

The Myth of Poissonian Spiking Interval and Count Statistics in Biological Neurons

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Workshop on Statistical Aspects of Neural Coding

Kyoto University, Nov 01, 2012

■ Introduction

- 1 Measures of 2nd order interval and count statistics
 - 2 The Poisson model is a bad model for neural spiking
 - 3 Neural spike trains violate assumption of a renewal process
 - 4 Non-renewal point process models and biophysics
- ## ■ Take-home summary

*„The variability of neuronal responses is proportional to the mean in many brain areas, which **suggests that neural responses might follow a Poisson distribution.**”*

Averbeck (2009) Neuron 62

■ Introduction

1 Measures of 2nd order interval and count statistics

2 The Poisson model is a bad model for neural spiking

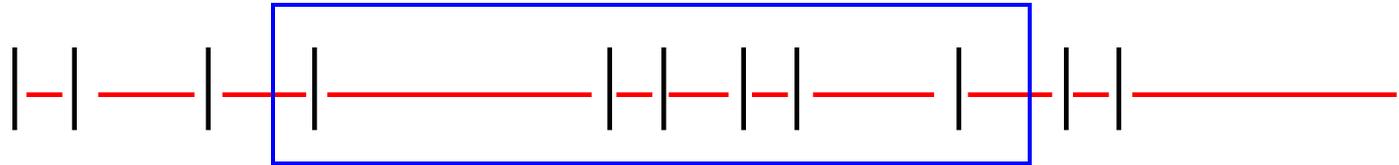
3 Neural spike trains violate assumption of a renewal process

4 Non-renewal point process models and biophysics

■ Take-home summary

2 basic random variables

- inter-event intervals X (continuous random variable)
- number of spikes N (discrete random variable) in interval of length T



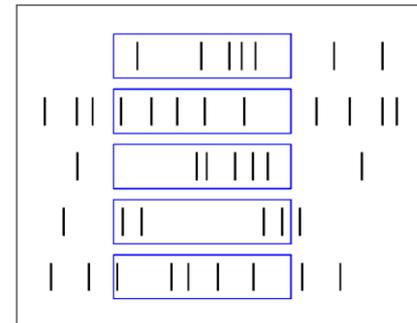
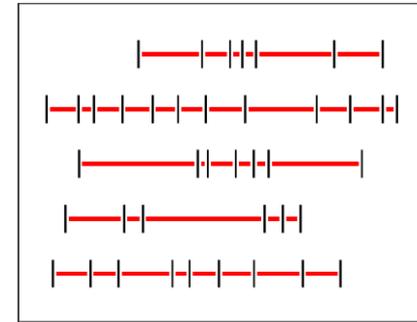
Any point process definition uniquely determines its interval and count stochastic, and both random variables are related.

Coefficient of variation (interval variability)

$$CV^2 = \frac{Var(ISI)}{mean^2(ISI)}$$

Fano factor (count variability)

$$FF = \frac{Var(count)}{mean(count)}$$



trial

time

Coefficient of variation

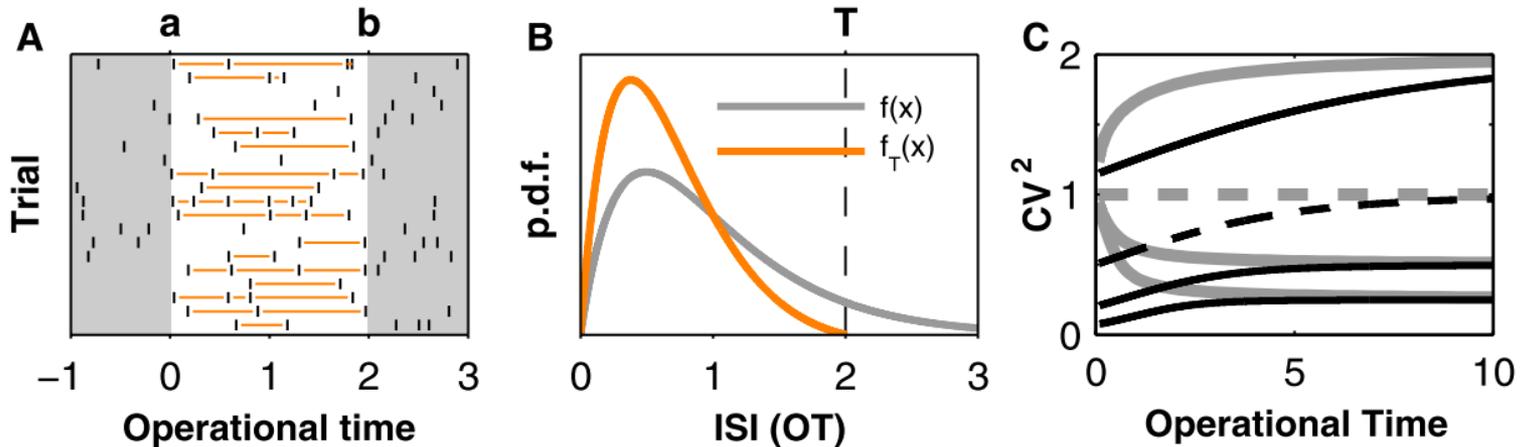
(of inter-spike intervals X)

$$CV^2 = \frac{\text{Var}(ISI)}{\text{mean}^2(ISI)}$$

Fano factor

(of spike count N)

$$FF = \frac{\text{Var}(\text{count})}{\text{mean}(\text{count})}$$



$$\hat{f}(x) = \begin{cases} \eta^{-1}(T-x)f(x) & \text{for } x \in [0, T], \\ 0 & \text{otherwise,} \end{cases}$$

$$\eta = \int_0^T (T-s)f(s) ds$$

Nawrot (2010) In: Grün, Rotter (eds.), Springer Series Comp Neurosci 7

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One possibility to define a point process is the **complete intensity function**.

Consider a point process as defined on the complete time axis $(-\infty, +\infty)$. Let H_t denote the **history of the process**, i.e. a specification of the position of all points in $(-\infty, t]$. Then a general description of this process maybe formulated in terms of the probabilities of observing a single event at an arbitrary time t

$$P(N(t, t + \delta t) = 1 | H_t)$$

The dependence on the process history can be arbitrarily complex

Poisson

- exponential interval distribution
 - Poisson count distribution
- events are uniformly distributed in time
 - special case of gamma process

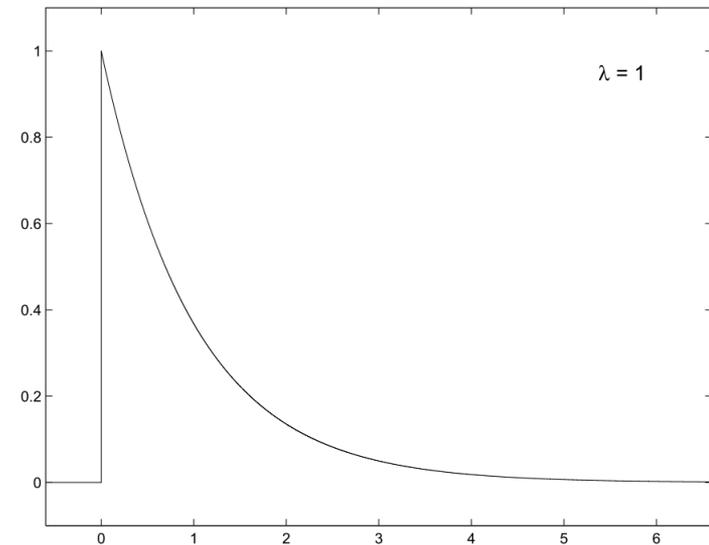
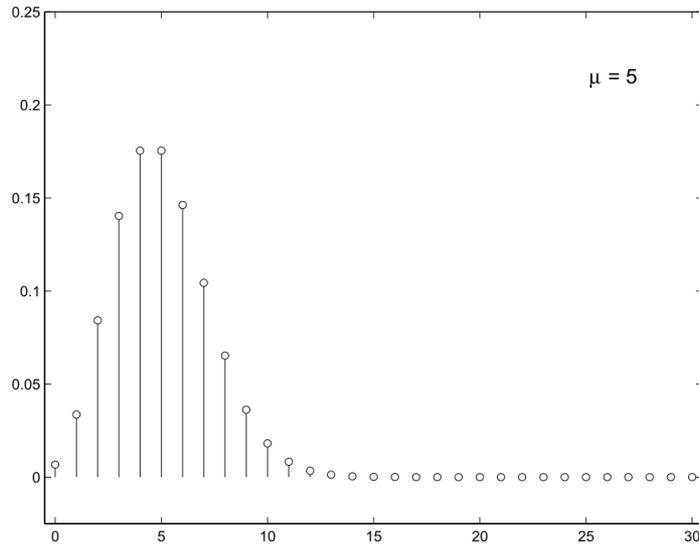
$$FF = CV^2 = 1$$

The **Poisson process** of intensity λ is defined by the requirements that for all t and for $\delta \rightarrow 0+$

$$P\{N(t, t + \delta t) = 1 | H_t\} = \lambda\delta + o(\delta)$$

The Poisson process is the only process for which

- all **events are completely independent**
- the hazard rate is flat (**maximizes entropy**)



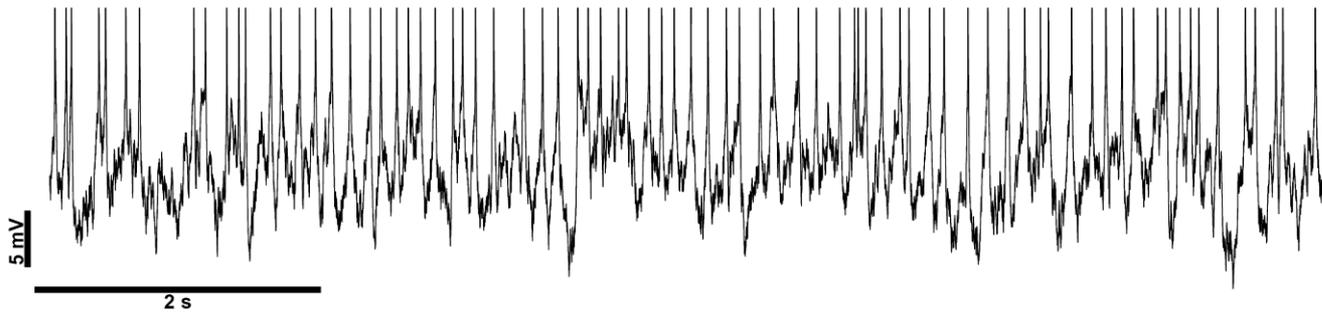
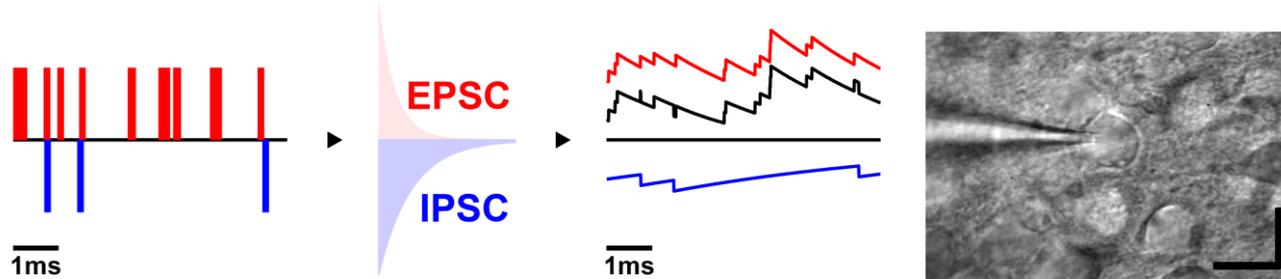
$$P\{N(A) = k\} = \frac{(\lambda t)^k}{k!} e^{-\lambda t}$$

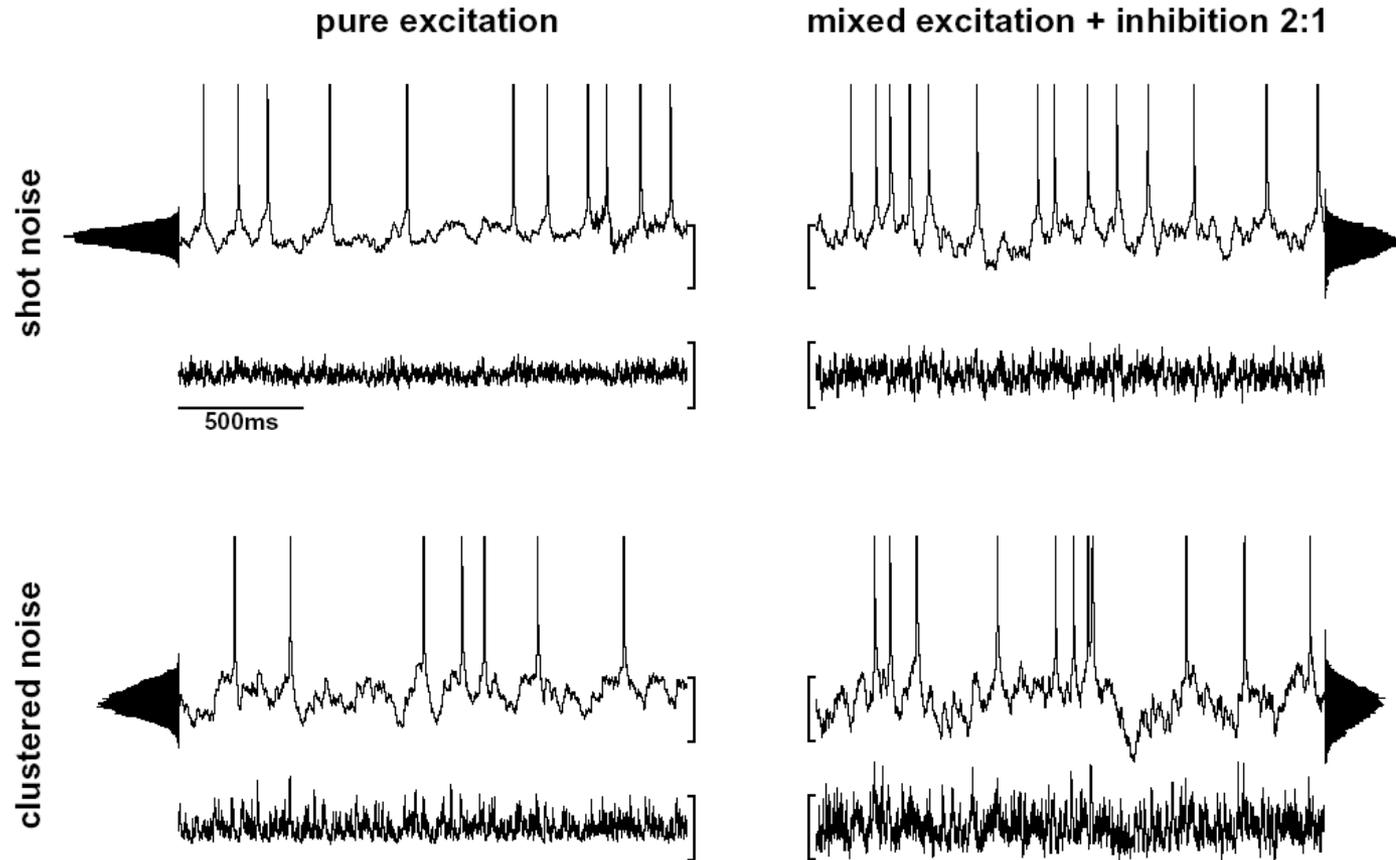
$$\mathbf{FF = 1}$$

$$\Pr\{X_1 > t\} = P\{N(t) = 0\} = \frac{\lambda t^0}{0!} e^{-\lambda t} = e^{-\lambda t}$$

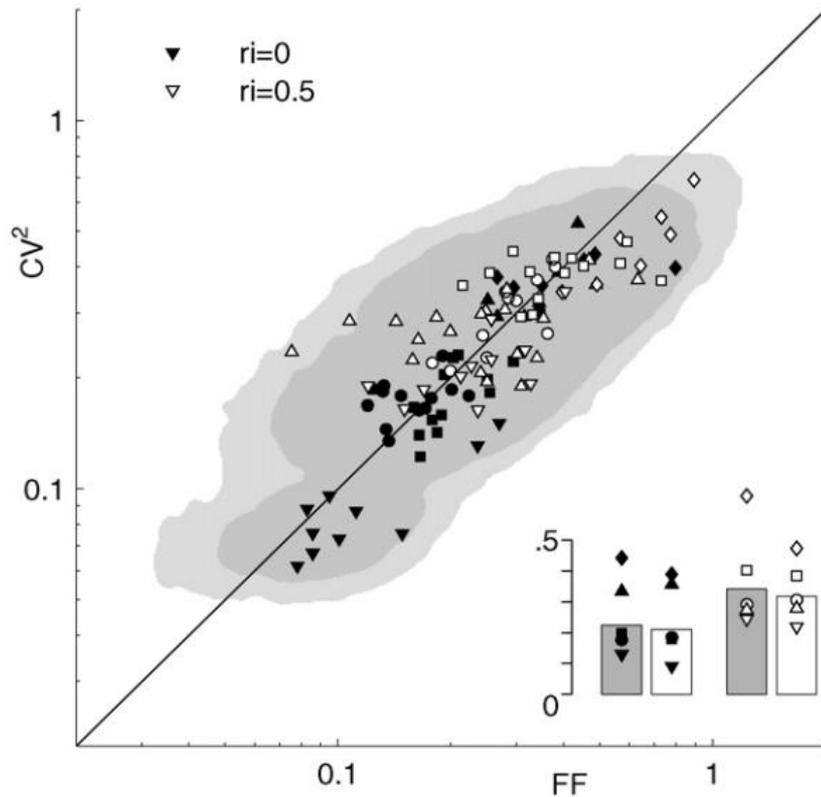
$$\mathbf{CV^2 = 1}$$

In vitro experiments: Controlled stationary input





- ▶ Cortical neuron *in vitro* show **sub-Poissonian interval and count variability**



$$FF \approx CV^2 \leq 0.4$$

CV - Holt et al. (1996) *J Neurophysiol* 75; Nowak et al. (1997) *Cereb Cortex* 7; Stevens & Zador (1998) *Nat Neurosci* 1; Harsch & Robinson (2000) *J Neurosci* 20; Badoual et al. (2005) *Neurocomp* 65; Arsiero et al. (2007) *J Neurosci* 27; Shinomoto

FF - Stevens & Zador (1998) *Nat Neurosci* 1; Harsch & Robinson (2000) *J Neurosci* 20

Nawrot et al. (2008) *J Neurosci Meth*

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constant intensity λ

Poisson

- exponential interval distribution
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- events are uniformly distributed in time
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$$FF = CV^2 = 1$$

Renewal

- iid interval distribution
 - $FF = CV^2$

$$FF = CV^2$$

increasing importance of process history

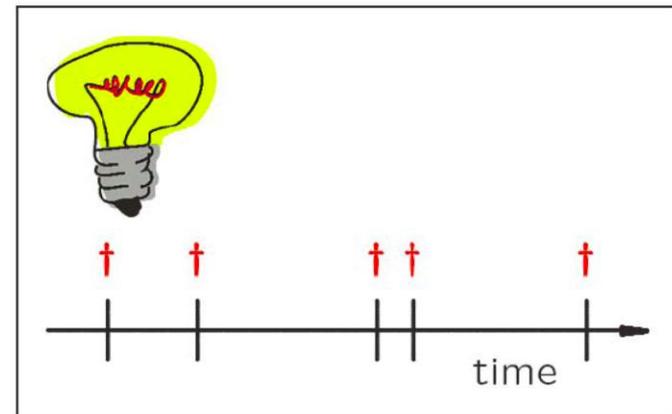


Definition

inter-event intervals are **independent** and **identically distributed** (iid)

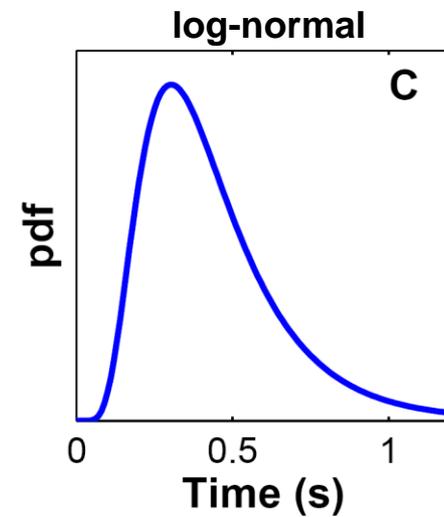
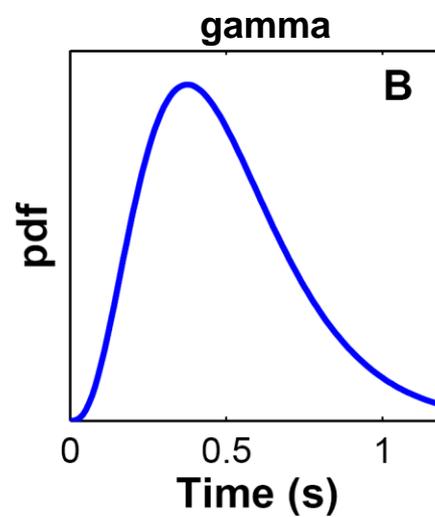
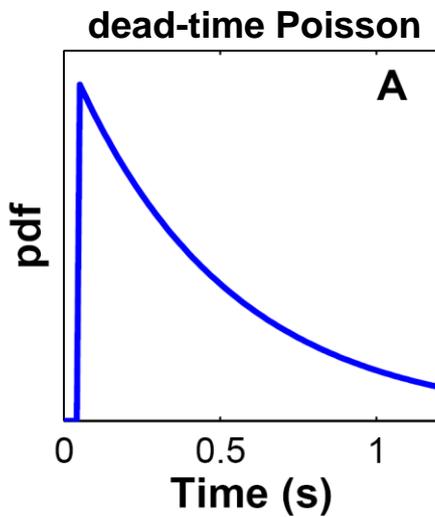
Thus

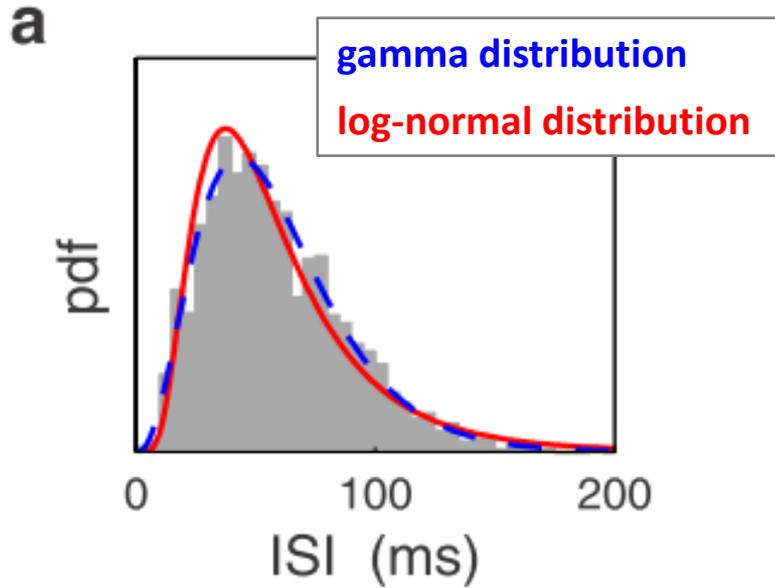
- individual intervals are serially independent
- process history is relevant only up to the previous event
- the intervals between successive points are mutually independent
- the Poisson process is a renewal process



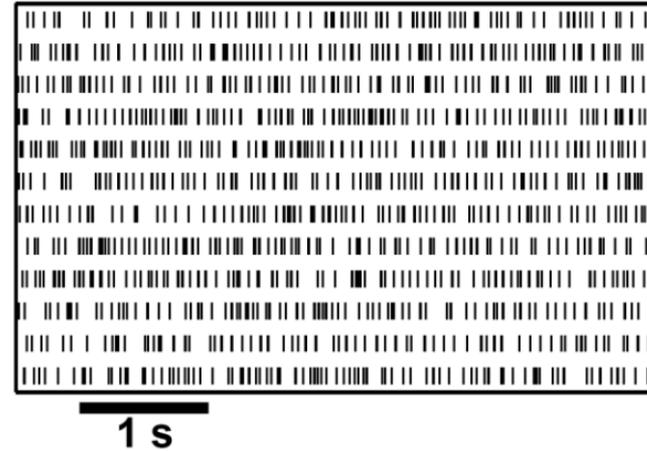
† = replacement from a homogeneous population

Prominent **interval** distributions used for renewal models of neural spiking



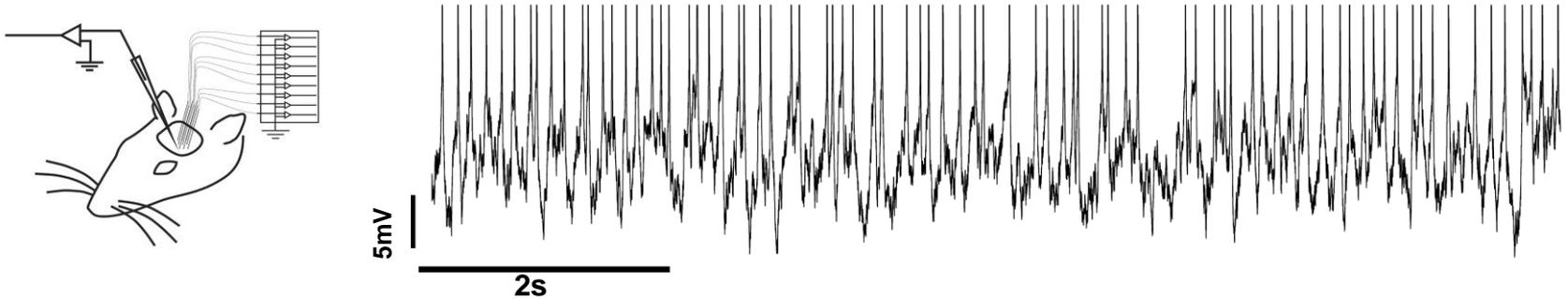


spn1-chan25-bee30.txt



Extracellular recordings of spontaneous activity from mushroom body extrinsic neurons in the Honeybee

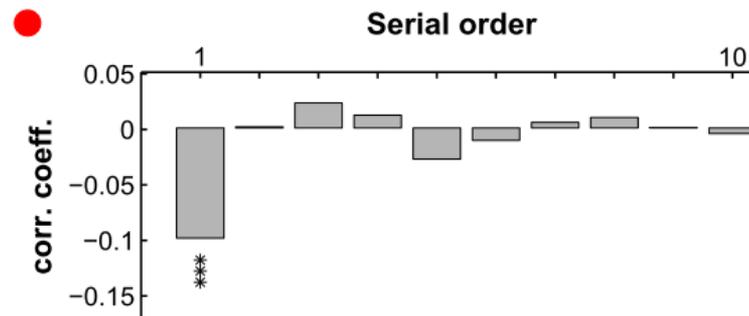
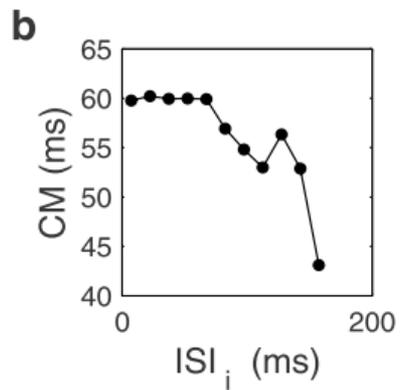
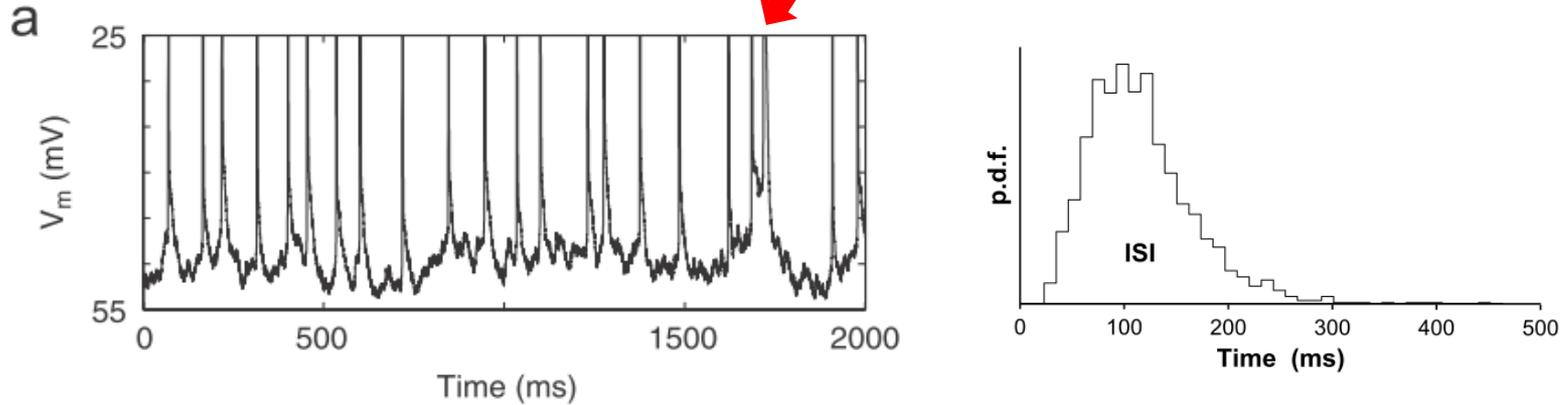
Intracellular recordings from cortical neurons in the somatosensory cortex of the anaesthetized rat



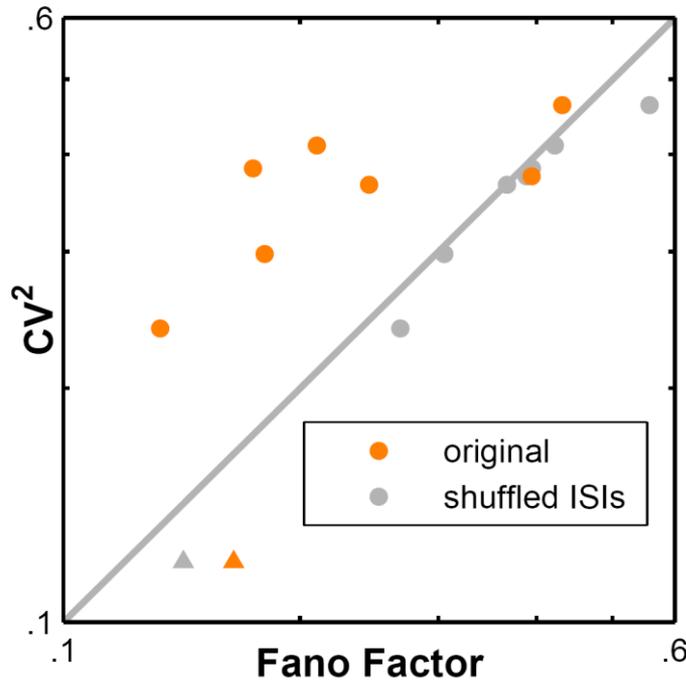
*Experiments by **Clemens Boucsein & Dymphie Suchanek***

University of Freiburg, Germany

Testing the renewal model *in vivo*



- ▶ negative serial correlations **reduce the Fano factor** ($FF < CV^2$)



$$FF < CV^2 \leq 0.5$$

Nawrot et al. (2007) Neurocomputing

$$\lim_{T \rightarrow \infty} FF = CV^2 \left(1 + 2 \sum_{i=1}^{\infty} SRC_i \right)$$

Cox & Lewis (1966) Methuen

Experimental evidence for serial ISI correlation

Reference	Model System & Neuron Type	SC
Ratnam and Nelson (2000)	Weak electric fish, isolated <i>P</i> -type Receptors afferent	-0.52
Chacron et al. (2000)	Weak electric fish, isolated <i>P</i> -type Receptors afferent	-0.35
Neiman and Russell (2004)	Paddle fish, sensory Ganglion	~ -0.4
Floyd et al. (1982)	Cat splanchnic and hypogastric nerves <i>in vivo</i>	-0.3
Levine (1996)	Goldfish retina, Ganglion cells <i>in vivo</i>	-0.13
Rodieck (1967)	Cat Retina, Ganglion cells <i>in vivo</i>	-0.06
Kuffler et al. (1957)	Cat Retina, Ganglion cells <i>in vivo</i>	-0.17
Tsuchitani and Johnson (1985)	Cat Lateral Superior Olive <i>in vivo</i>	-0.2
Nawrot et al. (2007)	Rat Somatosensory Cortex (S1) <i>in vivo</i> , regular spiking cells	-0.21
Nawrot et al. (2007)	Rat Somatosensory Cortex (S1) <i>in vitro</i> , pyramidal cells	-0.07
Engel et al. (2008)	Rat medial entorhinal cortex <i>in vitro</i> Layer II stellate and Layer III pyramidal neurons	[-0.1,-0.4]
Farkhooi et al. (2008)	Honeybee central brain <i>in vivo</i> Mushroom body extrinsic neurons	-0.15

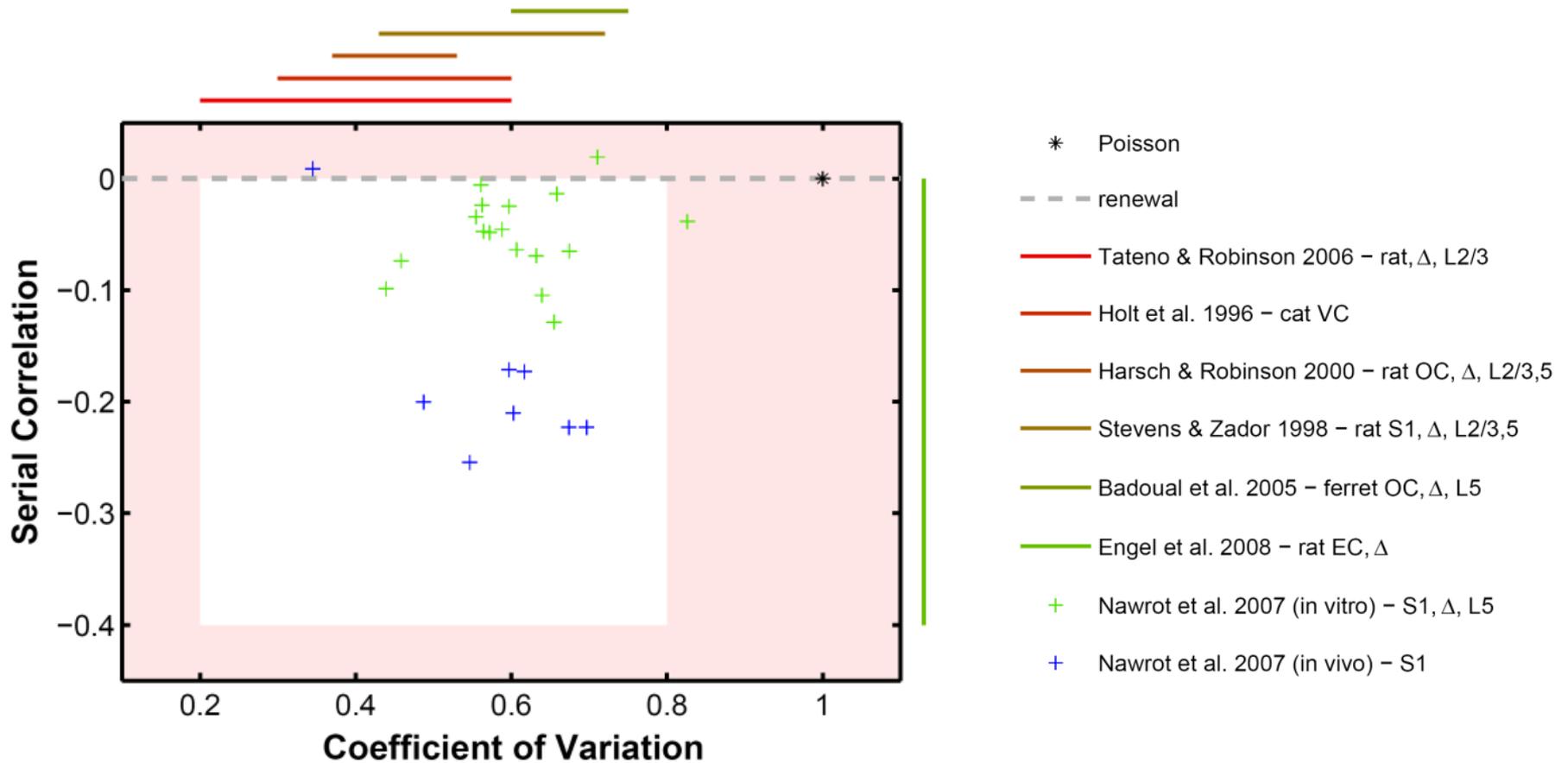
PERIPHERAL

CENTRAL

Table 1: Negative 1st order serial interval correlation in different preparations and cell types.

Farkhooi, Strube-Bloss, Nawrot (2009) *Phys Rev E*

Estimated parameters in the literature (neocortex)



Nawrot & Grün (in prep)

constant intensity λ

Poisson

- exponential interval distribution
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$$FF = CV^2 = 1$$

Renewal

- iid interval distribution
 - $FF = CV^2$

$$FF = CV^2$$

stationary non-Renewal

- constant intensity parameter
- non-trivial history dependence
- serial interval correlations

$$\lim_{T \rightarrow \infty} FF = CV^2 \left(1 + 2 \sum_{i=1}^{\infty} SRC_i \right)$$

increasing importance of process history



Autoregressive model approach

The autoregressive process in the general linear for up to lag p reads

$$X_s = \beta_1 X_{s-1} + \beta_2 X_{s-2} + \dots + \beta_p X_{s-p} + \varepsilon_s$$

where

ε_s i.i.d. with specific mean and finite variance.

β_i correlation coefficient for lag i and $|\beta| < 1$

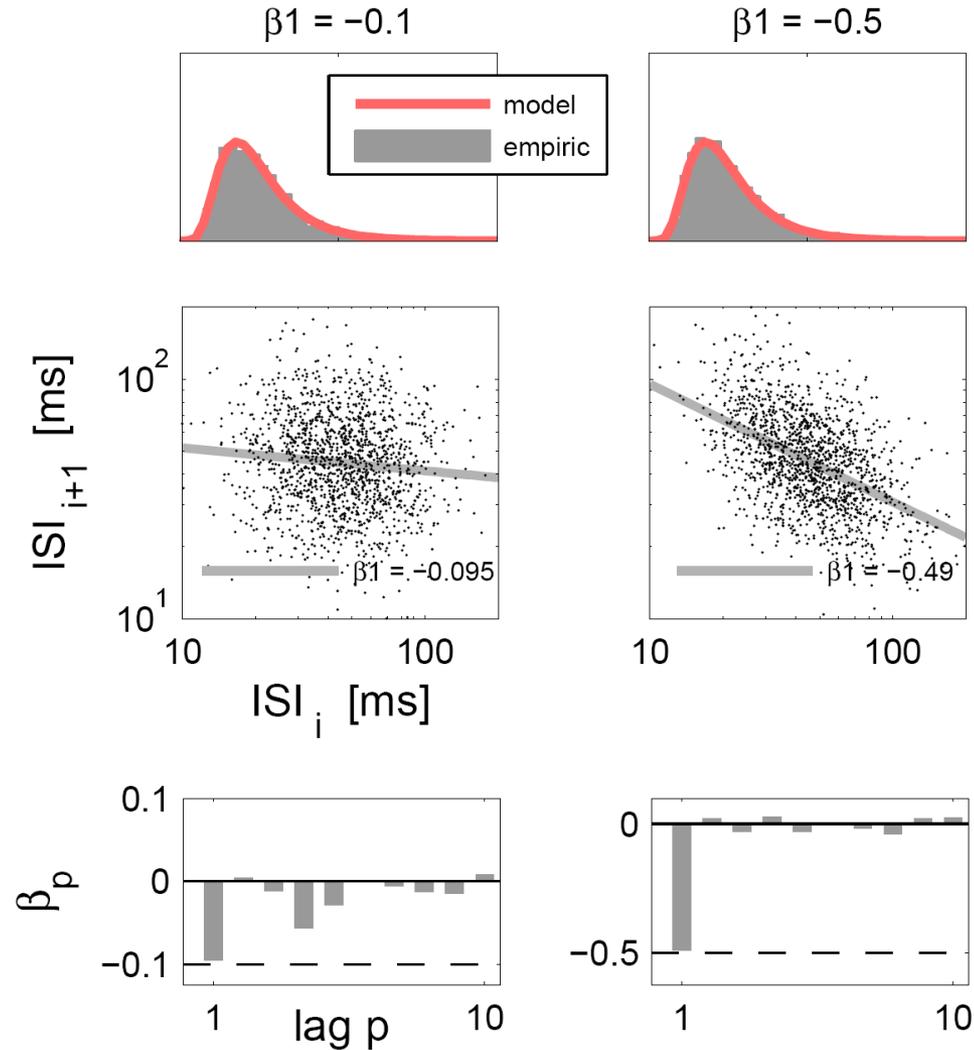
We propose the following process to model inter-event intervals

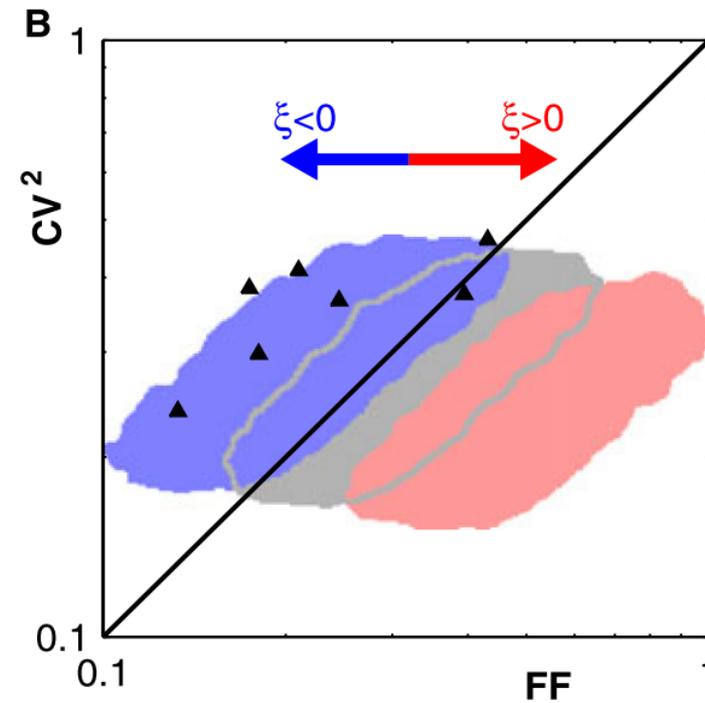
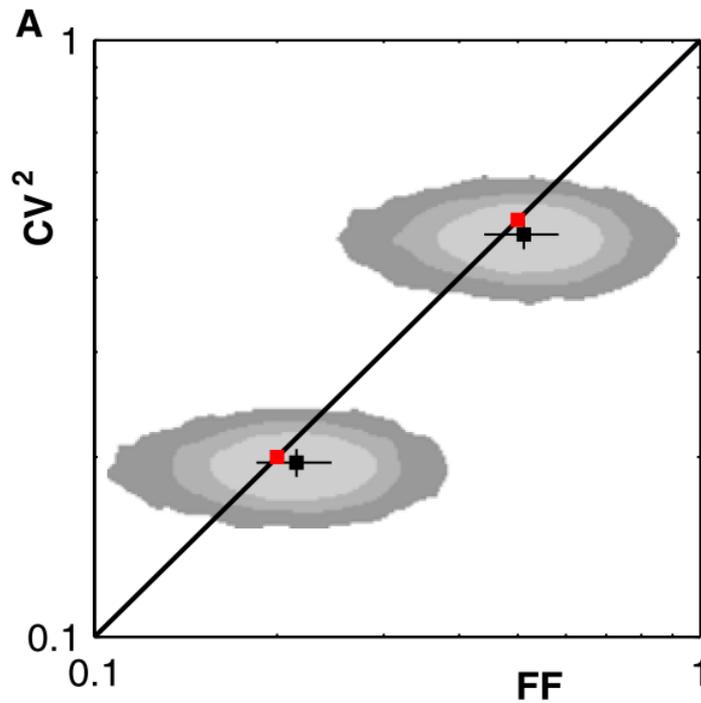
$$\Delta_s = \exp(X_s) = \exp(\beta X_{s-1} + \varepsilon_s) \quad (|\beta| < 1)$$

When we choose ε_s *normal distributed* with mean μ and variance σ^2 then Δ_s is *log-normal distributed*.

Non-renewal autoregressive point process

- *Numeric Simulation*
- log-normal
- CV = 0.5





$$\lim_{T \rightarrow \infty} FF = CV^2 \left(1 + 2 \sum_{i=1}^{\infty} SRC_i \right)$$

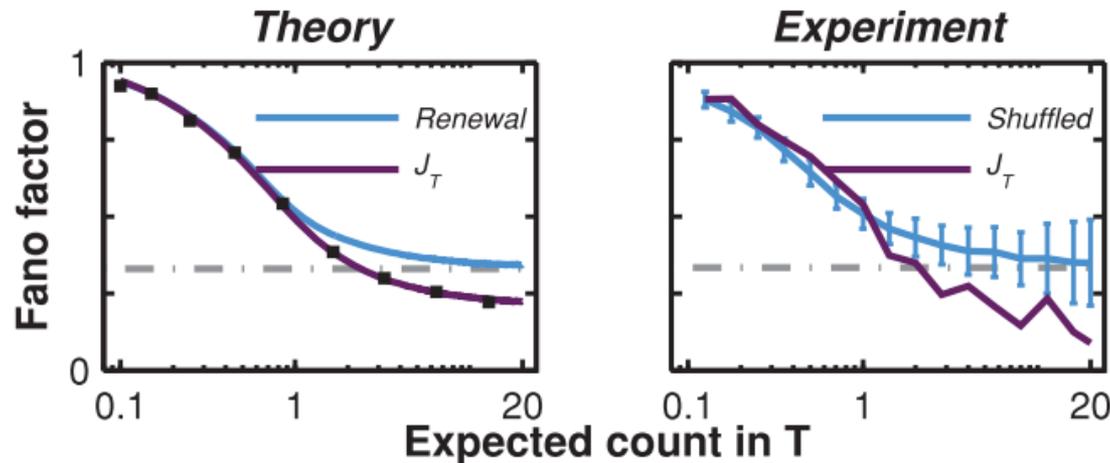
Nawrot (2010) In: Grün, Rotter (eds.), Springer Series Comp Neurosci 7



Thought experiment:

Superimpose N realizations of a gamma renewal processes of identical intensity and shape parameter. What happens to the CV^2 , what happens to FF of the *superimosed* process ?

- ▶ superposition **retains Fano factor**, but **increases CV** and adjusts SRCs accordingly
- ▶ **superposition** of renewal processes **results in a non-renewal process** (exception: Poisson)



$$\lim_{T \rightarrow \infty} FF = CV^2 \left(1 + 2 \sum_{i=1}^{\infty} SRC_i \right)$$

constant intensity λ

dynamic intensity $\lambda(t)$

Poisson

- exponential interval distribution
 - Poisson count distribution
- events are uniformly distributed in time
 - special case of gamma process

non-homogenous
Poisson

Renewal

- iid interval distribution
 - $FF = CV^2$

Rate modulated
Renewal

stationary non-Renewal

- constant intensity parameter
- non-trivial history dependence
 - serial interval correlations

increasing importance of process history



- The **Poisson model is a deficient model** for neural spiking
- Short-lived **negative serial interval correlations** exist in stationary cortical spike trains. Neuronal spiking is generally **non-renewal**
- Negative serial correlations **reduce variability in single neuron and population activity**. This benefits reliable population coding
- Biophysical mechanisms of self-inhibition such as **spike-frequency adaptation** provide a likely explanation for the negative ISI correlations (see also my talk tomorrow)

Averbeck BB (2009) Poisson or Not Poisson: Differences in Spike Train Statistics between Parietal Cortical Areas. *Neuron* 62: 310-11

Cox DR, Lewis PAW. The statistical analysis of series of events Methuen's monographs on applied probability and statistics. London: Methuen; 1966.

Farkhooi F, Müller E, Nawrot MP (2011) Adaptation reduces variability of the neuronal population code. *Physical Review E* 83: 050905

Farkhooi F, Strube M, Nawrot MP (2009) Serial correlation in neural spike trains: experimental evidence, stochastic modelling, and single neuron variability. *Physical Review E* 79: 021905

Nawrot MP (2010) Analysis and Interpretation of Interval and Count Variability in Neural Spike Trains. In: *Analysis of Parallel Spike Trains*, Grün S, Rotter S (Eds.), Springer, New York, August 2010

Nawrot MP, Boucsein C, Rodriguez-Molina V, Riehle A, Aertsen A, Rotter S (2008) Measurement of variability dynamics in cortical spike trains. *J Neurosci Meth* 169: 374-390

Nawrot MP, Boucsein C, Rodriguez-Molina V, Aertsen A, Grün S, Rotter S (2007) Serial interval statistics of spontaneous activity in cortical neurons in vivo and in vitro. *Neurocomputing* 70: 1717-1722