Statistical models of visual neurons

Mid Year Presentation

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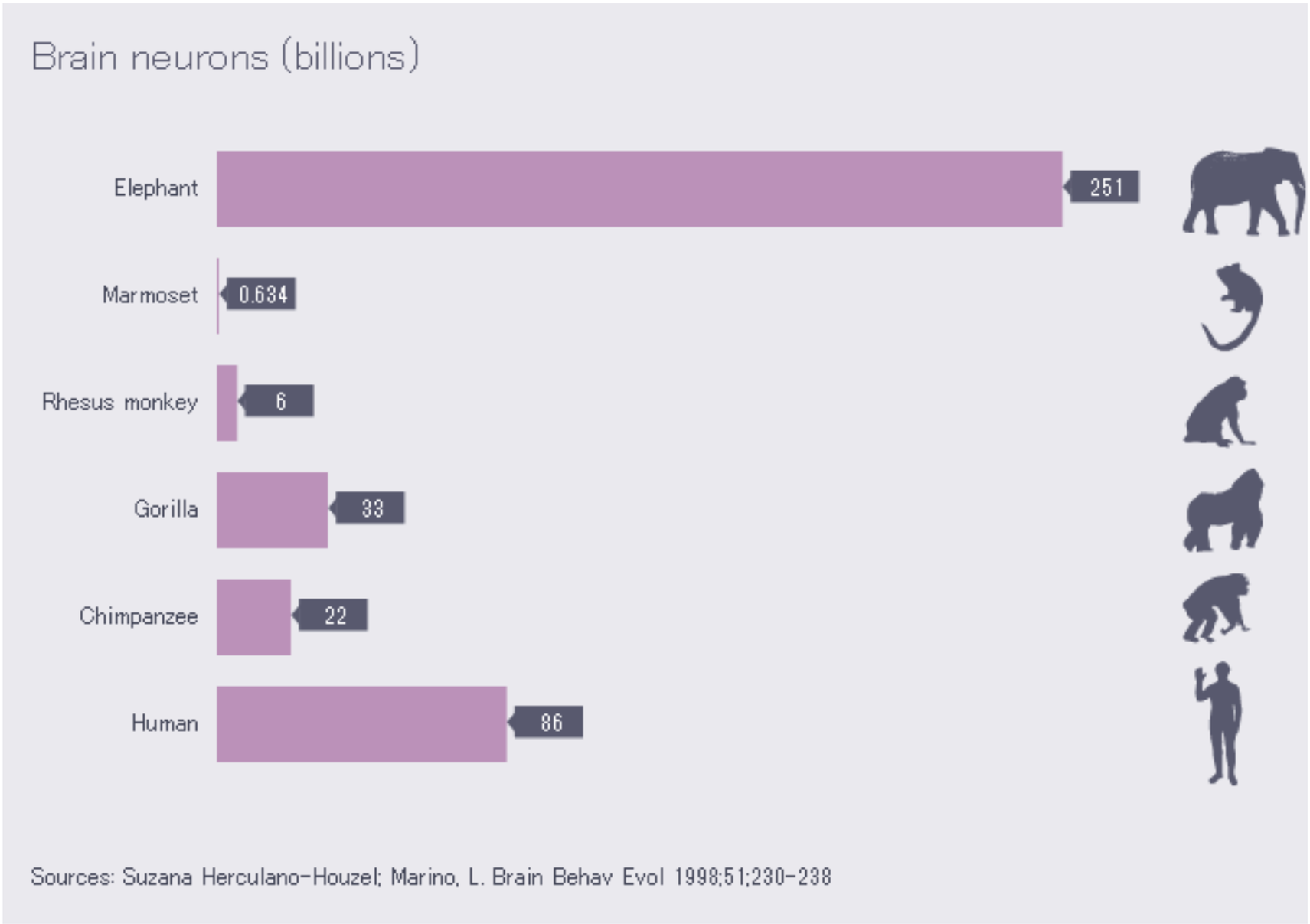
Introduction to “neurons”



If 1 neuron is 10 micrometers, then 86e9 neurons is 860 kilometers (534 miles)

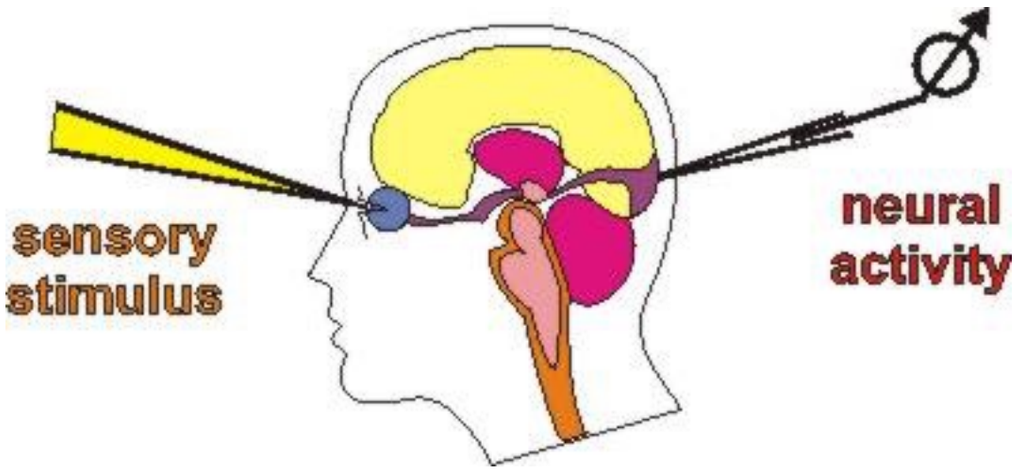
or

If one can count 1 neuron per second, then 86e9 neurons will take 2 727 years of counting

https://en.wikipedia.org/wiki/File:Brain_size_comparison_-_Brain_neurons_(billions).png

Visual system of a neuron

$\mathbf{S}(t)$

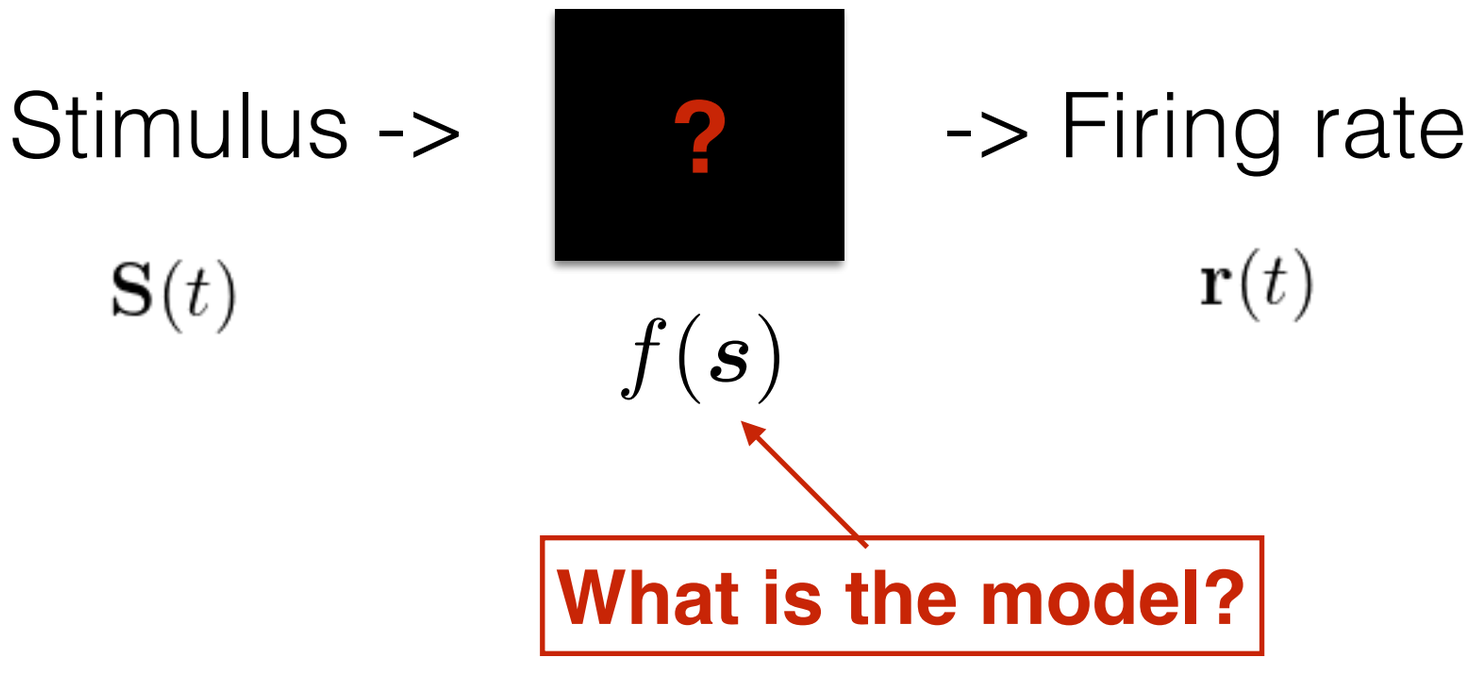


spikes

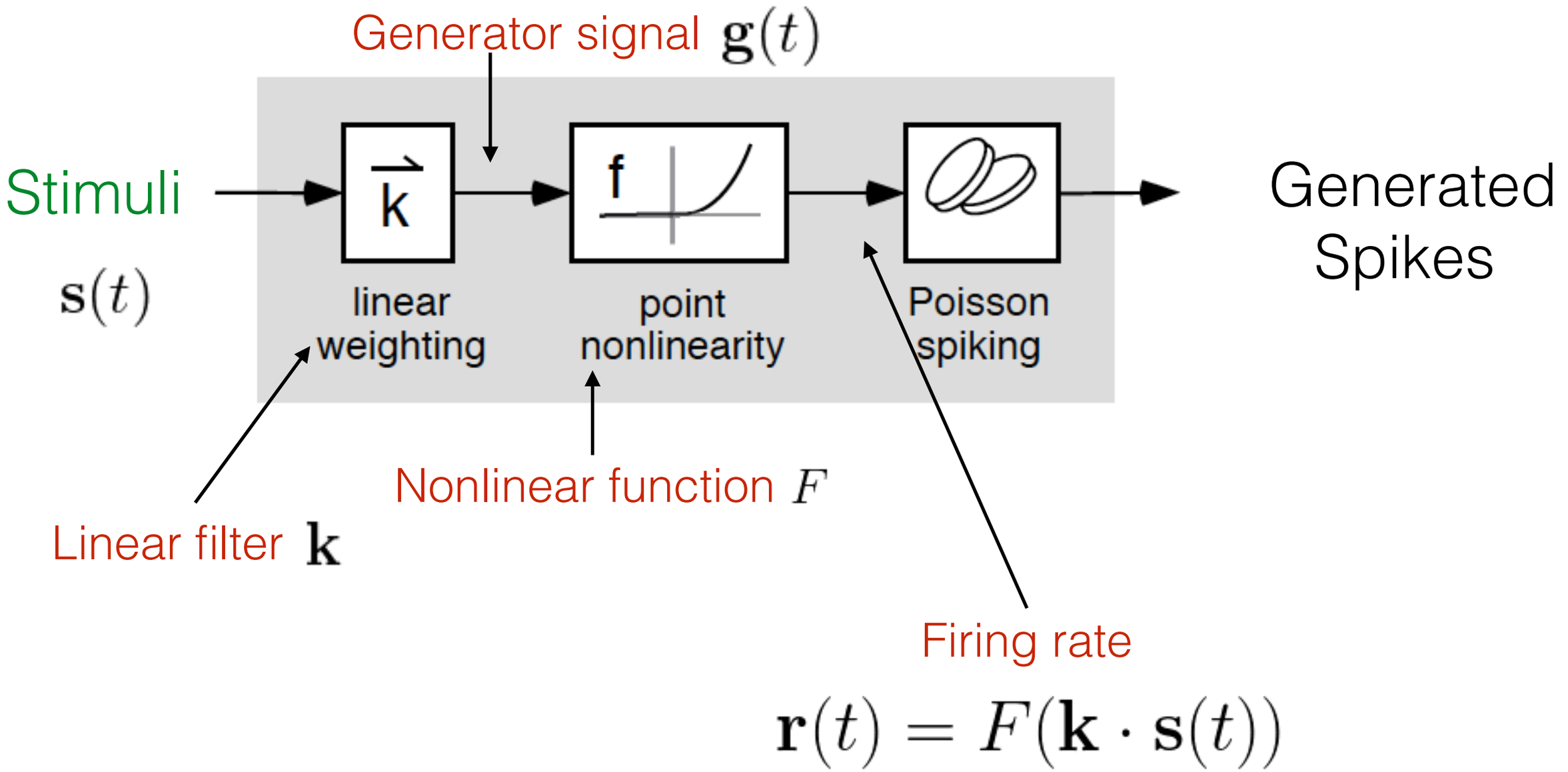
$\mathbf{n}(t)$

http://www.pc.rhul.ac.uk/staff/j.zanker/ps1061/l2/ps1061_2.htm

Modeling neuron's response



Linear-Nonlinear-Poisson Model



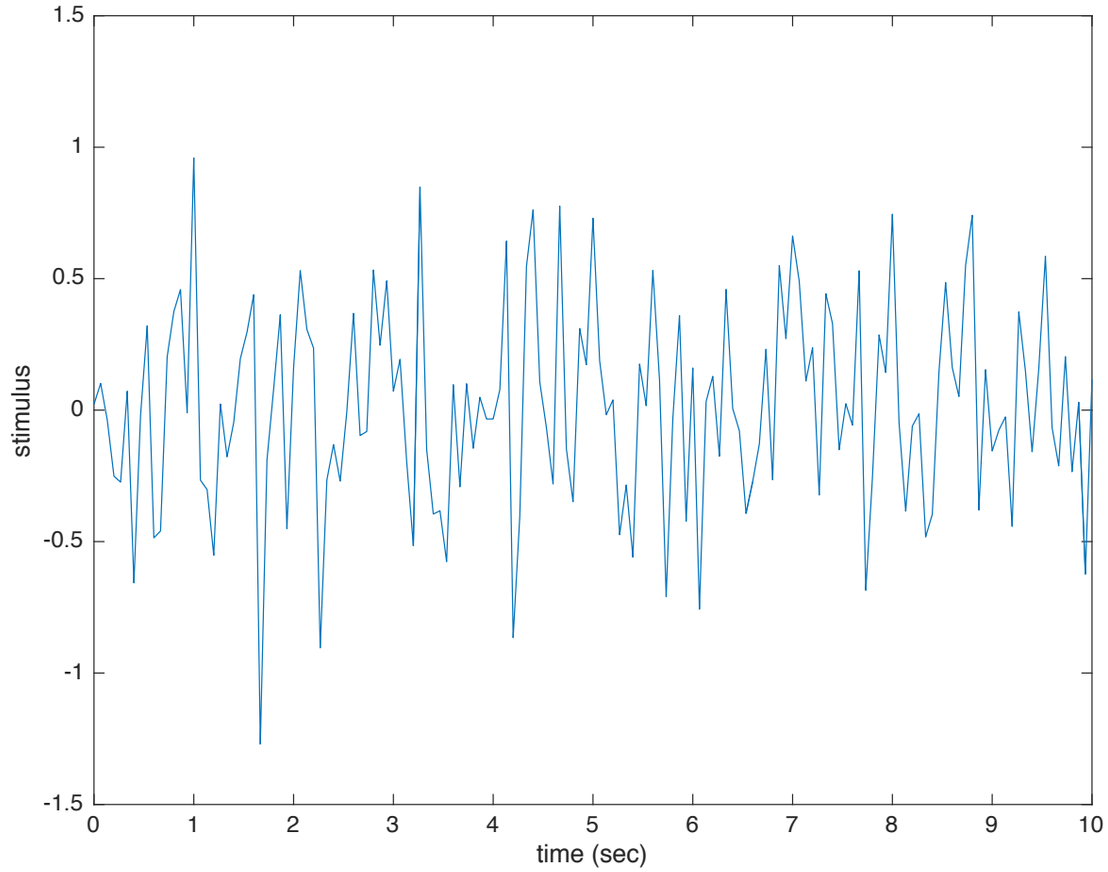
- - given : stimulus(stimuli) and number of spikes at moment t
- - need to find

Simoncelli EP, Pillow J, Paninski L, Schwartz O (2004) Characterization of neural responses with stochastic stimuli. In: The cognitive neurosciences (Gazzaniga M, ed), pp 327–338. Cambridge, MA: MIT

Synthetic(RGC) data: stimulus

Synthetic data set for retinal ganglion cells contains the following elements:

1. stimulus $\mathbf{S}(\mathrm{t})$



reformat stimulus into matrix of stimuli

$$\mathbf{s}[t,] = [S(t), S(t - dt)...S(t - P * dt)]$$

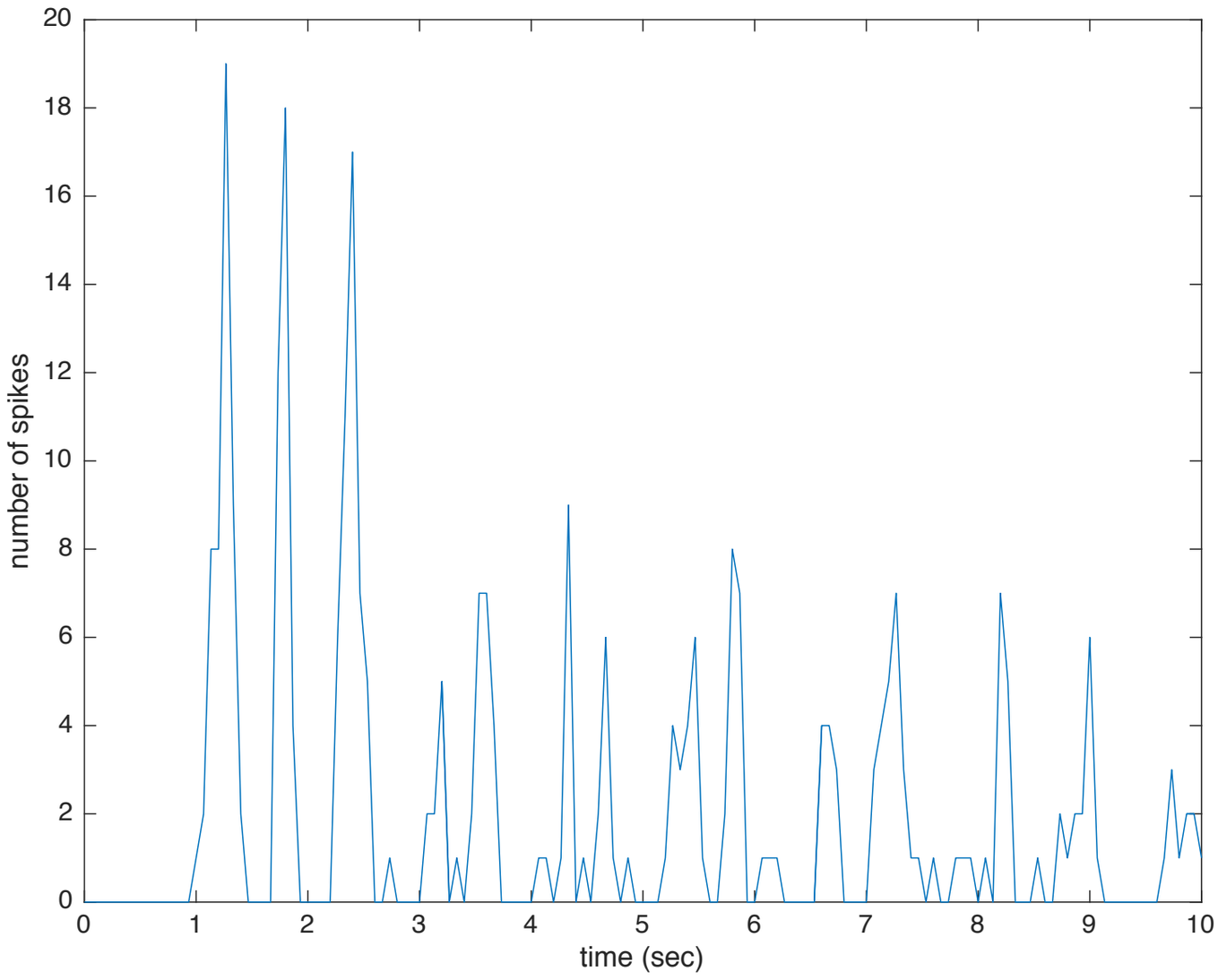
where P is a stimuli length

McFarland JM, Cui Y, Butts DA (2013) Inferring nonlinear neuronal computation based on physiologically plausible inputs. PLoS Computational Biology 9(7): e1003142.

Synthetic(RGC) data: response

2. spike times (in units of seconds) $(t_1, t_{23}, t_{23}, ...t_n)$

reformat spike times into $\mathbf{n}(t) = (1, 0, ..., 2, ...1)$



Real (LGN) data

Real data set, recorded from lateral geniculate nucleus of 3 cats, contains the following elements:

- stimulus for an experiment duration of 120 sec
- spike times (in units of seconds)
- repeated stimulus of 10 sec, 64 repetitions
- corresponding spike times for the repeated stimulus
- time interval of the stimulus update (dt)

Butts DA, Weng C, Jin JZ, Alonso JM, Paninski L (2011) Temporal precision in the visual pathway through the interplay of excitation and stimulus-driven suppression. J. Neurosci. 31: 11313-27.

Moment-based statistical models for filter estimation

- Spike Triggered Average (STA)
- Spike Triggered Covariance (STC)

Spike Triggered Average

$$\phi_{sta} = \frac{1}{N}\sum_{t=0}^{M} n(t)(\hat{\mathbf{s}}[t,] - \bar{\mathbf{s}})$$

$$\bar{\mathbf{s}} = \frac{1}{M}\sum_{t=0}^{M} \hat{\mathbf{s}}[t,]$$

N - the total number of spikes per experiment

n(t) - number of spikes at time t (an integer number)

M - number of stimuli per experiment

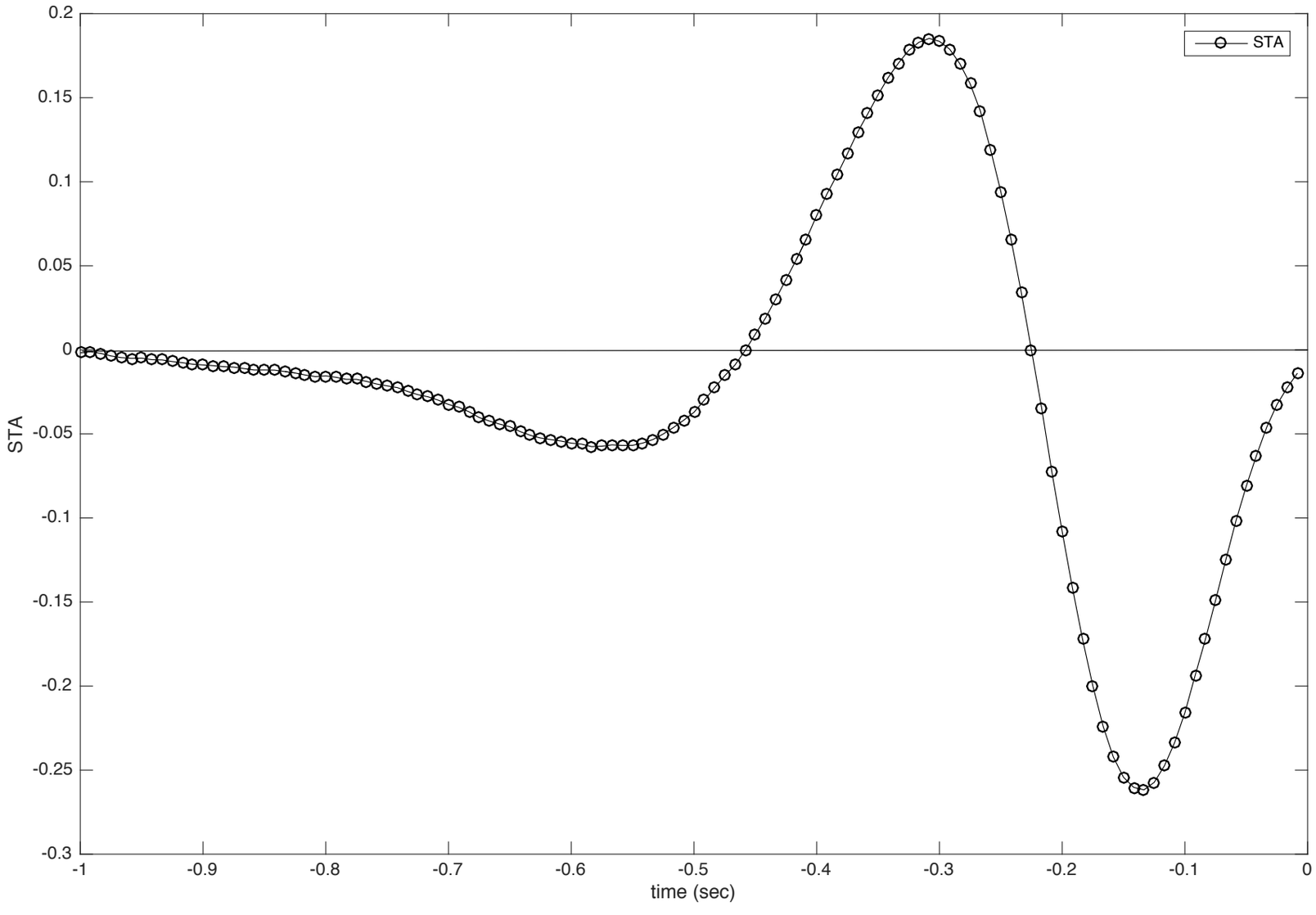
P - length of stimuli

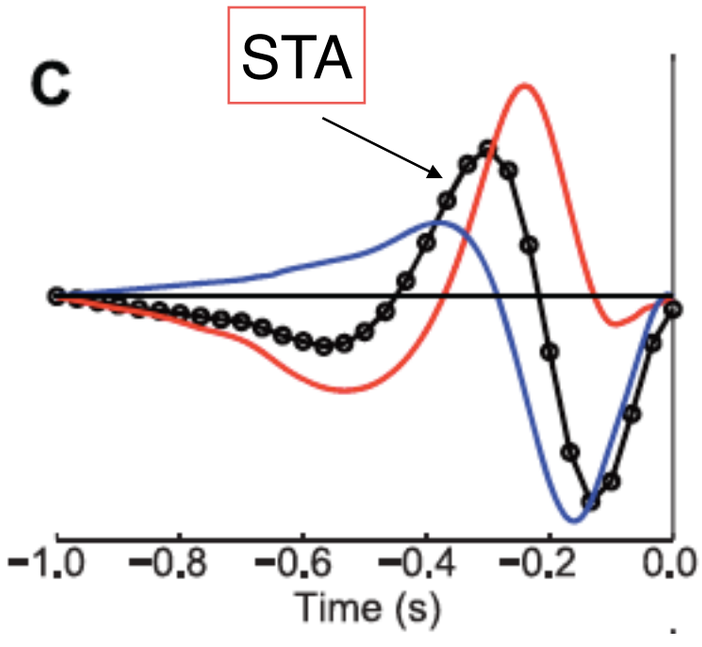
$\bar{\mathbf{s}}$ - average stimuli

$\hat{S}$ - matrix of stimuli with dimensions of [M,P]

$\hat{\mathbf{s}}[t,]$ - stimuli vector at moment t

STA for synthetic data





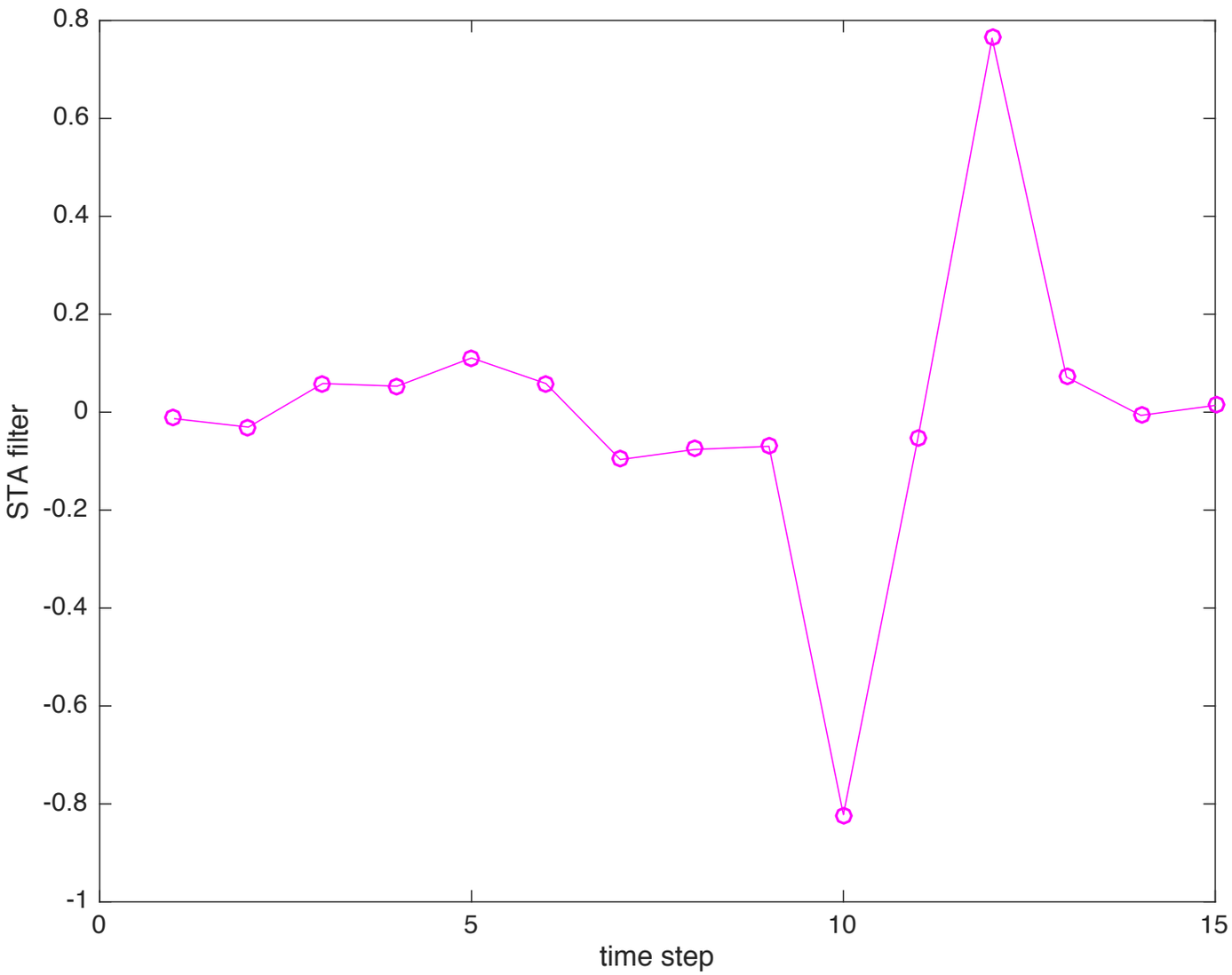
McFarland JM, Cui Y, Butts DA (2013) Inferring nonlinear neuronal computation based on physiologically plausible inputs. PLoS Computational Biology 9(7): e1003142.

stimuli length is 120
time steps <-> 1 sec

L-N-P model reconstruction scheme for real data

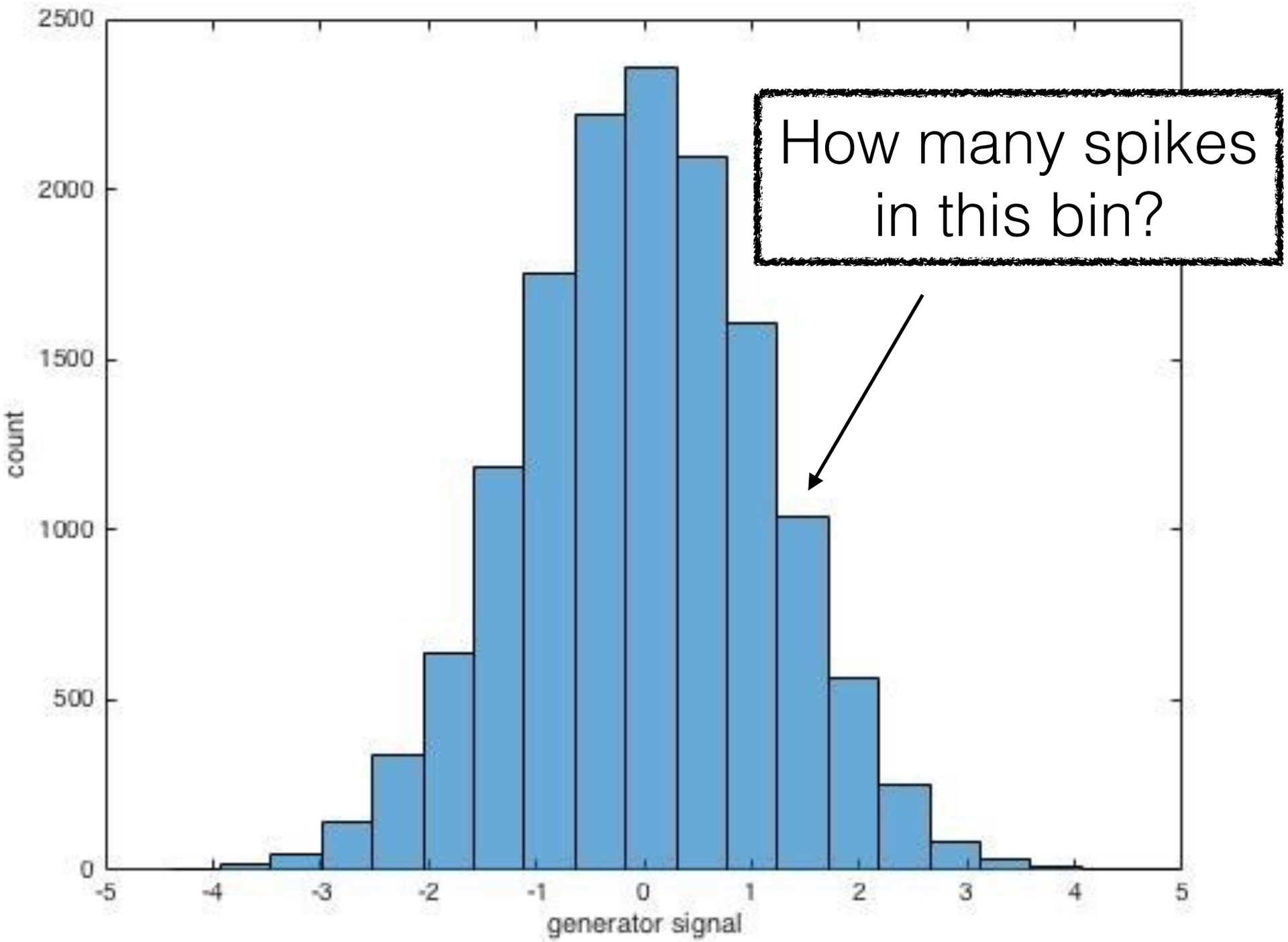
- Take 120 sec of stimulus/spikes data
- Estimate single linear filter k using STA model
- Estimate non-linearity function F
- Take repeated stimulus/spikes data (10 sec, repeated 64 times)
- Apply k & F to repeated stimulus to predict firing rate
- Calculate average spike rate by averaging repeated spikes data
- Compare predicted/measured spike rates

STA filter(k) for real data

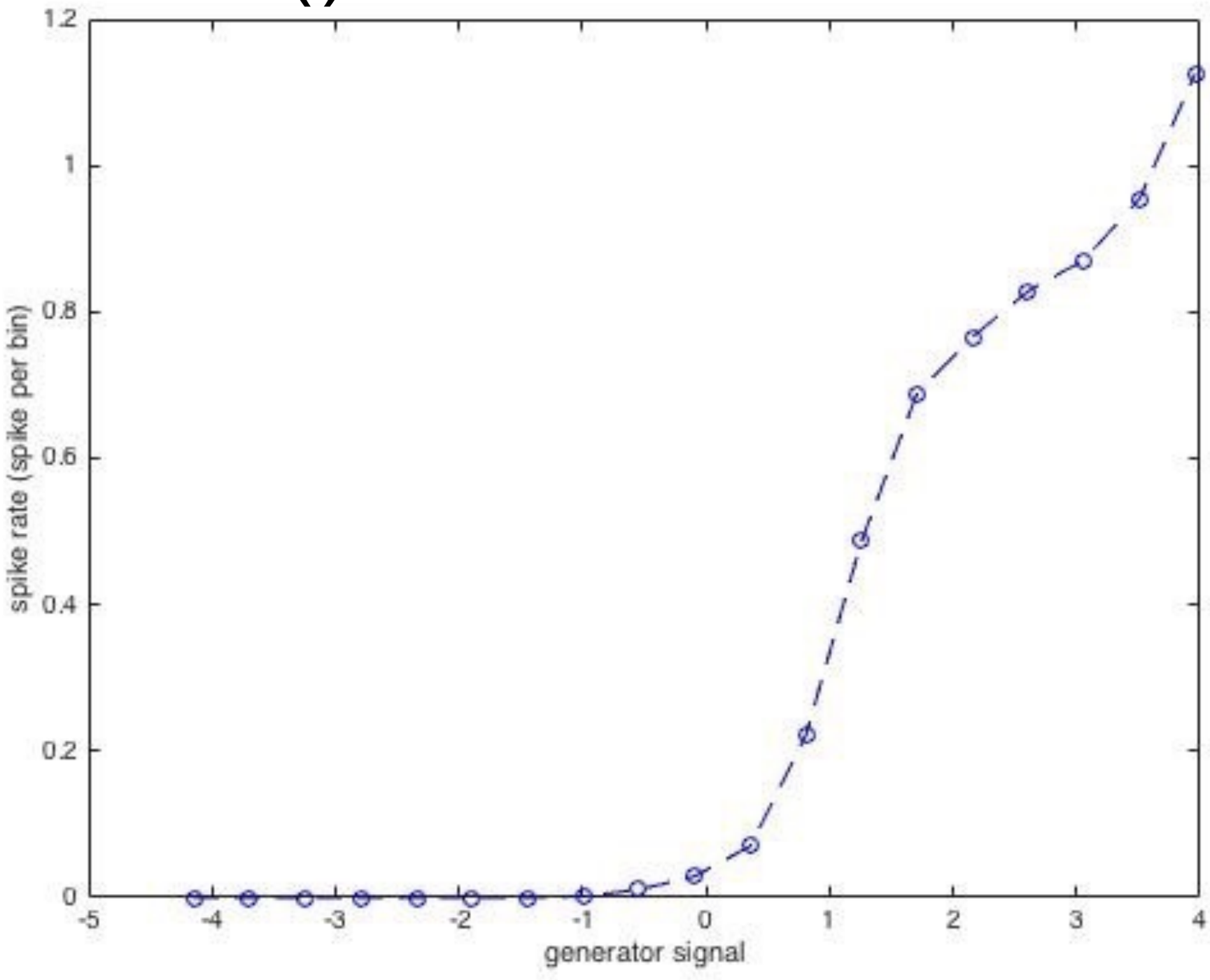


stimuli length is 15 time steps <-> 0.1251 sec

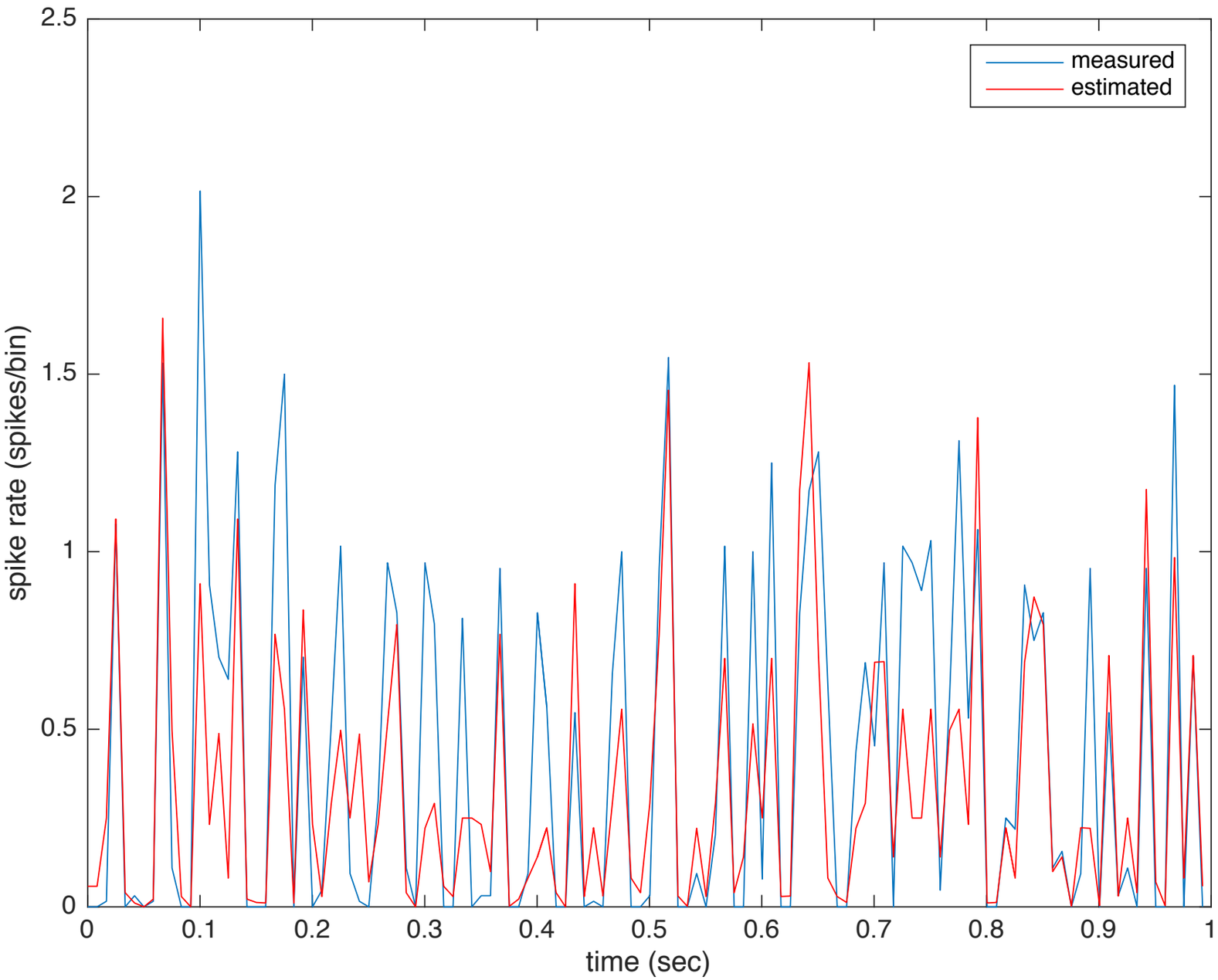
Generator signal (g(t)) for real data



Estimation of nonlinearity F() for real data



Cross validation results



$$R^2 = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i)^2}$$

where y_i - measured data,
$\hat{y}_i$ - estimated data

$$R^2 = 0.7696$$

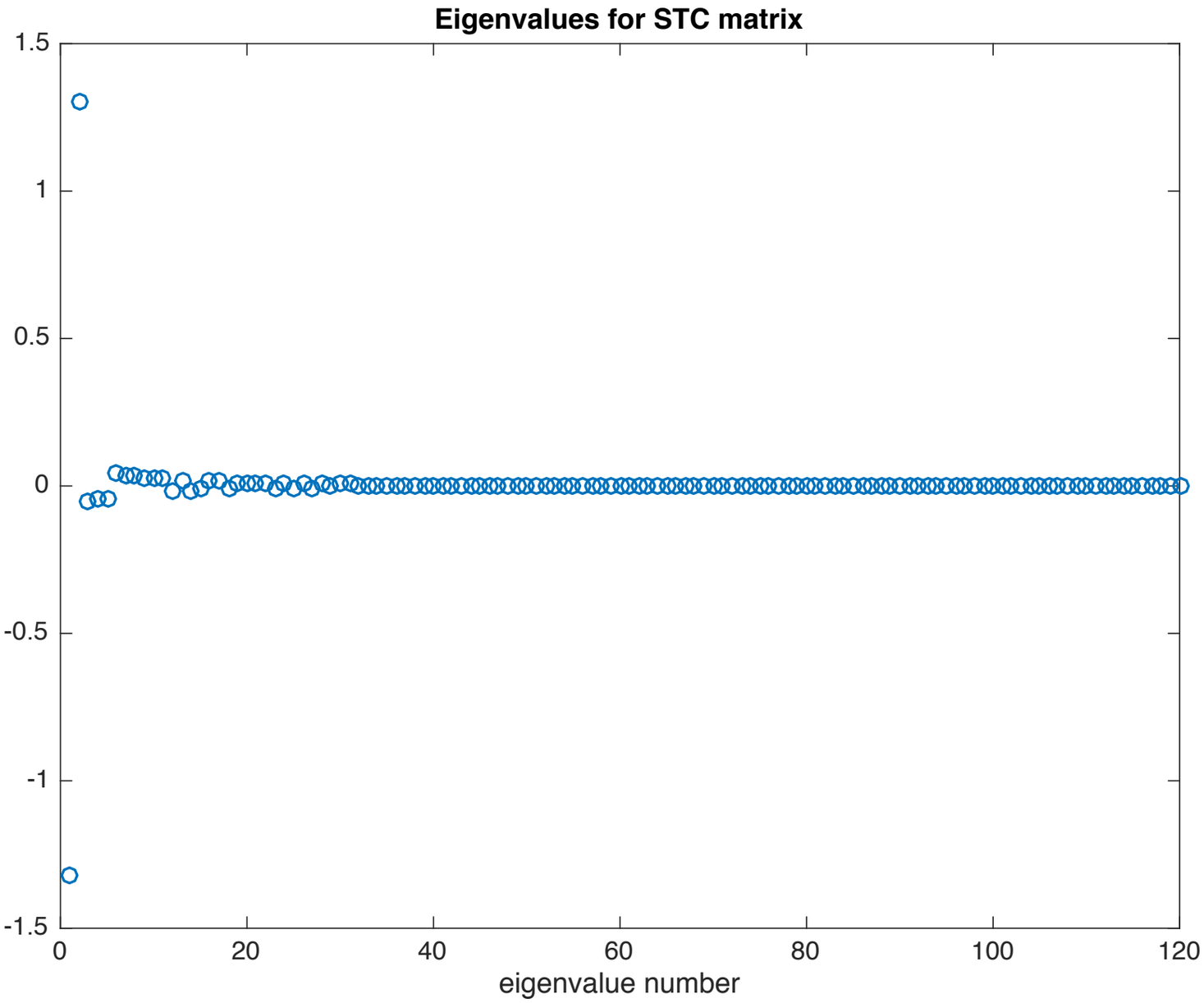
New model: Spike Triggered Covariance

$$\phi_{stc} = \phi_{trig.stc} - \phi_{untirg.stc}$$

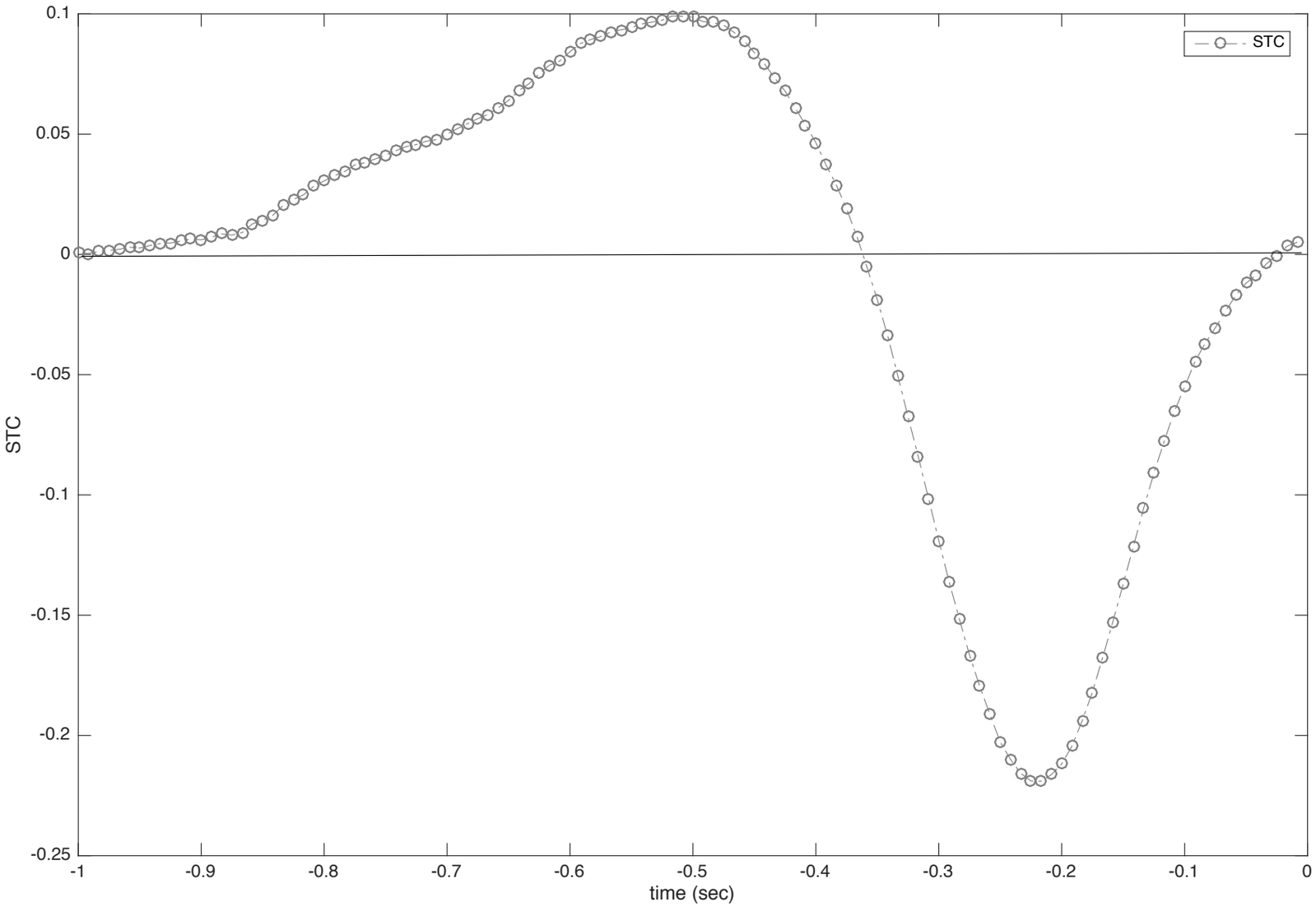
$$\phi_{trig.stc} = \frac{1}{N-1}\sum_{t=0}^{M} n(t)(\hat{s}[t,] - \phi_{sta})(\hat{s}[t,] - \phi_{sta})^T$$

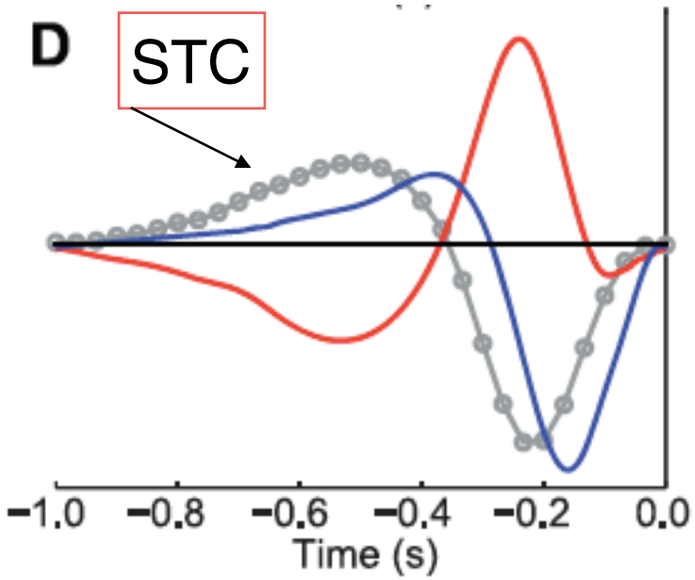
$$\phi_{untrig.stc} = \frac{1}{M-1}\sum_{t=0}^{M}(\hat{s}[t,] - \phi_{sta})(\hat{s}[t,] - \phi_{sta})^T$$

STC for synthetic data



STC for synthetic data





stimuli length is 120
time steps <-> 1 sec

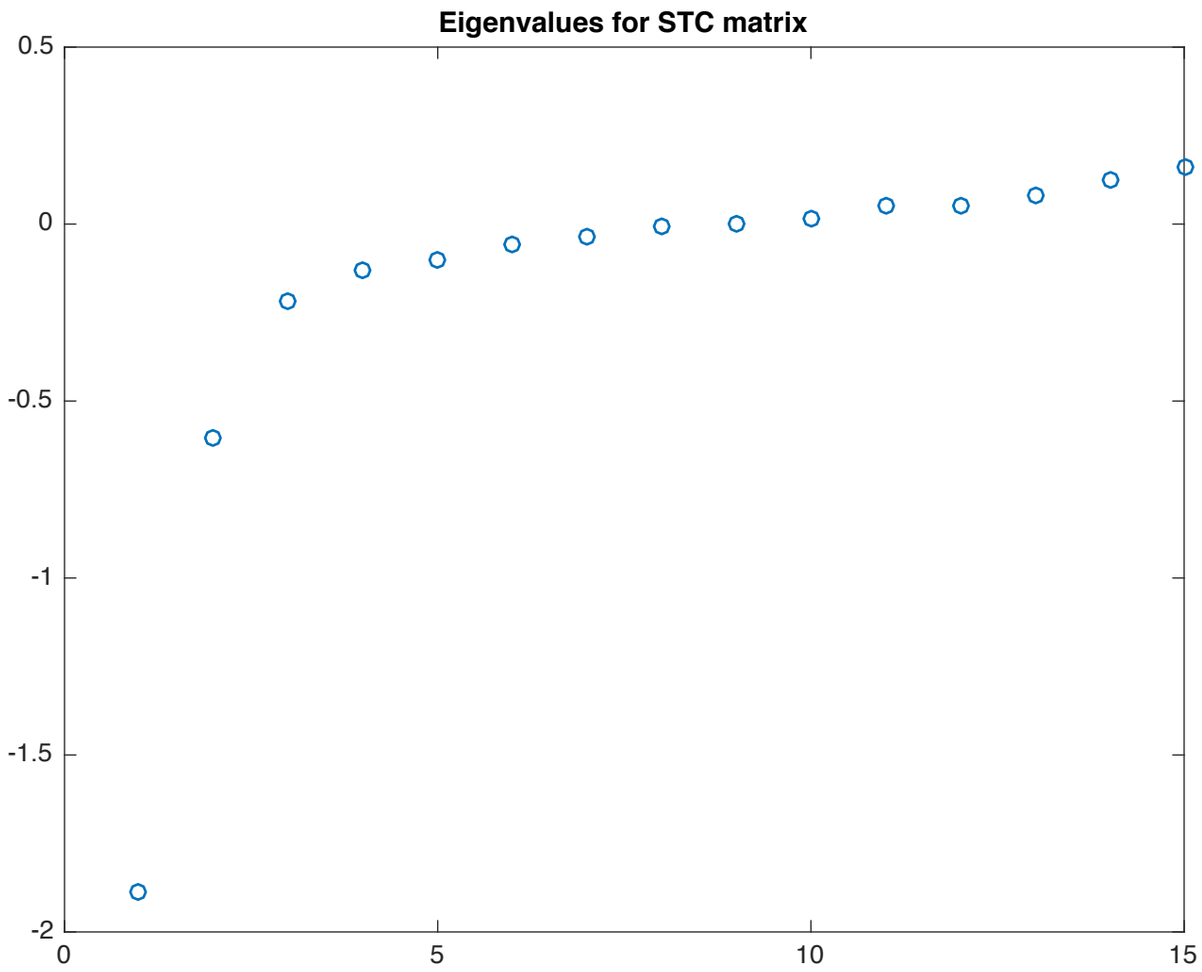
McFarland JM, Cui Y, Butts DA (2013) Inferring nonlinear neuronal computation based on physiologically plausible inputs. PLoS Computational Biology 9(7): e1003142.

L-N-P model reconstruction scheme for real data

- Take 120 sec of stimulus/spikes data
- Estimate two filters k1 and k2 using STC and STA models
- Estimate 2D non-linear function F
- Take repeated stimulus/spikes data (10 sec, repeated 64 times)
- Apply k1,k2 & F to repeated stimulus to predict firing rate
- Calculate average spike rate by averaging repeated spikes data
- Compare predicted/measured spike rates

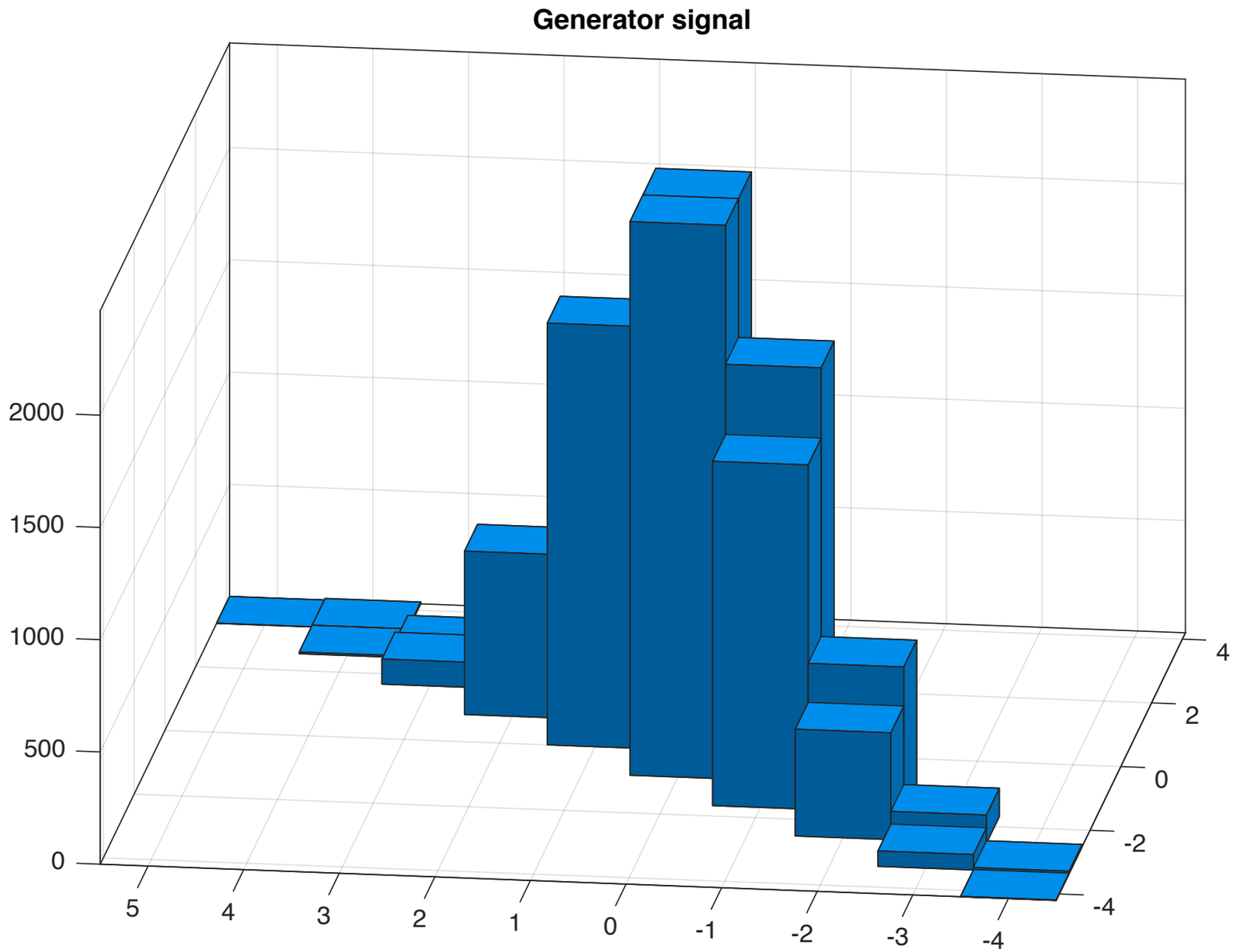
$$\mathbf{r}(t) = F(\mathbf{k1} \cdot \mathbf{s}(t), \mathbf{k2} \cdot \mathbf{s}(t))$$

Finding STC filter for real data

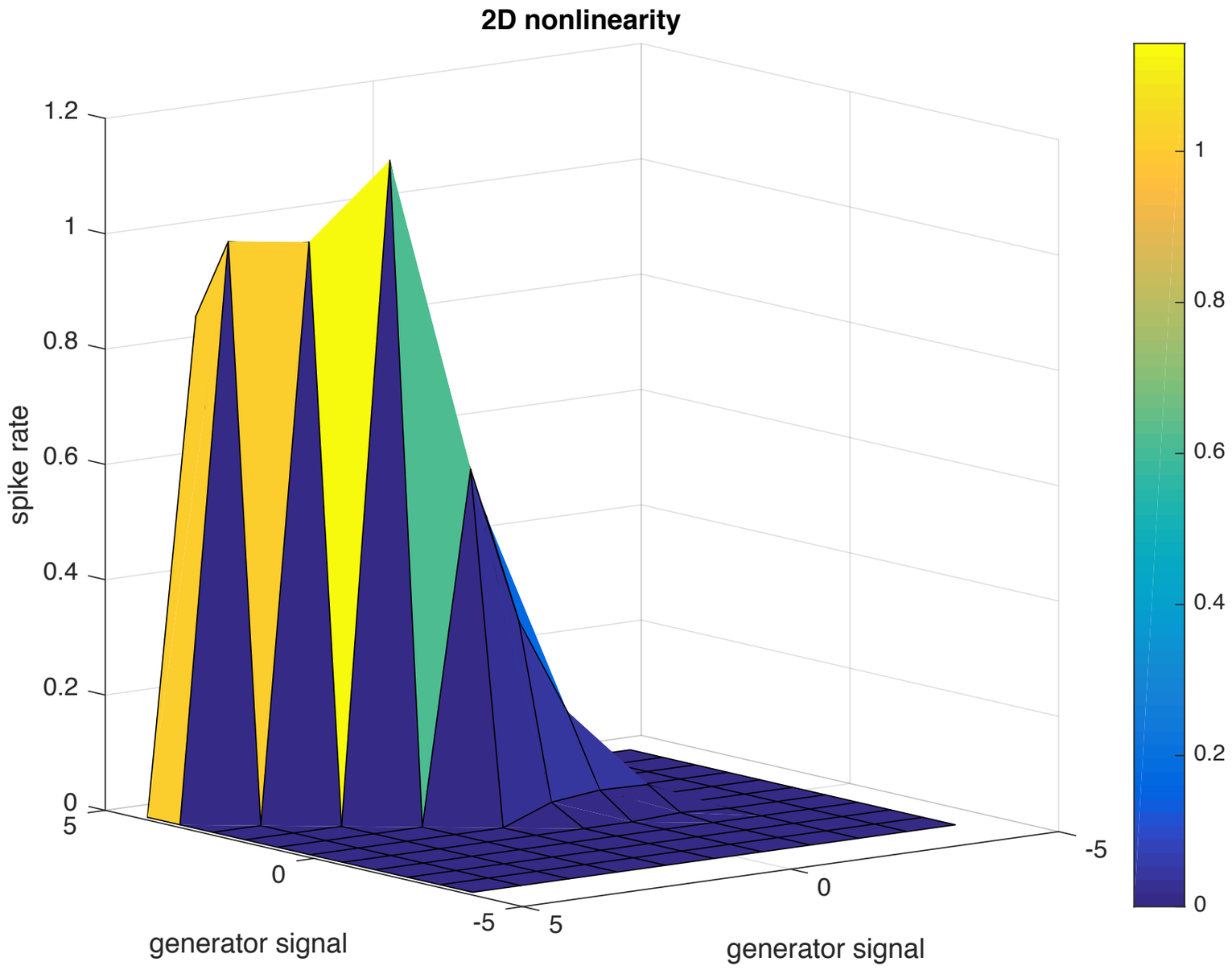


stimuli length is 15 time steps <-> 0.1251 sec

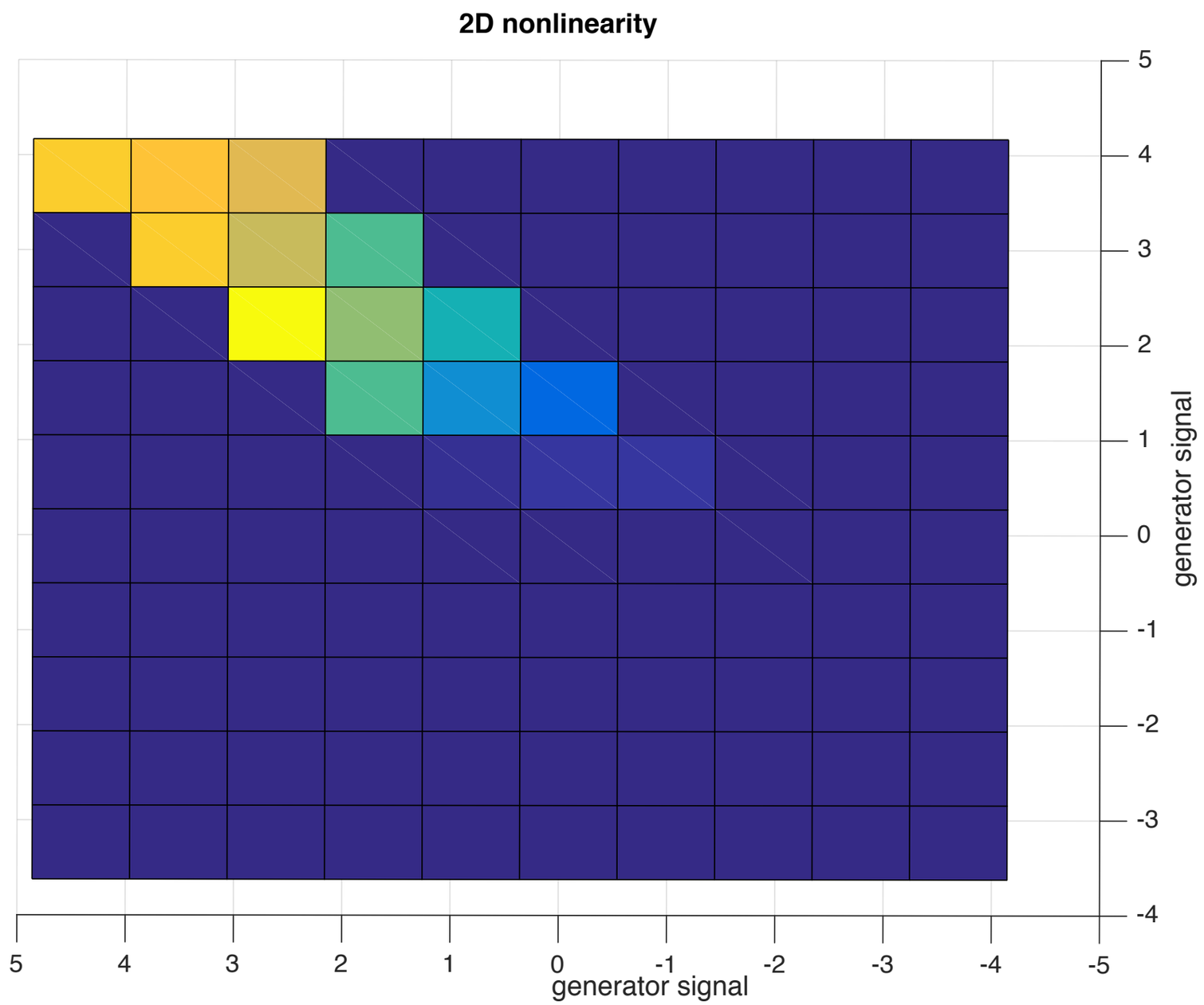
Finding g(t) for real data



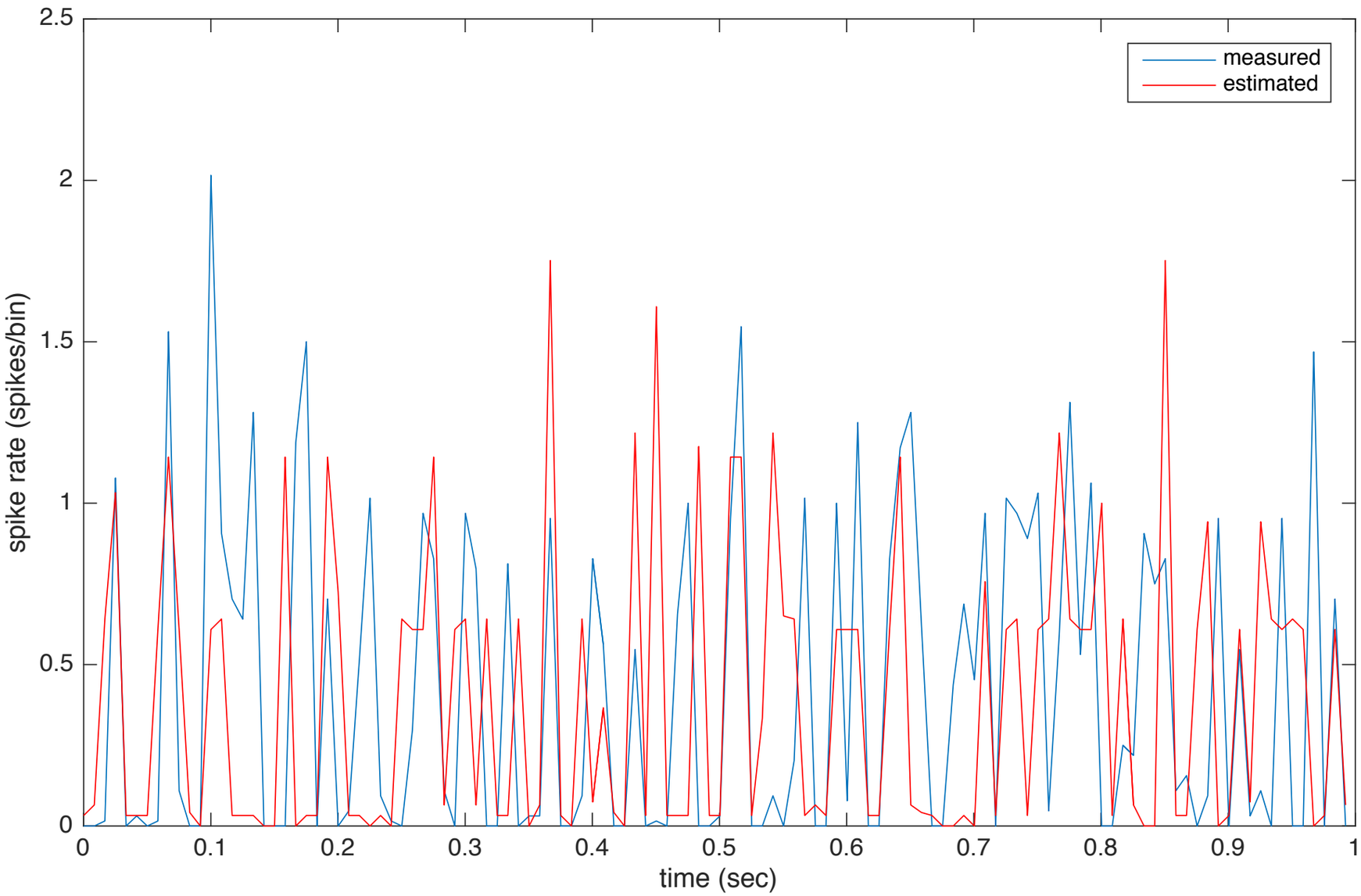
Estimation of nonlinearity F(*,*) for real data



Estimation of nonlinearity F(*,*) real data



Cross validation results



$$R^2 = 0.2424$$

Updated project schedule

October - ~~mid November~~ November

- ✓ Implement STA and STC models
- ✓ Test models on synthetic data set and validate models on real data set

~~November - December~~ December - mid February

- Implement Generalized Linear Model (GLM)
- Test model on synthetic data set and validate model on LGN data set

~~January - March~~ mid February - mid April

- Implement Generalized Quadratic Model (GQM) and Nonlinear Input Model (NIM)
- Test models on synthetic data set and validate models on LGN data set

~~April - May~~ Mid April - May

- Collect results and prepare final report

References

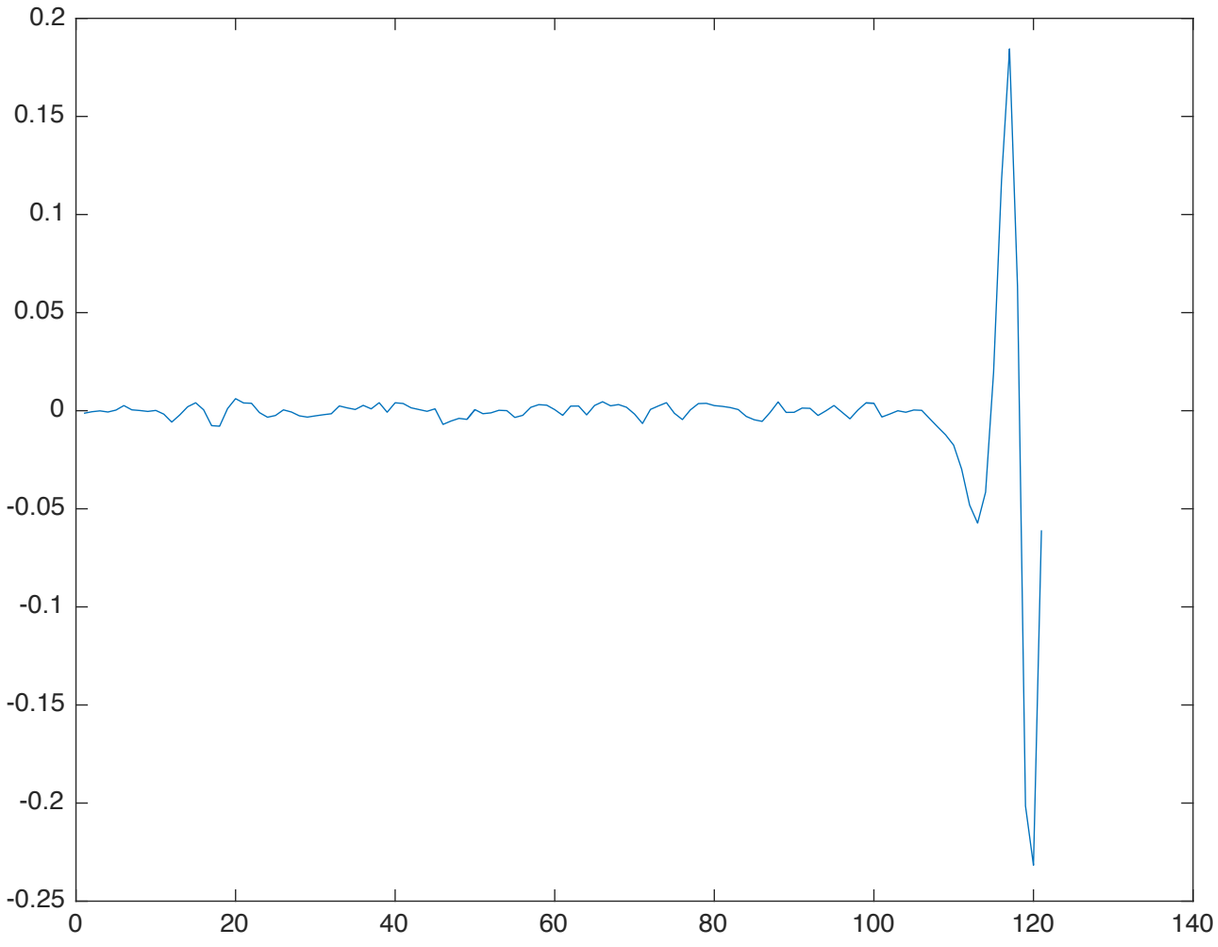
1. McFarland JM, Cui Y, Butts DA (2013) Inferring nonlinear neuronal computation based on physiologically plausible inputs. PLoS Computational Biology 9(7): e1003142.

2. Butts DA, Weng C, Jin JZ, Alonso JM, Paninski L (2011) Temporal precision in the visual pathway through the interplay of excitation and stimulus-driven suppression. J. Neurosci. 31: 11313-27.

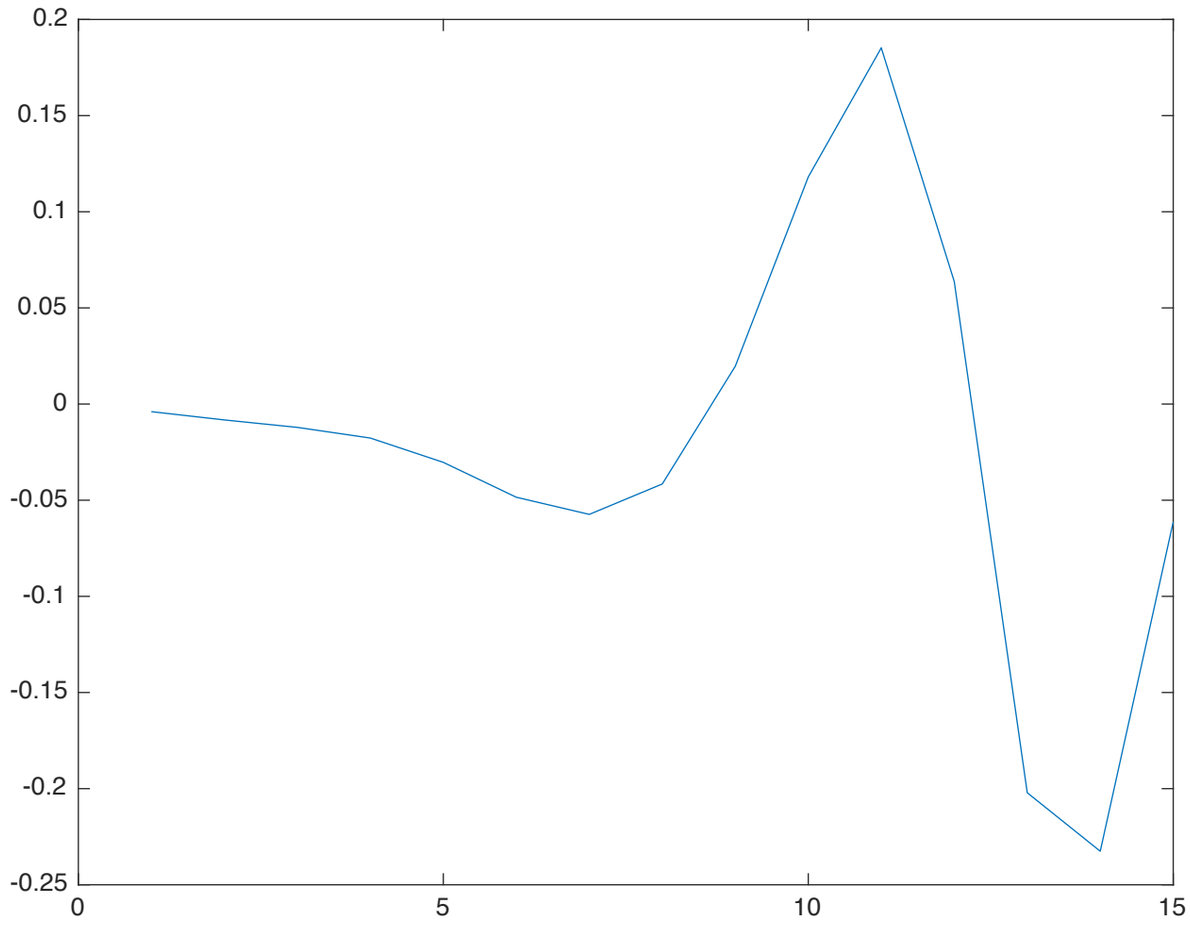
3. Simoncelli EP, Pillow J, Paninski L, Schwartz O (2004) Characterization of neural responses with stochastic stimuli. In: The cognitive neurosciences (Gazzaniga M, ed), pp 327–338. Cambridge, MA: MIT.

4. Chichilnisky EJ (2001) A simple white noise analysis of neuronal light responses. Network 12:199 –213.

Appendix: define stimuli length (for STA of synthetic data)

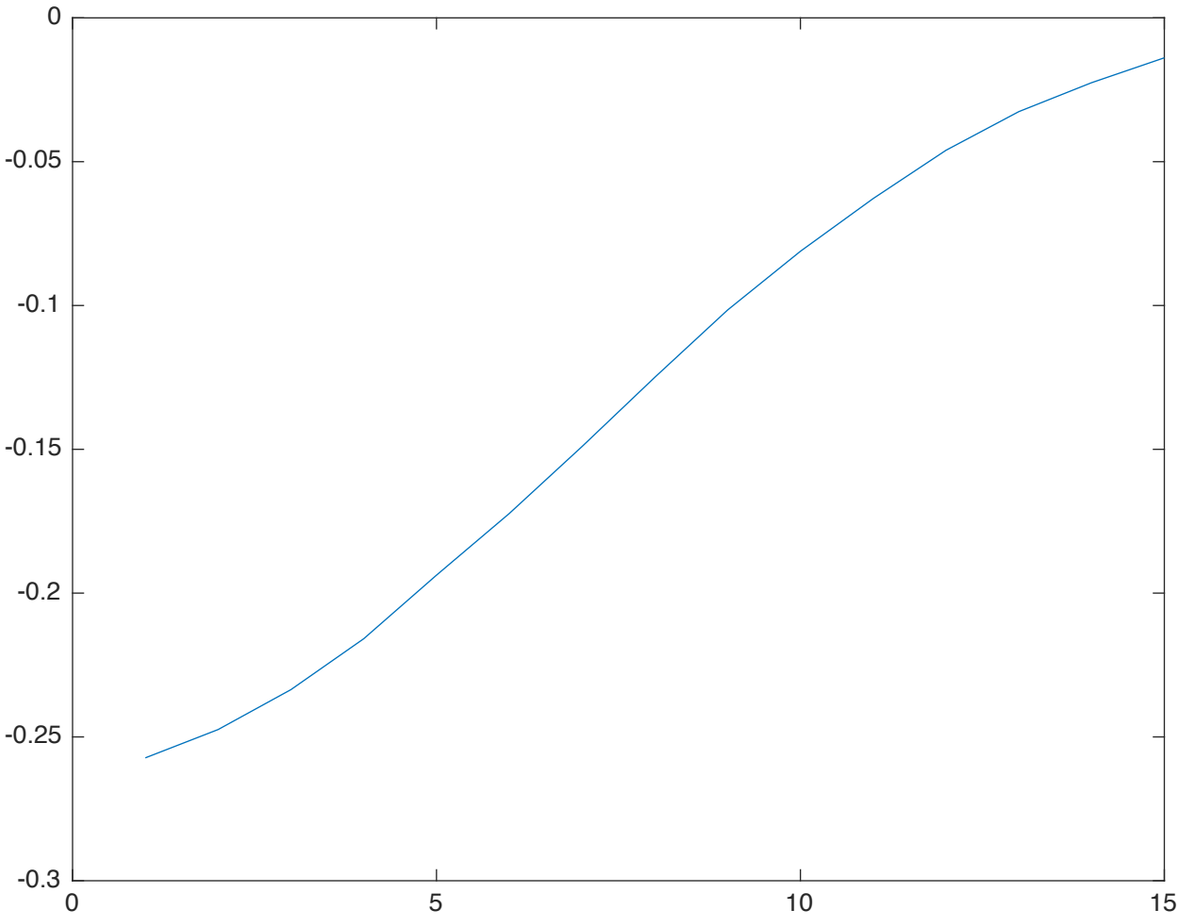


dt is unchanged
the stimuli length is 121 time points

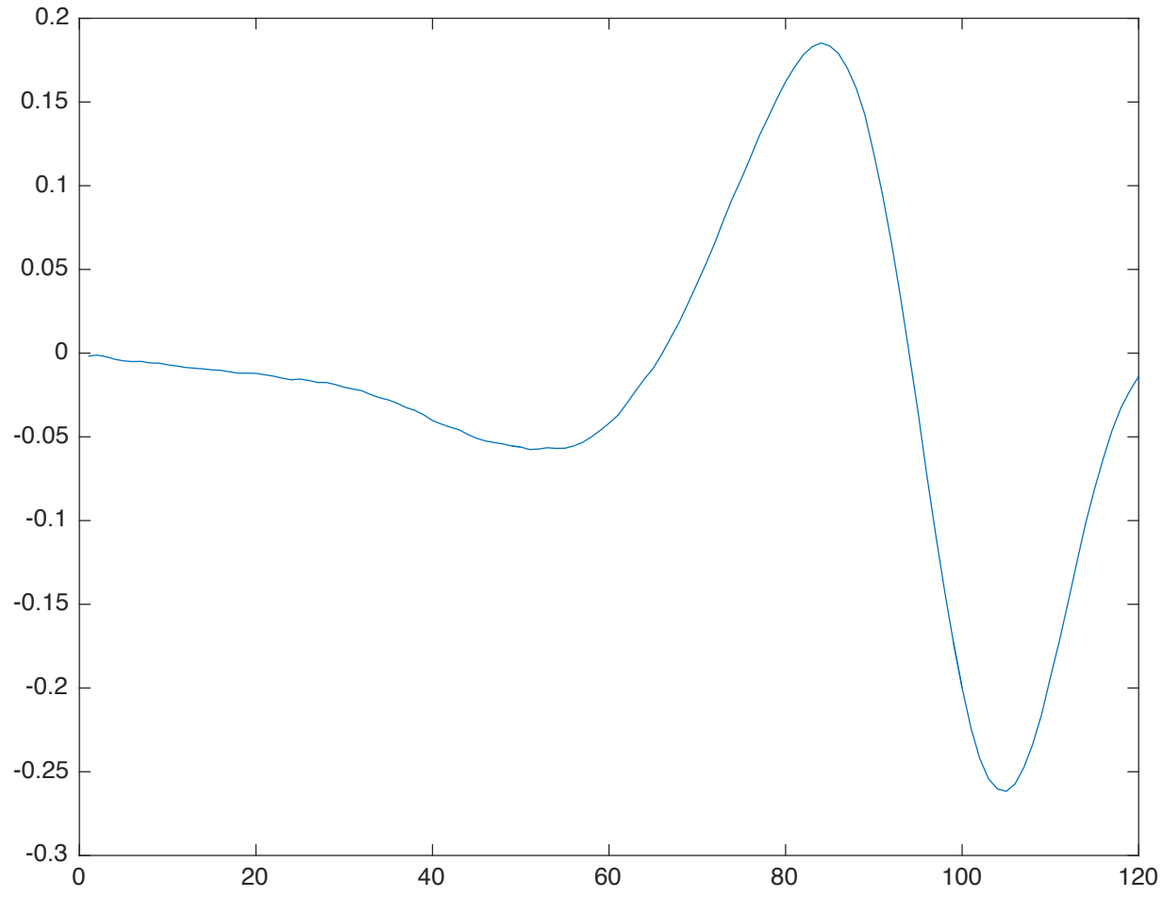


dt is unchanged
the stimuli length is 15 time points

Appendix: define dt (for STA of synthetic data)



dt -> dt/8
the stimuli length is 15 time points



dt -> dt/8
the stimuli length is 15*8 time points