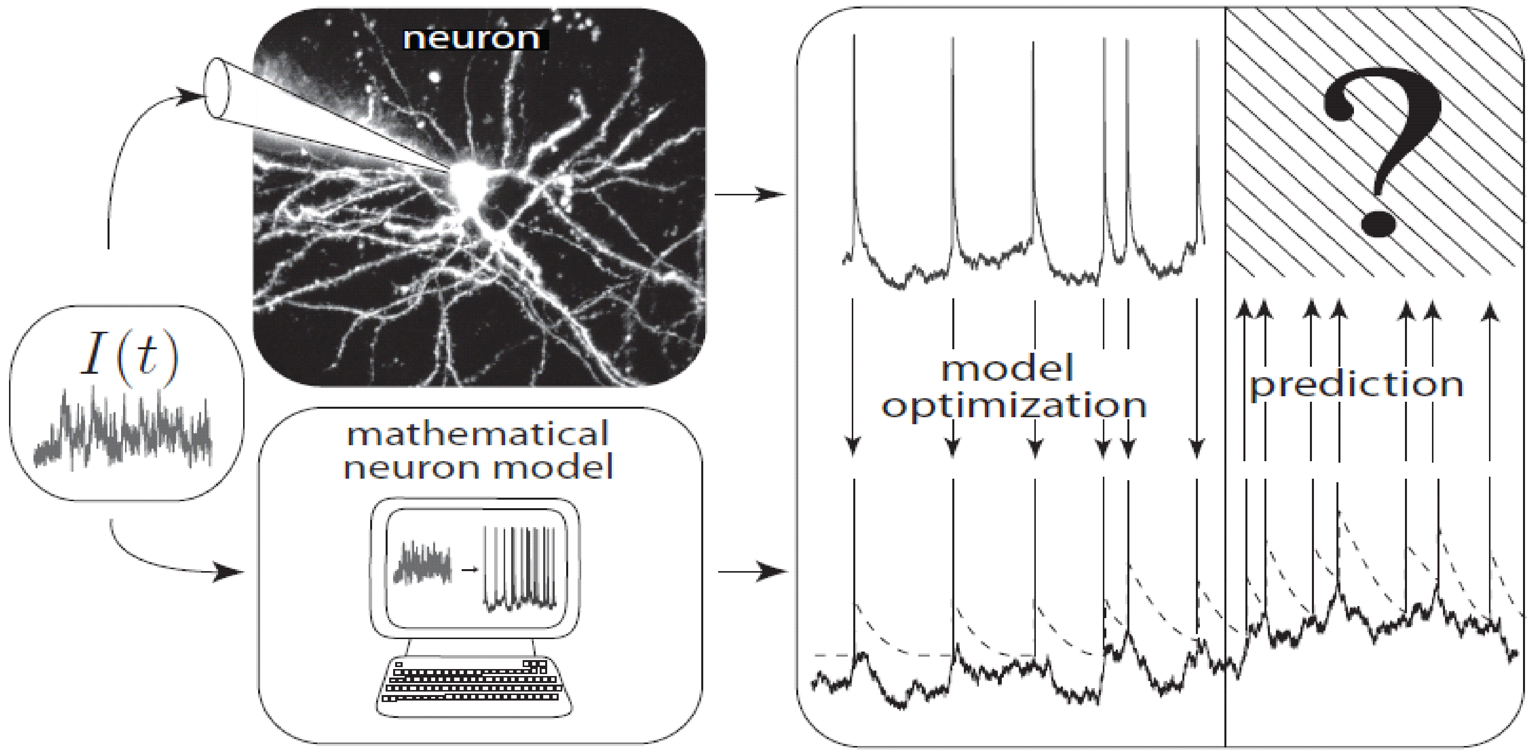
Neuronal Dynamics – Review: Models and Data

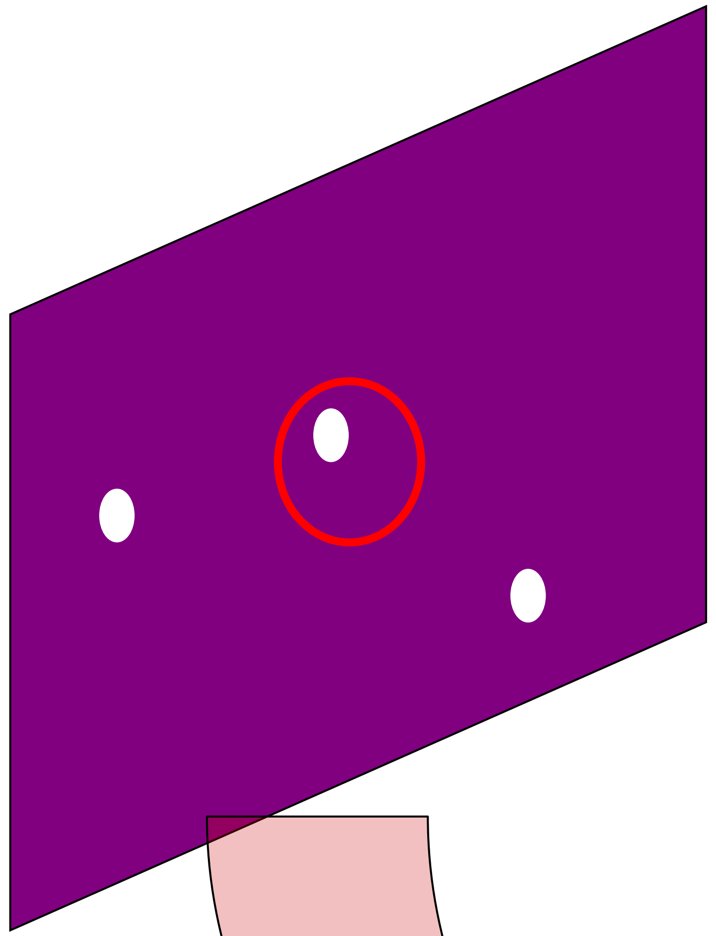


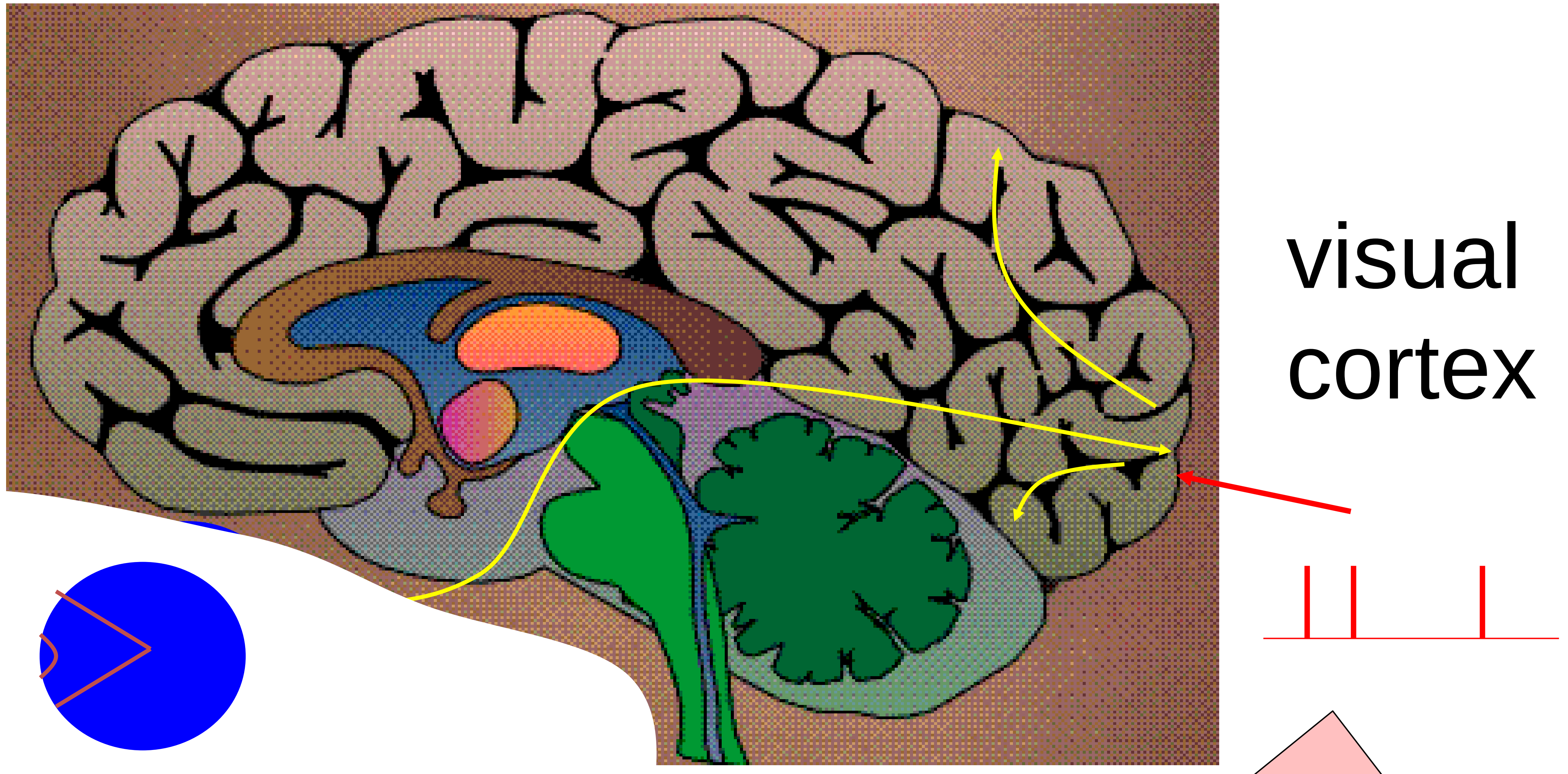
-Predict spike times
-Predict subthreshold voltage
-Easy to interpret (not a 'black box')
-Variety of phenomena
-Systematic: 'optimize' parameters

BUT so far limited to in vitro

Neuronal Dynamics – 9.7 Systems neuroscience, in vivo

Now: extracellular recordings





A) Predict spike times, given stimulus
B) ~~Predict subthreshold voltage~~
C) Easy to interpret (not a 'black box')
D) Flexible enough to account for a variety of phenomena
E) Systematic procedure to 'optimize' parameters

Model of 'Encoding'

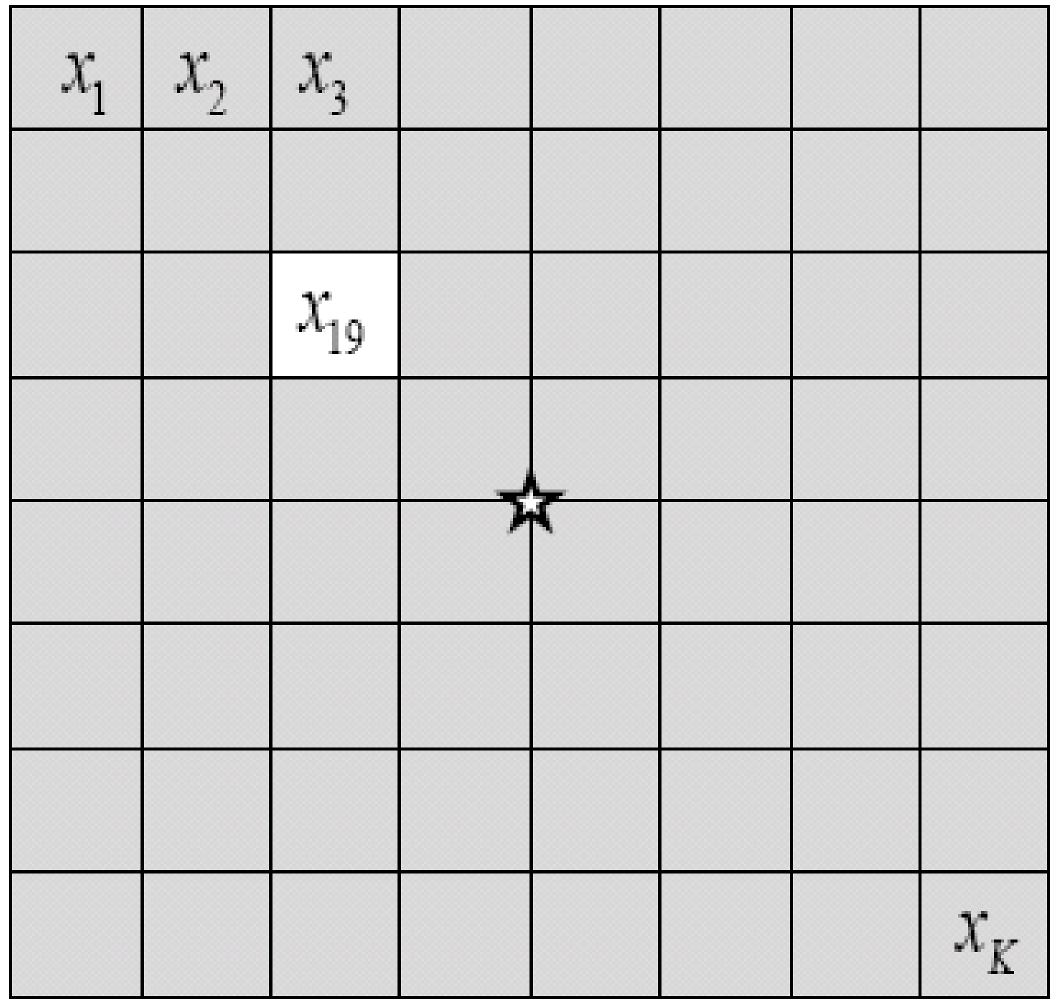
Estimation of spatial (and temporal) receptive fields

$$u(t) = \sum k_k \, I_{K-k} + u_{rest}$$

LNP

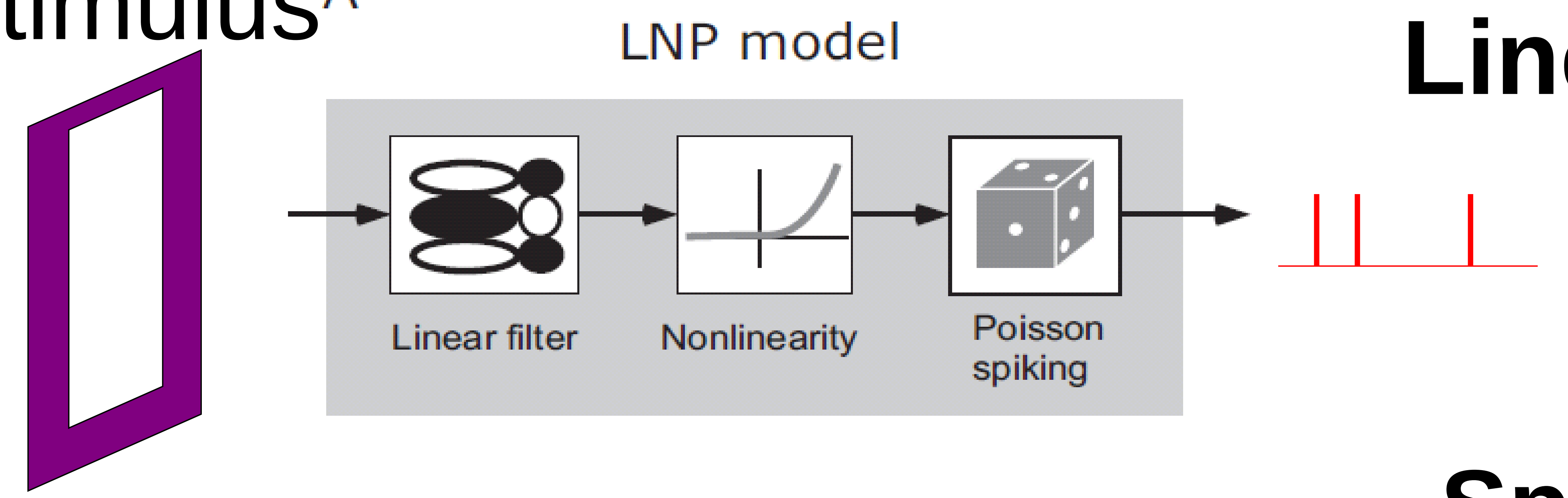
firing intensity $\rho(t) = f\,(u(t) - \vartheta(t))$

$$\vec{x}_t = (x_1, \; x_2, \; x_3, \; \ldots, \; x_K)$$

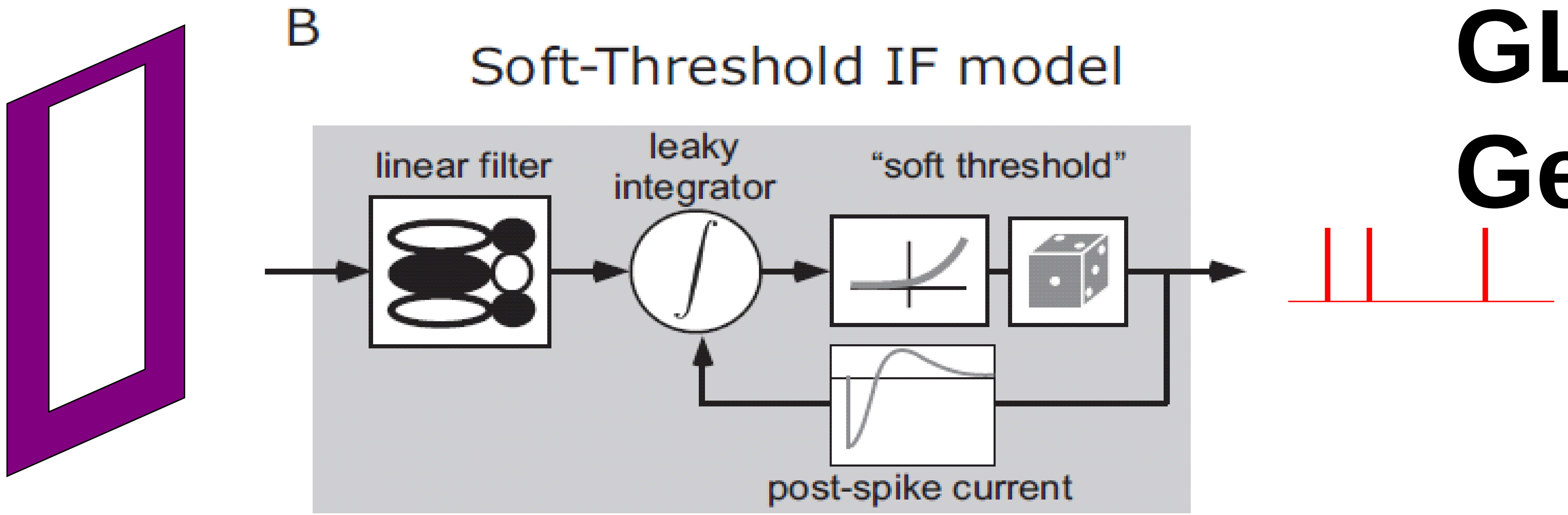


$$\begin{array}{l|c}
\text{time} \diagdown \text{input } \vec{\mathbf{x}} & \begin{array}{cccccc} x_1 & x_2 & x_3 & \ldots & & x_K \end{array} \\
\hline
\begin{array}{l} t=1 \\ t=2 \\ t=3 \\ . \\ . \\ . \\ t=T \end{array} & \left(\begin{array}{cccccc} 0 & 1 & 0 & 0 & & 0 \\ 0 & 0 & 1 & 0 & & 0 \\ 0 & 0 & 0 & 0 & & 1 \\ & & & & & \\ & & & & & \\ & & & & & \\ 0 & 0 & 0 & 0 & 1 & 0 \end{array} \right) \mathrm{d}t
\end{array}$$

visual stimulus

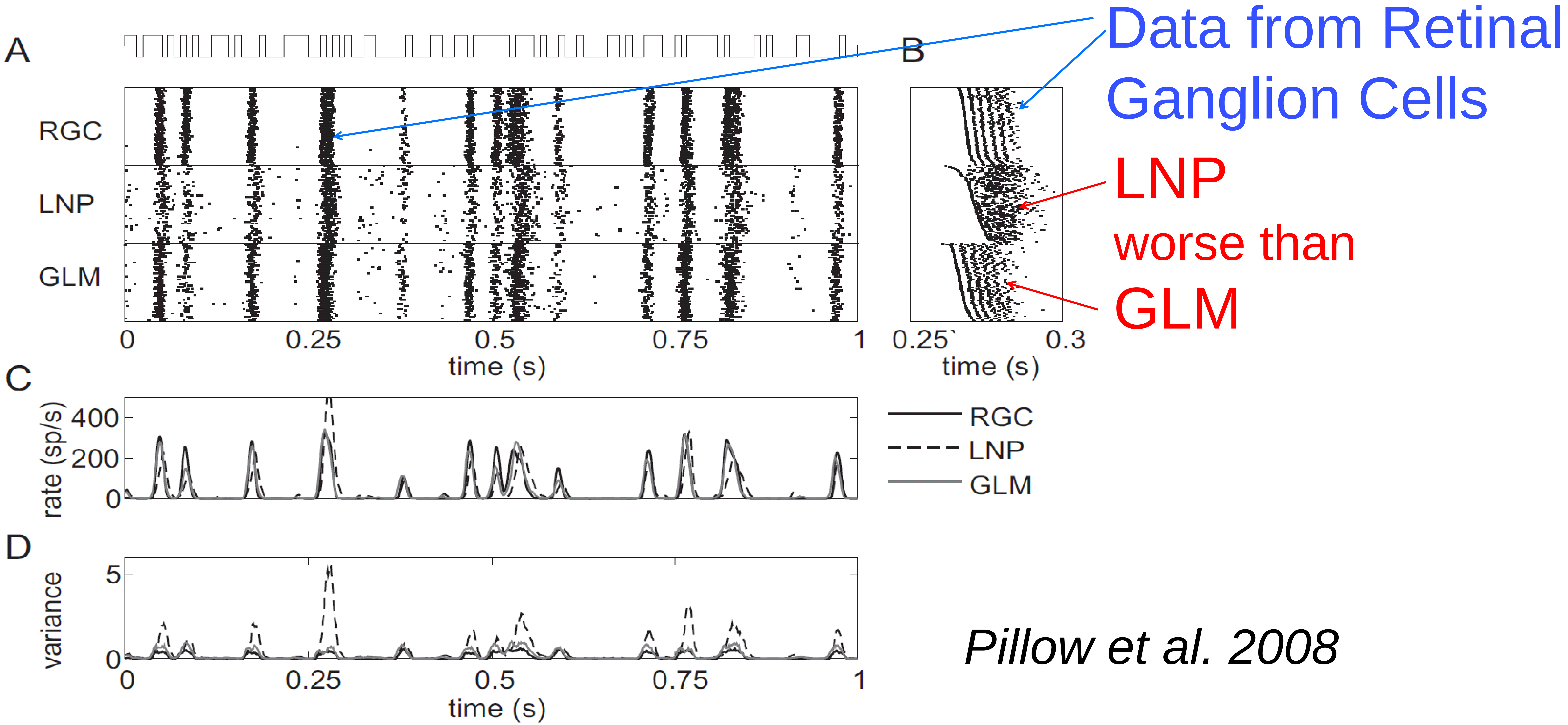


LNP = Linear-Nonlinear-Poisson



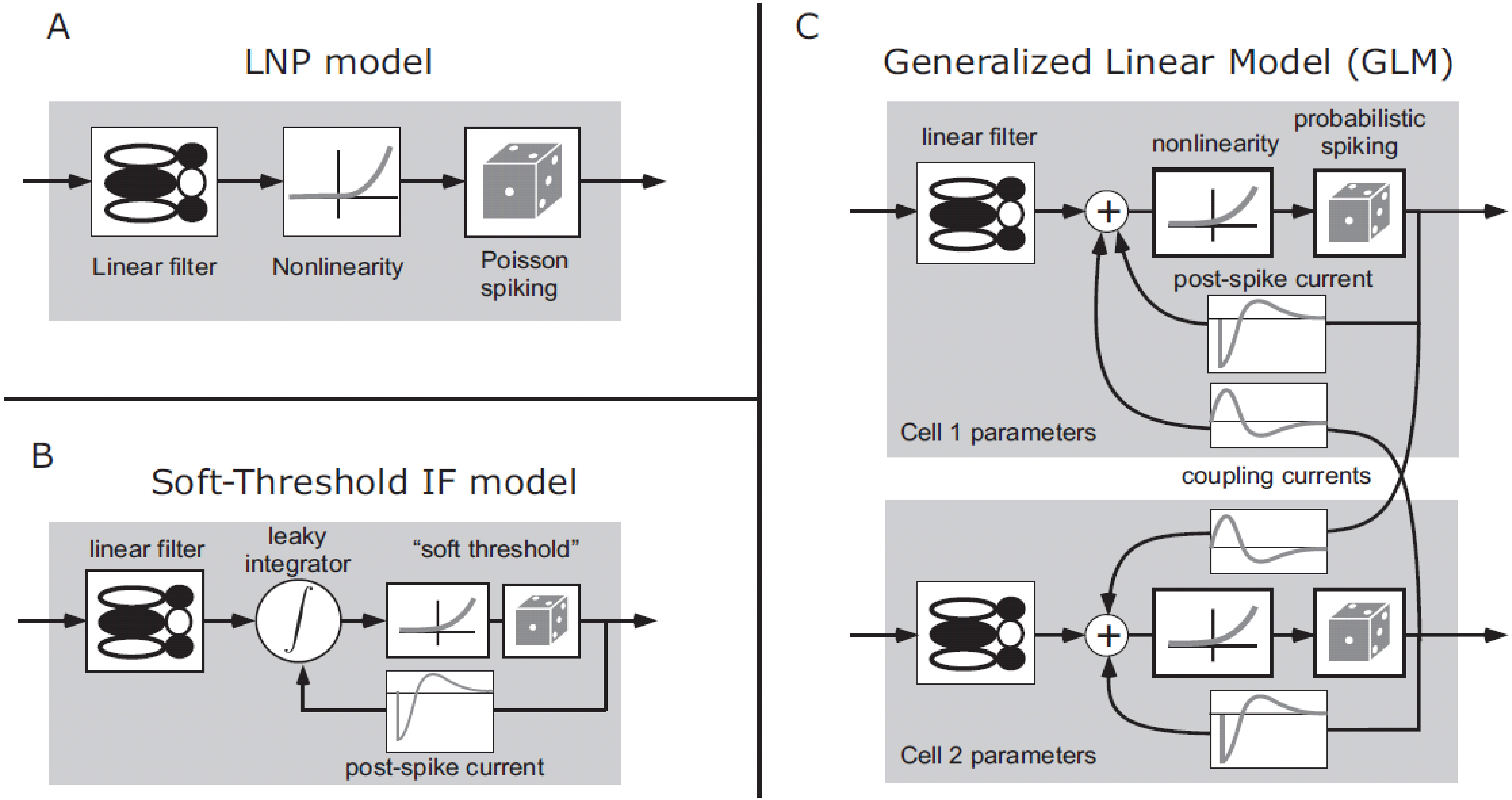
Special case of GLM= Generalized Linear Model

GLM for prediction of retinal ganglion ON cell activity



Pillow et al. 2008

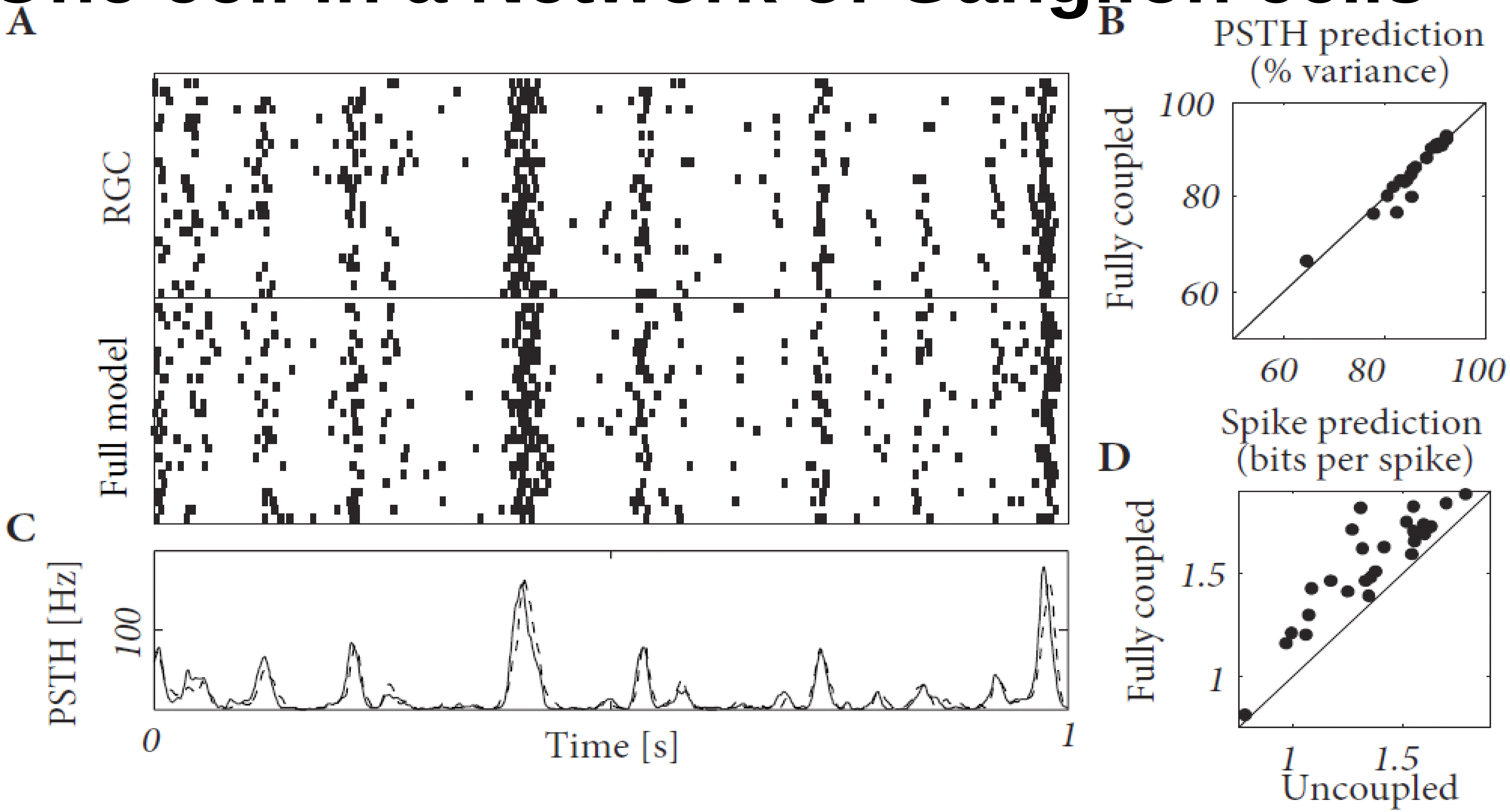
Neuronal Dynamics – 9.7 GLM with lateral coupling



Neuronal Dynamics – 9.7 GLM with lateral coupling

One cell in a Network of Ganglion cells

Pillow et al. 2008

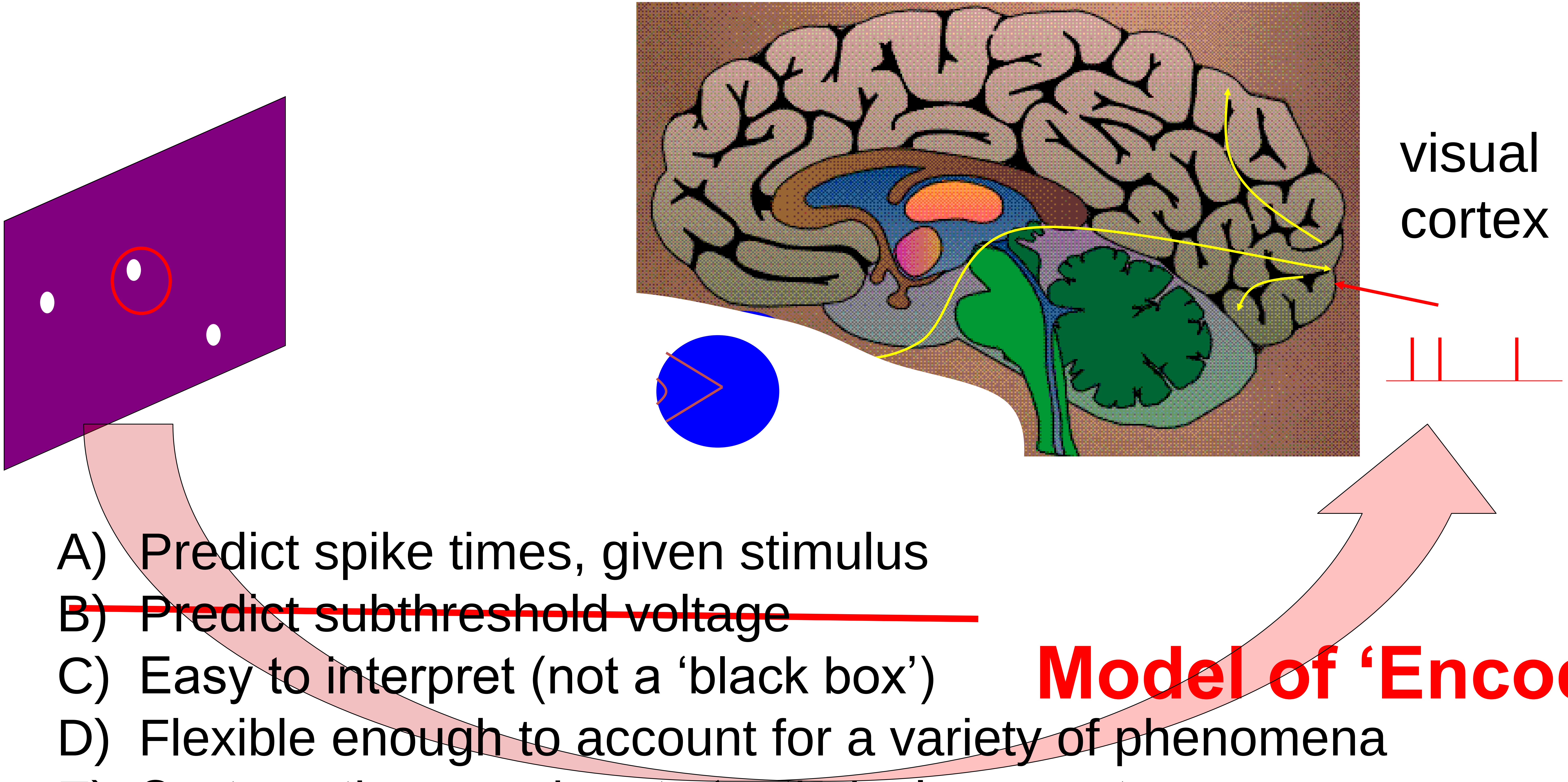


coupled GLM

Better than Uncoupled GLM

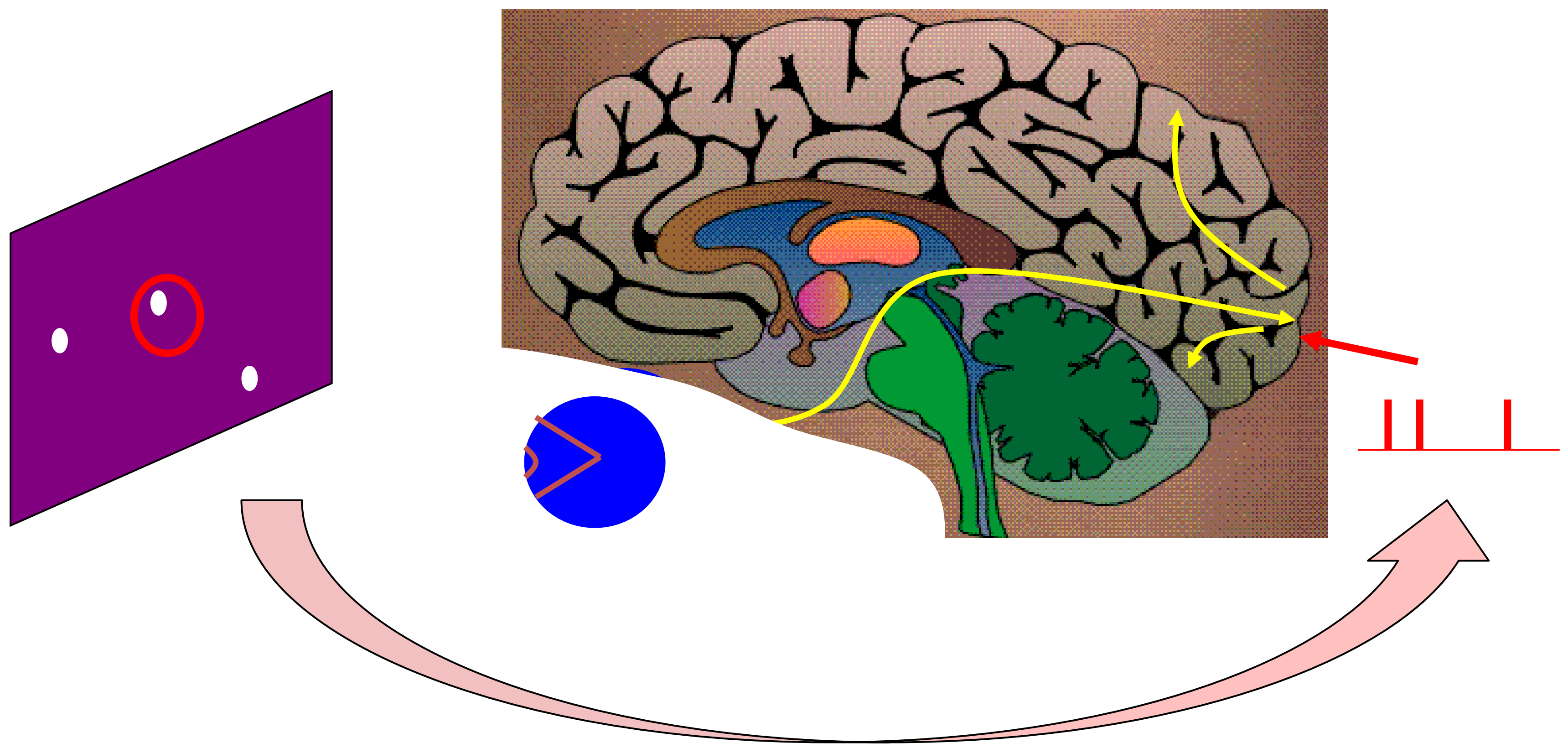
Image: Gerstner et al., Neuronal Dynamics, Cambridge 2014

Neuronal Dynamics – 9.7 Model of ENCODING



A) Predict spike times, given stimulus
B) ~~Predict subthreshold voltage~~
C) Easy to interpret (not a 'black box')
D) Flexible enough to account for a variety of phenomena
E) Systematic procedure to 'optimize' parameters

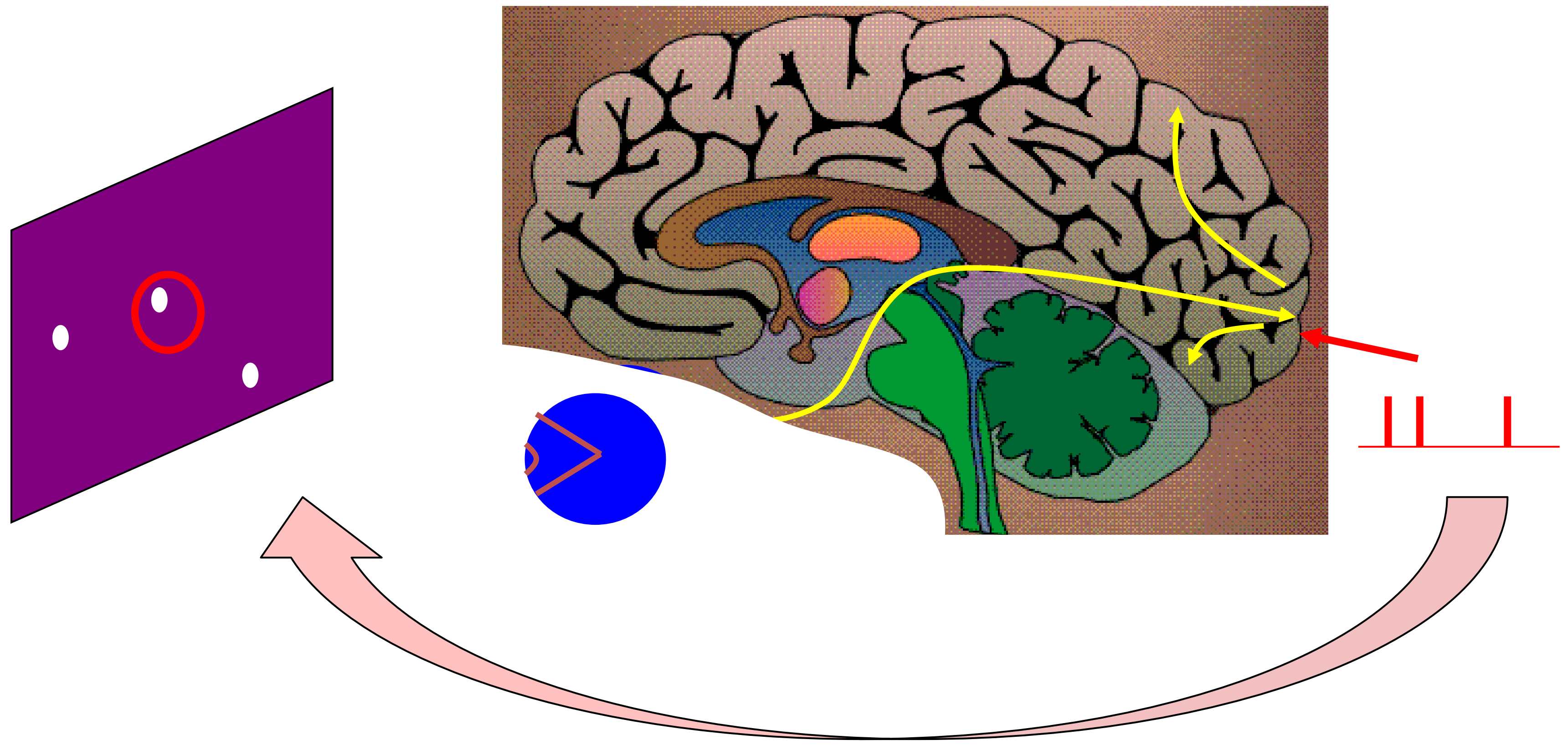
Model of 'Encoding'



Model of 'Encoding'

Generalized Linear Model (GLM)

- flexible model
- systematic optimization of parameters

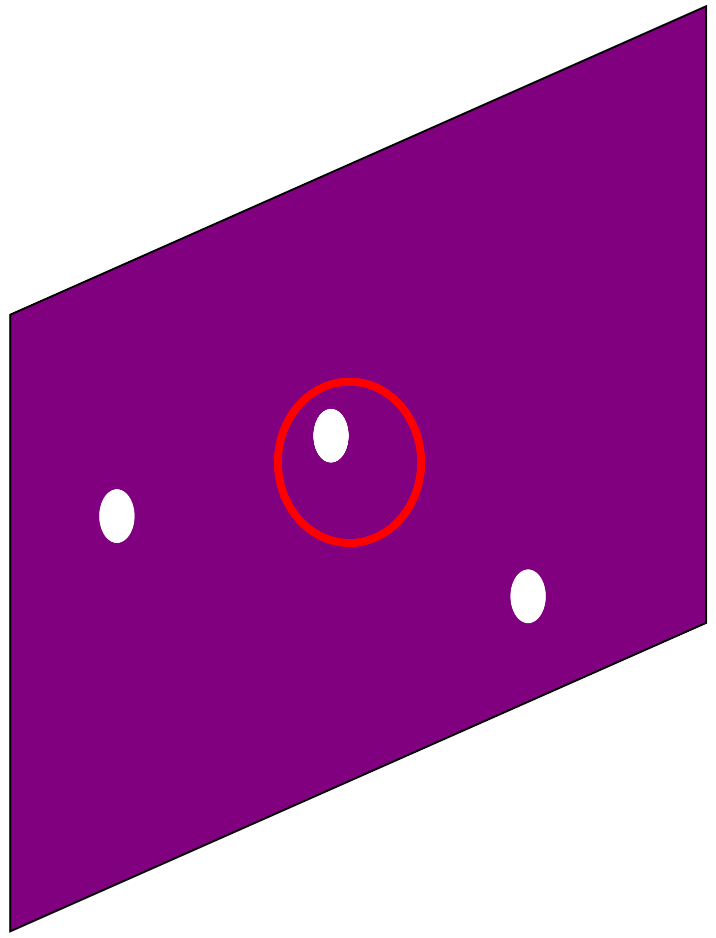


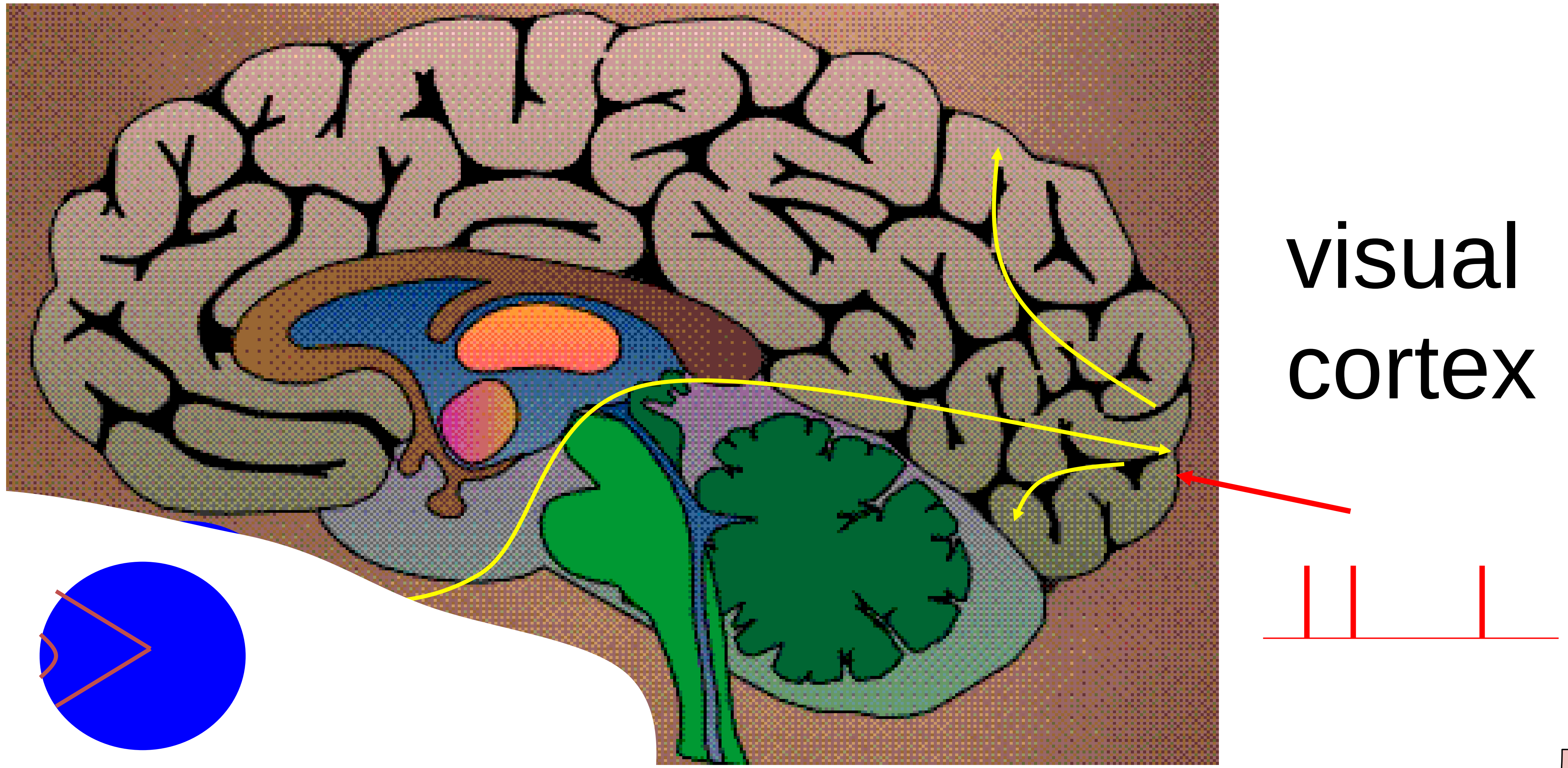
Model of 'Decoding'

The same GLM works!

- flexible model
- systematic optimization of parameters

Predict stimulus!

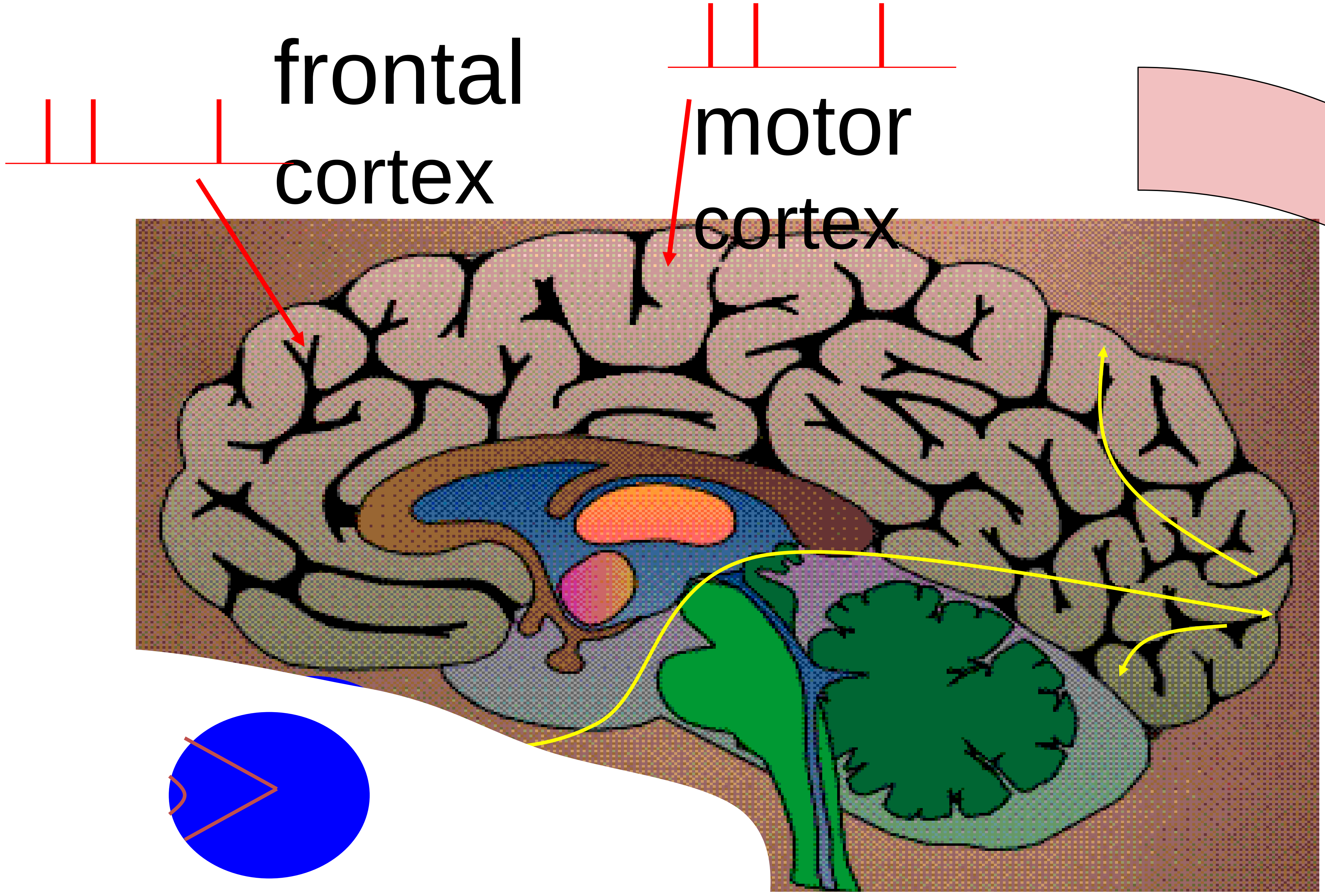




Model of ‘Decoding’:

predict stimulus, given spike times

Application: Neuroprosthetics



Many groups world wide work on this problem!

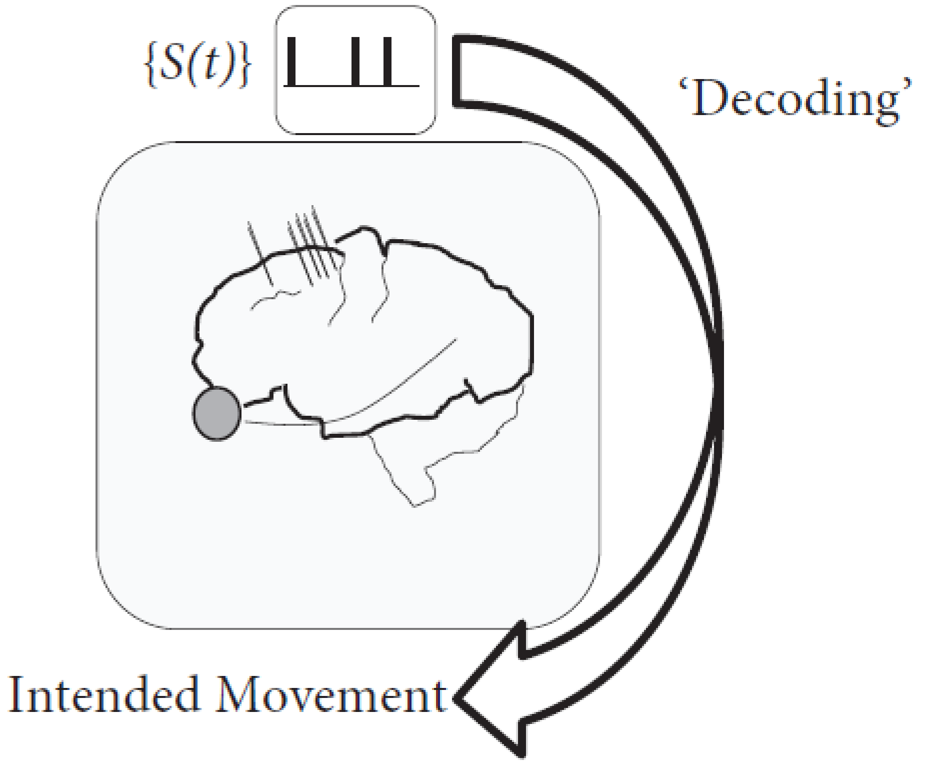
Model of 'Decoding'

Predict intended arm movement, given Spike Times

Application: Neuroprosthetics

Decode the intended arm movement

Hand velocity



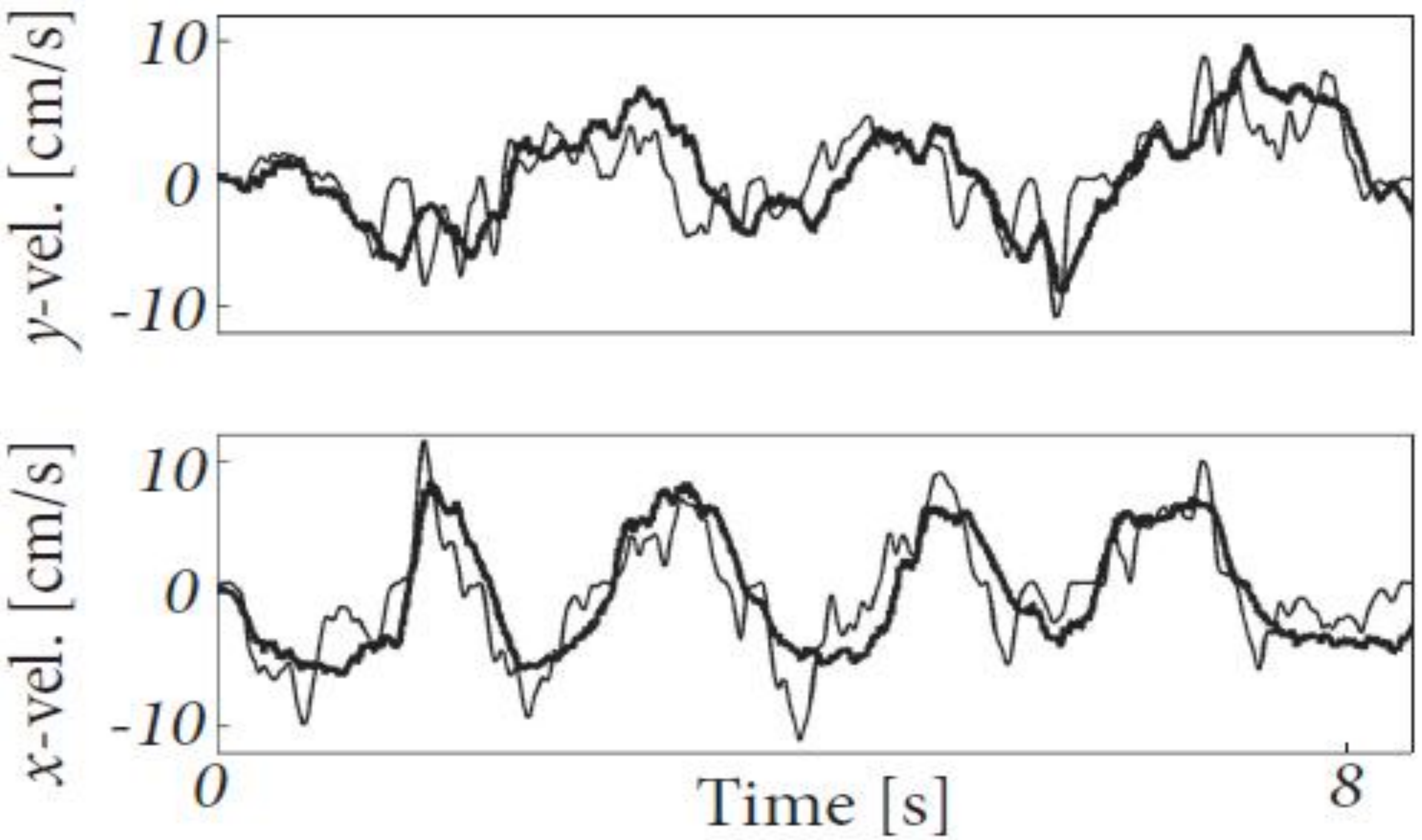


Image:
Gerstner et al.,
Neuronal Dynamics,
Cambridge 2014

Fig. 11.12: Decoding had velocity from spiking activity in area MI of cortex. The real hand velocity (thin black line) is compared to the decoded velocity (thick black line) for the $x-$ (top) and the $y-$components (bottom). Modified from Truccolo et al. (2005).

Mathematical models for neuroscience

↓

help humans

The end

Neuronal Dynamics week 9– Suggested Reading/selected references

Reading: W. Gerstner, W.M. Kistler, R. Naud and L. Paninski,
Neuronal Dynamics: from single neurons to networks and models of cognition. Ch. 10,11*:* Cambridge, 2014

Optimization methods for neuron models, max likelihood, and GLM

-Brillinger, D. R. (1988). Maximum likelihood analysis of spike trains of interacting nerve cells. *Biol. Cybern*., 59:189-200.

-Truccolo, et al. (2005). A point process framework for relating neural spiking activity to spiking history, neural ensemble, and extrinsic covariate effects. Journal of Neurophysiology, 93:1074-1089.

- Paninski, L. (2004). Maximum likelihood estimation of … *Network: Computation in Neural Systems*, 15:243-262.
- Paninski, L., Pillow, J., and Lewi, J. (2007). Statistical models for neural encoding, decoding, and optimal stimulus design. In Cisek, P., et al. , *Comput. Neuroscience: Theoretical Insights into Brain Function*. Elsevier Science.

Pillow, J., ET AL.(2008). Spatio-temporal correlations and visual signalling… . Nature, 454:995-999.

Encoding and Decoding

Rieke, F., Warland, D., de Ruyter van Steveninck, R., and Bialek, W. (1997). Spikes - Exploring the neural code. MIT Press,

Keat, J., Reinagel, P., Reid, R., and Meister, M. (2001). Predicting every spike … *Neuron*, 30:803-817.

Mensi, S., et al. (2012). Parameter extraction and classication …. *J. Neurophys.,*107:1756-1775.

Pozzorini, C., Naud, R., Mensi, S., and Gerstner, W. (2013). Temporal whitening by . *Nat. Neuroscience,*

Georgopoulos, A. P., Schwartz, A.,Kettner, R. E. (1986). Neuronal population coding of movement direction. *Science*, 233:1416-1419.

Donoghue, J. (2002). Connecting cortex to machines: recent advances in brain interfaces. Nat. Neurosci., 5:1085-1088.