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JÜLICH FORSCHUNGSZENTRUM

Spike Synchrony: From Cross-Correlations to Higher Order Analysis Methods

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Outline

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Cross-correlation

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Effect of Neuronal Properties on Correlation Analysis

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Implementation of Null-Hypothesis by Surrogates

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Data Driven Analysis: Framework

Development of Statistical Tools	Development of Numerical Methods	Analysis of Experimental Data
▪ Reformulate concepts of neural information processing in testable predictions ▪ Development of stochastic models ▪ Calibration and testing of analysis tools by simulated data ▪ Cooperation with theoretician and modelers	▪ Often complexity of the data does not allow analytical description ▪ Realize test statistics numerically (Monte Carlo, Boot-strap etc) ▪ Development of algorithms for reducing time consumption	▪ Analysis of experimental data ▪ Relevance of observation for behavior and cognition ▪ Close cooperation with experimenters

Cortex in Numbers

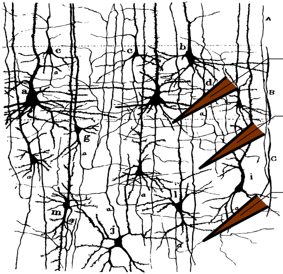
Table 1.5.4. *Typical compositions of cortical tissues*

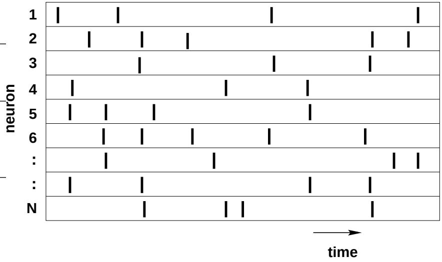
Variable	Value
Neuronal density	40,000/mm^3
Neuronal composition:	
Pyramidal	75%
Smooth stellate	15%
Spiny stellate	10%
Synaptic density	$8 \cdot 10^8$/mm^3
Axonal length density	3,200 m/mm^3
Dendritic length density	400 m/mm^3
Synapses per neuron	20,000
Inhibitory synapses per neuron	2,000
Excitatory synapses from remote sources per neuron	9,000
Excitatory synapses from local sources per neuron	9,000
Dendritic length per neuron	10 mm

Abeles (1991) Corticonics, Cambridge Univ. Press
Braitenberg & Schüz (1991) Anatomy of the Cortex, Springer

- High density of neurons
- Strong convergence and divergence
- Highly interconnected network
- Neurons do not act in isolation

Hypothesis





- Cell assemblies act as building blocks for information processing (Hebb, 1949)
- Assembly members exhibit coordinated activity
- Different assemblies active in different behavioral context

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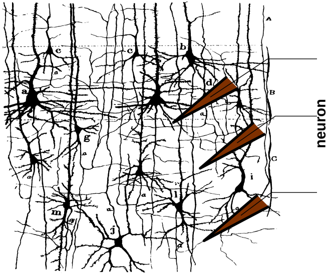

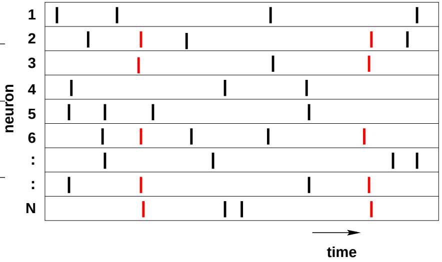

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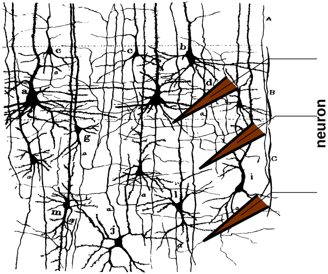

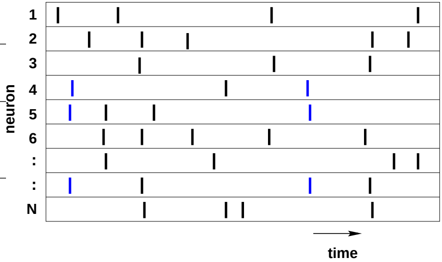

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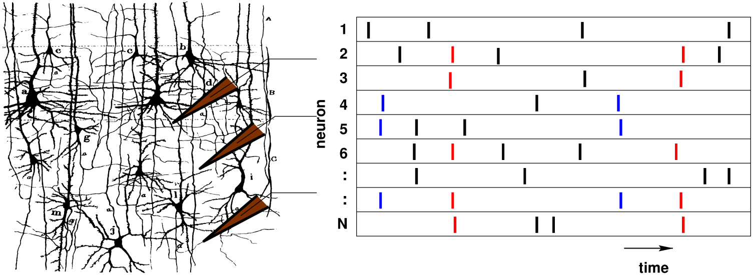

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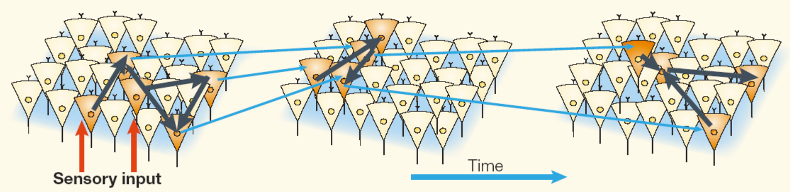
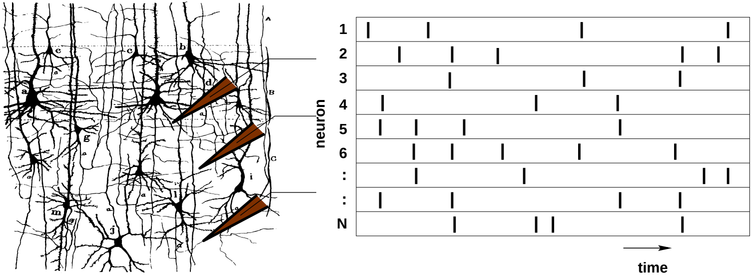
Dynamics of Network Interaction



Harris (2005)

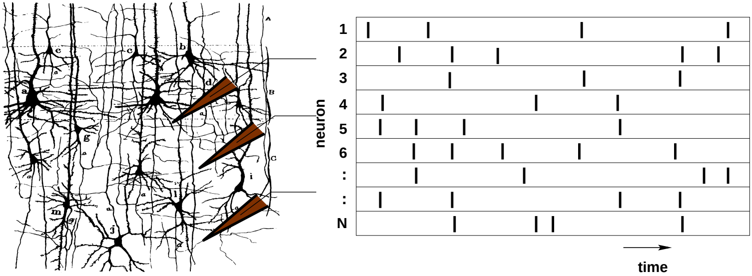
- Neuronal activity in relation to behavior and function is dynamic
- Structure (anatomy) provides the ground for activity
- Assembly may be active or not, depending on coherent activity
- Correlation based information processing

Goal



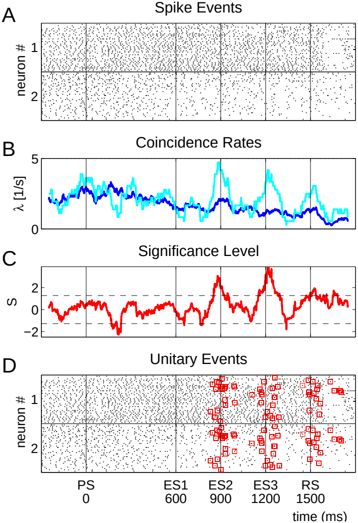
- Detect and identify expressions of assembly activity
- Relate network dynamics to stimuli and/or behavior
- Identify temporal and spatial scales of assembly activity

Approach



- Observe many neurons simultaneously
- Analyze activity for correlated activity
- Identify (dynamics of) correlation and relate to stimuli/behavior

Dynamics of Synchronous Activity

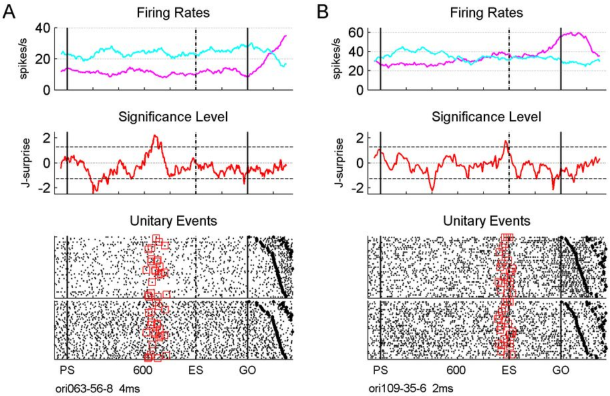


- Behavior related occurrence of Unitary Events: occur at times when the monkey expects the GO-signal

* Riehle, Grün, Diesmann, Aertsen (1997) Science 278: 1950-1953

Timing of Excess Synchrony Adapted by Practice

Before practice | After practice



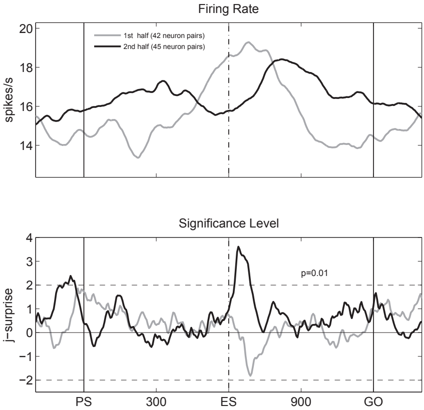
- Unitary Events occur at behaviorally relevant time instances
- Timing occurrence changes to newly learned timing pattern

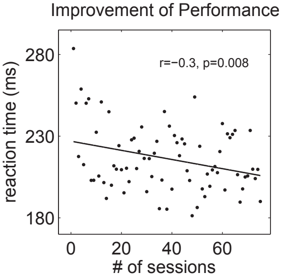
* Kilavik, Roux, Ponce-Alvarez, Confais, Grün, Riehle (2009) J Neuroscience 29(40):12653-12663

* Riehle, Grün, Diesmann, Aertsen (1997) Science

Timing of UEs adjusts by Practice

Population Data





Practice leads to

- decreasing reaction times
- synchrony at behaviorally relevant times

* Kilavik, Roux, Ponce-Alvarez, Confais, Grün, Riehle (2009) J Neuroscience 29(40):12653-12663

Outline

- Standard approach: Cross-correlation analysis
- Necessity: consider statistical features of neuronal activity
- Correlation analysis for massively parallel data

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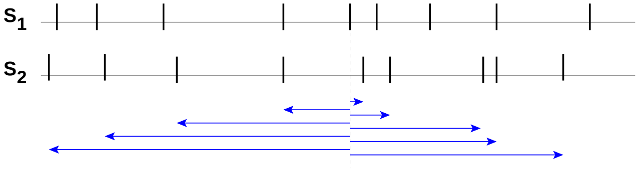
Cross-Correlation

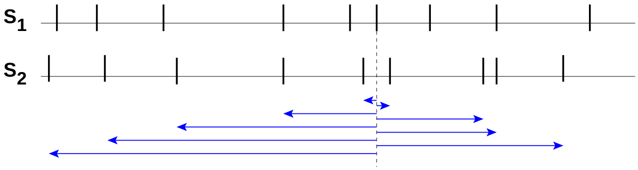


- The cross-correlation represents the probability of finding any event in train s_2 as a function of time before or after an actual event in train s_1:

$$\rho_{1,2}(\tau) = \int s_1(t) s_2(t-\tau) d\tau$$

* Perkel et al, 1967

Cross-Correlation



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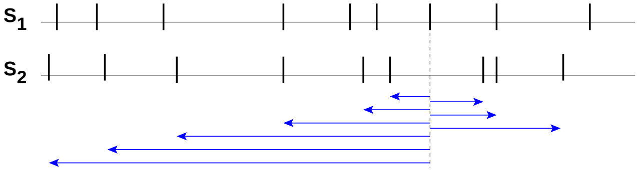

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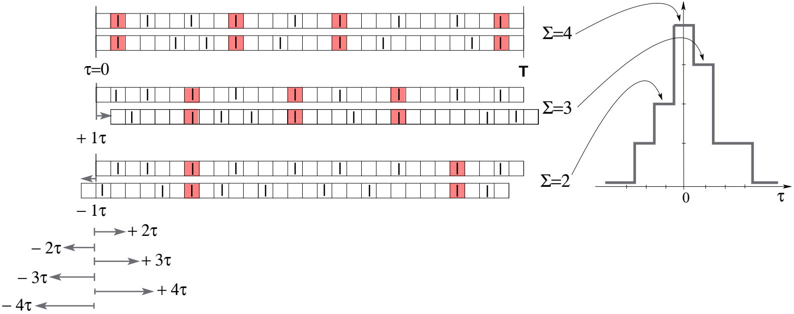
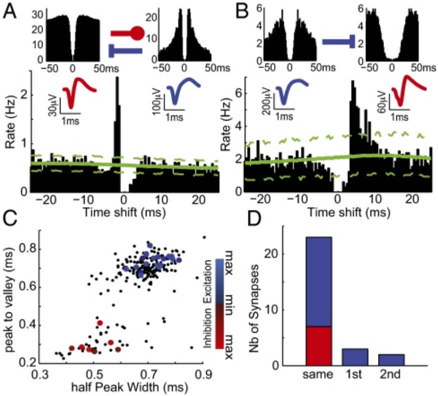
Cross-Correlation Histogram



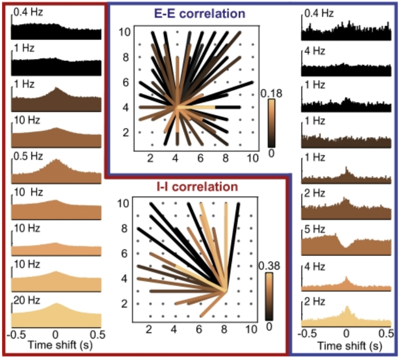
Cross-Correlations - Dependencies



Peyrache et al (2012) PNAS

- **Physical direct connectivity**: neuron synaptically connected $\rightarrow$ delayed peak (or trough)

Cross-Correlations - Dependencies



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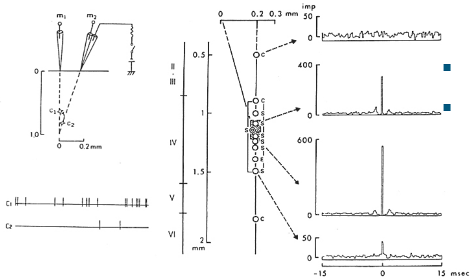
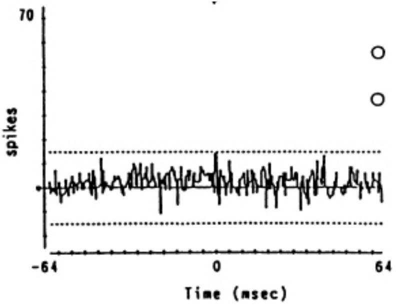


Fig. 8.4. Correlation between two simple (*s*) cells in the visual cortex usually results from shared excitatory input. The extent of interaction is about 300 µm both ways in the column, the strength decreases with distance. (Toyama et al. 1981 b)

Eggermont (1990) Correlative Brain, Springer

- **Physical direct connectivity**: neuron synaptically connected $\rightarrow$ delayed peak (or trough)
- Spatial dependence of correlation
- Depth dependence of correlation

Cross-Correlations - Dependencies



auditory

- **Physical direct connectivity**: neuron synaptically connected $\rightarrow$ delayed peak (or trough)
- Spatial dependence of correlation
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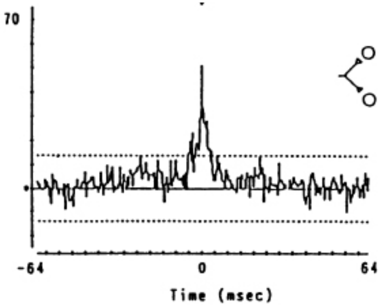
- **Stimulus induced**: both neurons are activated by the same stimulus, but are not connected

Sakurai (1999) http://dx.doi.org/10.1016/S0149-7634(99)00017-2

Cross-Correlations - Dependencies



visual

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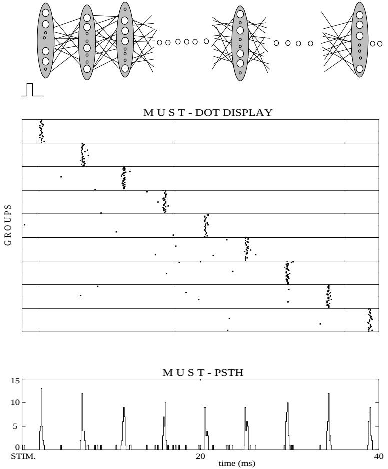

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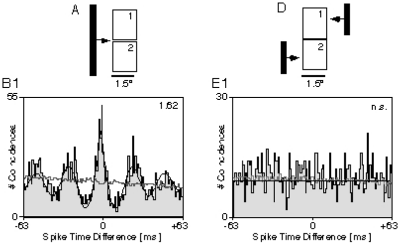
Abeles (1990); Diesmann et al (1999)

Cross-Correlations - Dependencies



Freiwald et al. (1995) NeuroReport 6: 2348–2352

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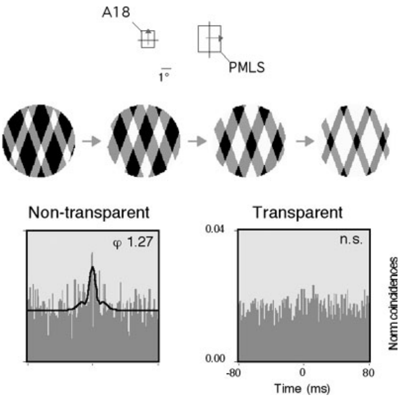
Cross-Correlations - Dependencies



Castelo-Branco et al (2000) Nature 405: 685–689

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Interpretation of Cross-Correlation

- Rate increase or interaction?
- Even if neurons fire independently from each other, we find (delayed) coincidences. They occur by chance.
- The higher the firing rate, the more coincidences
- Changes in rate may also induce a peak (typically broad)
- Solution: Calculate and subtract 'predictor', i.e. the cross-correlogram for the uncorrelated case, but with the same firing rates
- Approaches: analytically (often difficult or impossible) $\rightarrow$ numerical procedures

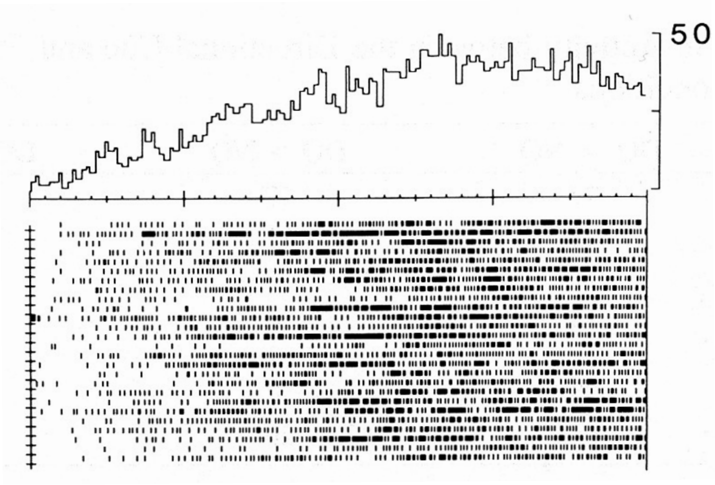
Correction for Rate Effects

- Calculate CCH of empirical data ('raw')
- Generate CCH of independent data, with same statistical properties as the spike trains ('predictor')
- Corrected empirical CCH (covariance) $\rightarrow$ indicates presence of correlation
- Most done: entries expressed as correlation coefficient, i.e. divided by product of standard deviations of processes

* from: http://mulab.physiol.upenn.edu/analysis.html

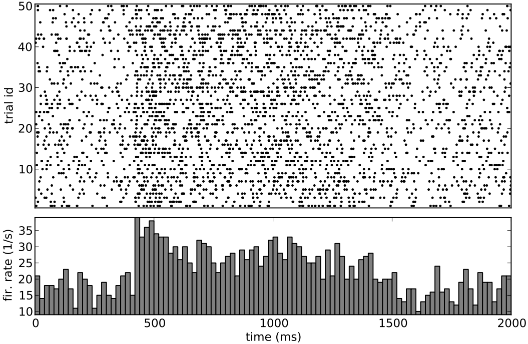
Outline

Experimental Data



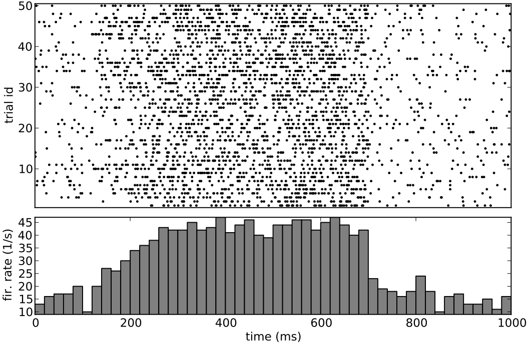
Vaadia et al (1988)

Estimating Firing Rate from Repeated Trials: PSTH



- Bin the time axis; sum spikes across trials in bin
- Normalize number of spikes to time: firing rate
- Bin size? Depends on the data $\hookrightarrow$ Rule of thumb: avoid wild fluctuations

Estimating Rates across Trials?



- Does the neuron behave the same across trials?
- Are fluctuations purely stochastic, or is there qualitative difference across trials?

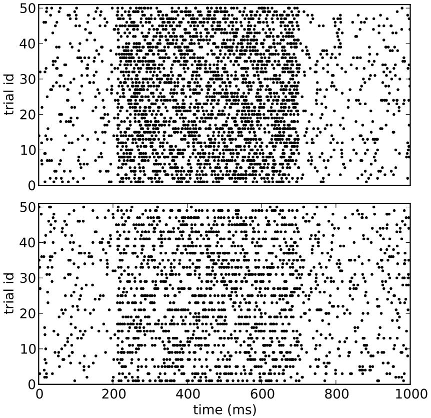
Cross-trial variability and Fano Factor

- Cross-trial statistics (e.g. PSTH) assume cross-trial stationarity (e.g. of spike count)
- The Fano Factor (FF) quantifies cross-trial spike count variability:

$$\mathrm{FF} = \frac{\mathrm{var}(\#\textit{spikes}/\textit{trial})}{\mathrm{mean}(\#\textit{spikes}/\textit{trial})}$$

- For a cross-trial homogeneous Poisson process, the theoretical FF is 1
- Non-Poisson processes (e.g. Gamma process) lead to deviations from 1
- Deviations from cross-trial stationarity may lead to misinterpretation of results

Cross-trial variability and Fano Factor



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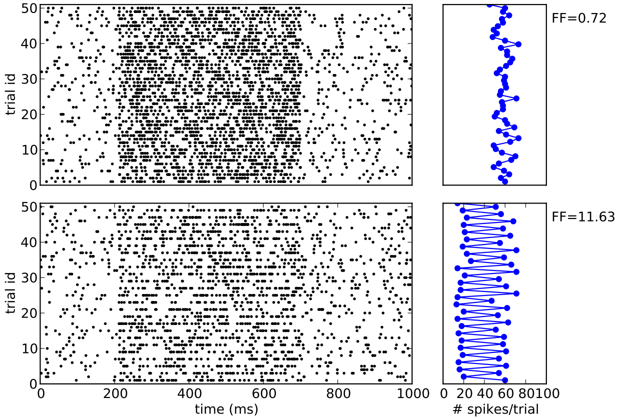
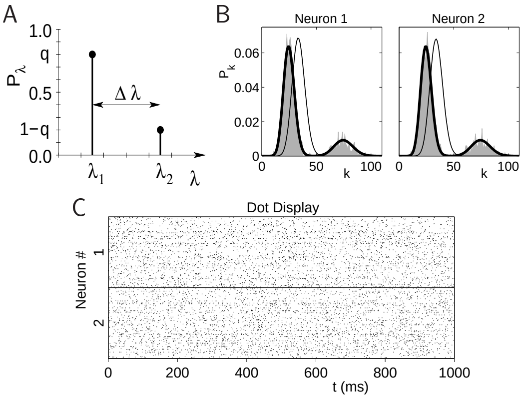


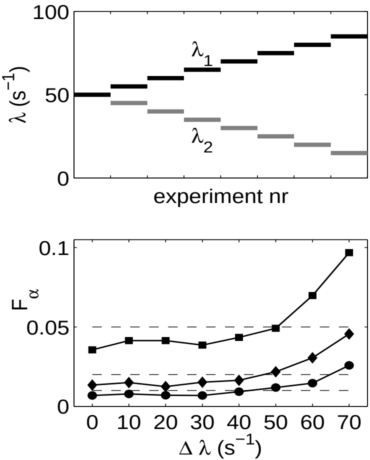
Effect of Cross-Trial Non-Stationarity on Correlation Analysis



- Rates drawn from two rate states: λ_1, λ_2
- Non-stationarity across trials: $\Delta\lambda = \lambda_1 - \lambda_2 > 0$
- Occupation probability of rate states: q for λ_1, $1 - q$ for λ_2

* Grün, Riehle, Diesmann (2003) Biol Cybern 88(5): 335–351

False Positives by Cross-trial Non-Stationarity

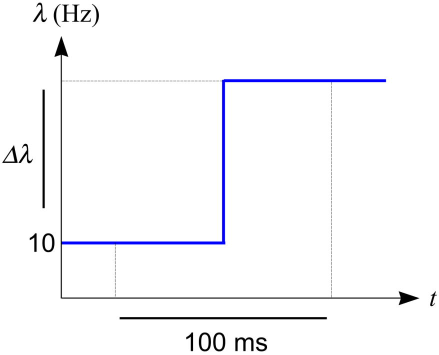


Simulation Experiment:

- Simulate independent spike trains with given parameters $\lambda_1, \lambda_2, q, M$
- Count coincidences: n_{emp}
- Calculate expected number of coincidences: $\bar{n}_{pred}$
- Empirical counts significant? $(\Psi(n_{emp}|\bar{n}_{pred}))$; repeat many times
- The larger the cross-trial rate differences, the more FPs

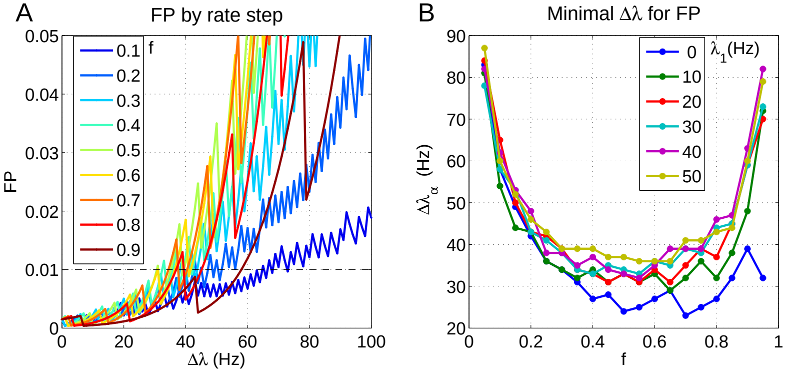
* Grün, Riehle, Diesmann (2003) Biol Cybern 88(5): 335–351

Non-Stationarity in Time



- Model system: two neurons, changing their rates coherently
- Amount of rate step ($\Delta\lambda$) and relative duration of rate levels varied ($t_1 = f \cdot T_w$)

False Positives by Non-Stationary Rates

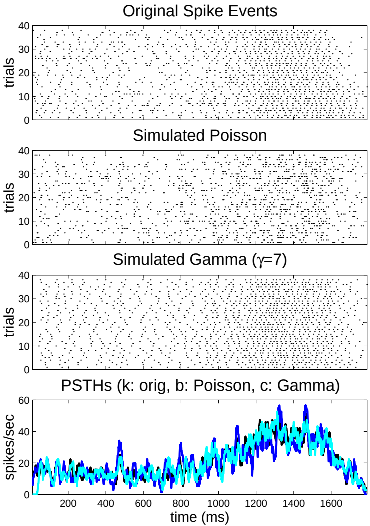


- For $\Delta\lambda > 30$Hz FPs start to occur
- The larger the rate step the more FP
- FP threshold lowest for $f \approx 0.7$

Poisson Process?

e.g. modeled as process with γ-distributed intervals

$$f(\tau) = \lambda \cdot e^{-\lambda\tau} \cdot \frac{(\lambda\tau)^{(\gamma-1)}}{\Gamma(\gamma)}$$



Spiking variability and Coefficient of Variation

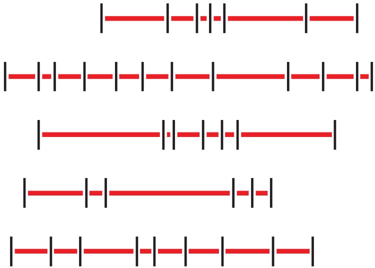


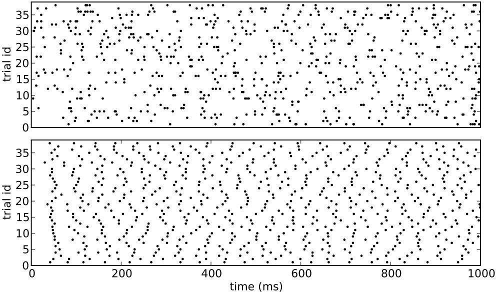
Figure: Stefan Rotter

- Regularity of spiking activity (i.e. the inter-spike intervals, ISIs) is measured by the Coefficient of Variation (CV):

$$CV = \frac{\text{std(ISIs)}}{\text{mean(ISIs)}}$$

- For a Poisson process, the theoretical CV is 1
- Higher (lower) inter-spike interval variability $\Rightarrow$ higher (lower) CV

Spiking variability and Coefficient of Variation



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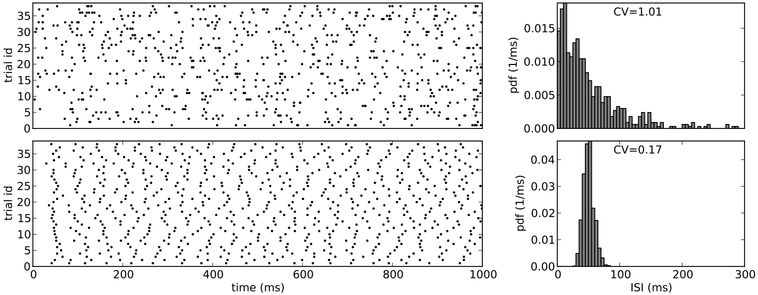
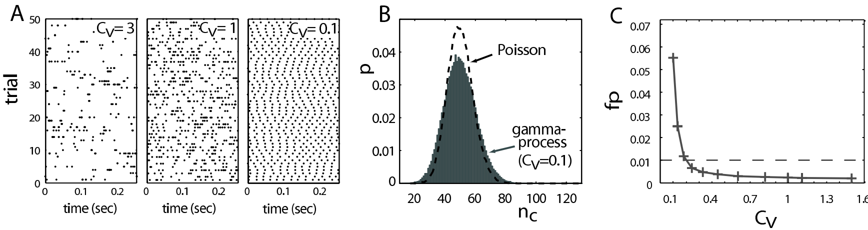


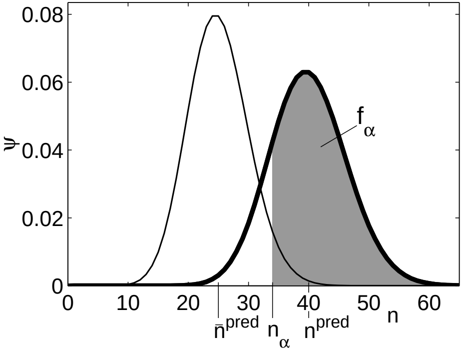
Impact of Deviation from Poisson



- Process determines shape of coincidence distribution
- for wide range of regularity parameter γ
  $\rightarrow$ Poisson assumption leads to conservative estimates
- for high regularity false positive rate increases
- CV of experimental data typically $>$ 0.2 (Nawrot et al, 2008)

* Grün (2009) J Neurophysiol; * Pipa, Grün, van Vreeswijk (2013) Neural Comput

Reason for False Positives



- Statistical features not included in null-hypothesis

* Grün, Diesmann, Aertsen. *Unitary Event Analysis*. In: Analysis of parallel spike trains. eds. Grün & Rotter. Springer Series in Computational Neuroscience (2010)

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Correlation Analysis of Massively Parallel Data

How to Avoid False Positives

- If possible: Include non-stationarities in analytical expression of the prediction
- Check for 'safe' parameter ranges (tested by simulations)
- Use surrogates for implementing the null-hypothesis

What and how?

- Experimental data often too complex to enable analytical expression of relevant measures
- Critical parameters cannot reliably estimated

What and how?

- Experimental data often too complex to enable analytical expression of relevant measures
- Critical parameters cannot reliably estimated
- Surrogate data: generated from the original data to implement a null-hypothesis of interest
- Goal: destroy the feature in the data you aim to test for, and leave all (if possible) other features of the data intact

What and how?

- Experimental data often too complex to enable analytical expression of relevant measures
- Critical parameters cannot reliably estimated
- Surrogate data: generated from the original data to implement a null-hypothesis of interest
- Goal: destroy the feature in the data you aim to test for, and leave all (if possible) other features of the data intact
- Example:
  - Interested in testing for significant spike sychrony in a pair of spike trains
  - Implement null-hypothesis by intentional destruction of correlation, but leave features like rates, spike train structure, etc as in the original data
  - Estimate significance based on distribution generated from surrogates

What and how?

- Experimental data often too complex to enable analytical expression of relevant measures
- Critical parameters cannot reliably estimated
- Surrogate data: generated from the original data to implement a null-hypothesis of interest
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- Example:
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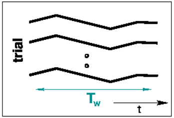
  - Estimate significance based on distribution generated from surrogates
- Other purposes: controls, validation, etc

Reminder: Neuronal Data Violate Conventional Assumptions

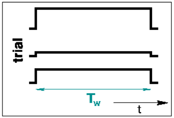
Care!

→ Rejection of the null-hypothesis, falsely due to violation of an inherent assumption of the method.

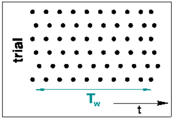
→ False positives and/or wrong interpretation of data.



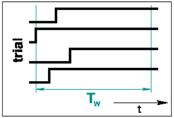
Non-stationary rates in time



Non-stationary rates across trials

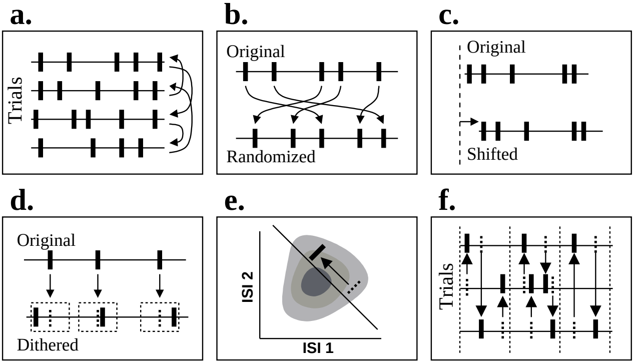


Non-Poissonian spike trains



Latency variability

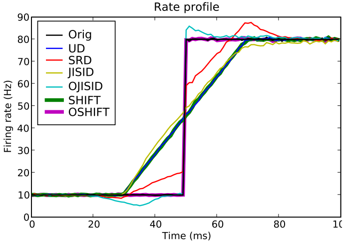
Surrogates

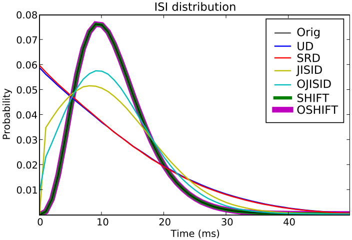


- Implement predictor by destruction of correlation
- e.g. spike time randomization, ISI shuffling, dithering, trial shuffling...

* Louis et al. In: Analysis of parallel spike trains. Eds. Grün and Rotter, Springer, 2010

Impact of Surrogates

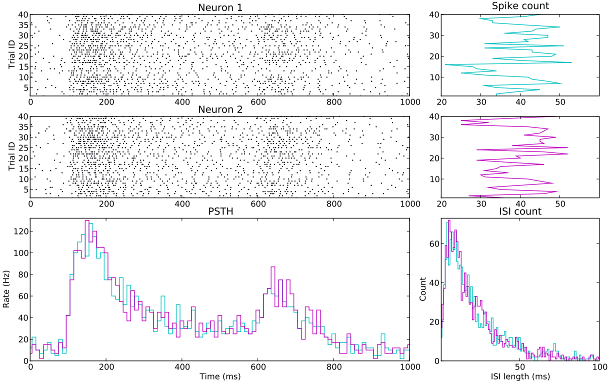




- Affect often other features of data, may lead to FPs/FNs
- Test and calibrate methods !
- Choose appropriate surrogate !

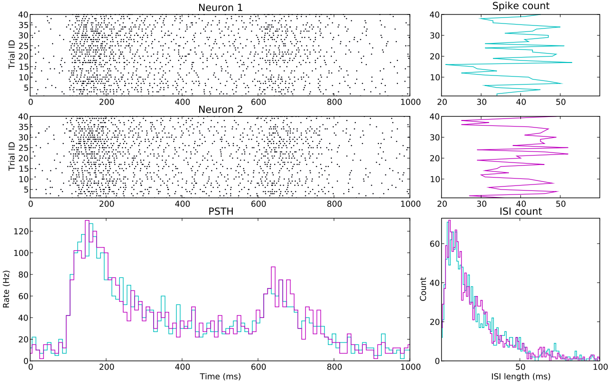
* Grün. J Neurophysiol (2009) 101: 1126-1140 (review)
* Louis, Borgelt, Grün (2010) In: Analysis of parallel spike trains. Eds. Grün & Rotter, Springer
* Louis, Gerstein, Grün, Diesmann (2010) Frontiers Comput Neuroscience

Example



* Louis et al. In: Analysis of parallel spike trains. Eds. Grün and Rotter, Springer Series Computational Neuroscience, 2010

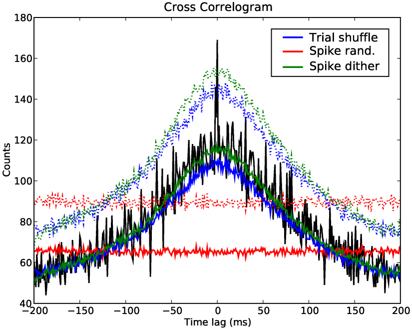
Example



- Non-stationary, in time, across trials, non-Poisson, covarying firing rates
- Analytical predictor not available

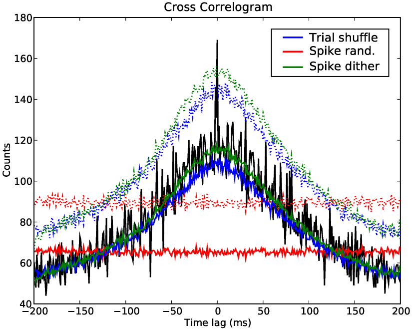
* Louis et al. In: Analysis of parallel spike trains. Eds. Grün and Rotter, Springer Series Computational Neuroscience, 2010

Cross-Correlations - of Data and Surrogates



* Louis et al. In: Analysis of parallel spike trains. Eds. Grün and Rotter, Springer Series Computational Neuroscience, 2010

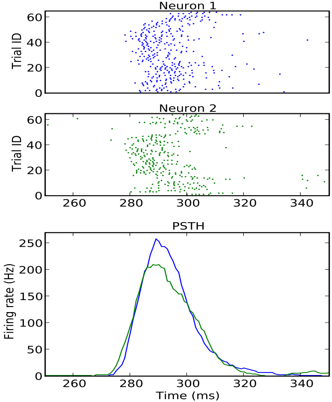
Cross-Correlations - of Data and Surrogates



- Narrow peak reflects spike correlation
- Broad peak: due to non-stationarities
- Non-proper surrogates may alter the rate induced peak

* Louis et al. In: Analysis of parallel spike trains. Eds. Grün and Rotter, Springer Series Computational Neuroscience, 2010

Proper Choice of Surrogate Avoids FPs

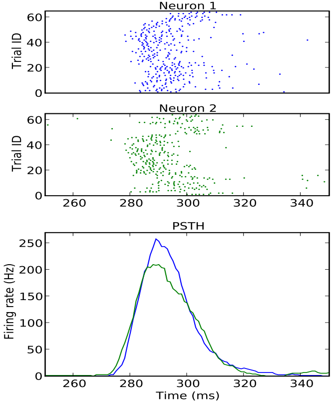


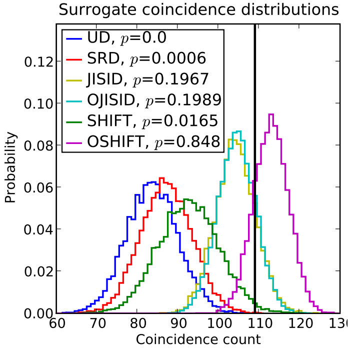
- Neurons **not** simultaneously recorded

from: neurodatabase.org

* Louis, Gerstein, Grün, Diesmann (2010) Frontiers Comput Neuroscience

Proper Choice of Surrogate Avoids FPs





- Neurons **not** simultaneously recorded

from: neurodatabase.org

- Different surrogates lead to very different p-values

* Louis, Gerstein, Grün, Diesmann (2010) Frontiers Comput Neuroscience

Outline

Introduction

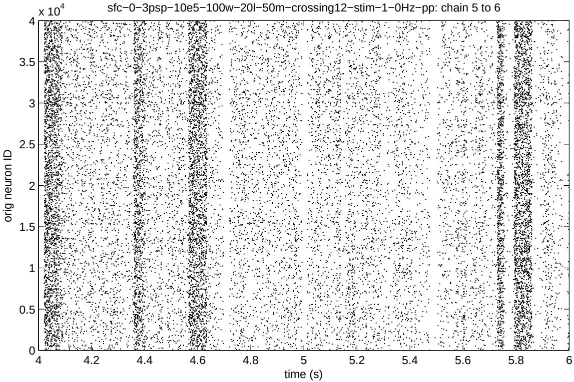
Cross-correlation

Effect of Neuronal Properties on Correlation Analysis

Implementation of Null-Hypothesis by Surrogates

Correlation Analysis of Massively Parallel Data

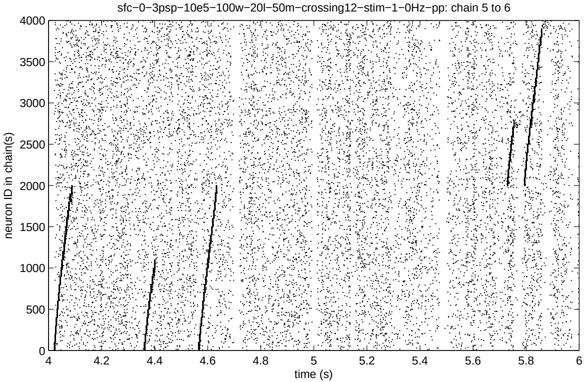
Aim: Uncover Correlation Structure



* Schrader, Grün, Diesmann, Gerstein (2008) J Neurophysiol, 100(4):2165–2176

- Intuition: Increasing the number of neurons increases the chances to detect assembly activity
- How to detect structure in data?

Aim: Uncover Correlation Structure



* Schrader, Grün, Diesmann, Gerstein (2008) J Neurophysiol, 100(4):2165–2176

- Intuition: Increasing the number of neurons increases the chances to detect assembly activity

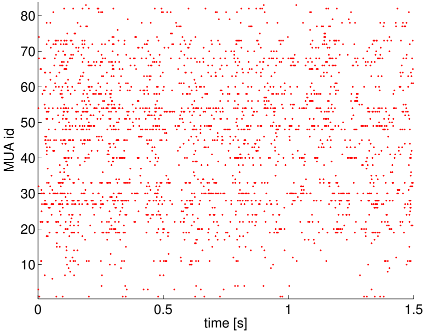
New Analysis Strategies Required

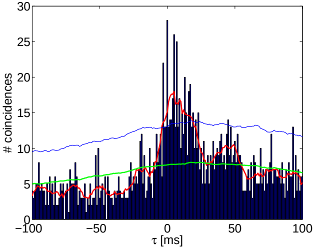
- Extension of e.g. UE analysis to massively parallel spike trains leads to combinatorial explosion of parameters
  - $2^N - 1$ parameters (individual activity patterns), e.g. $N = 100 \rightarrow \sim 10^{30}$ parameters
  - Needs very long, stationary data stretches for reliable estimates

Development of Methods !

* Berger, Warren, Normann, Arieli, and Grün (2007) Neurocomputing 70: 2112-2116
* Grün, Abeles, Diesmann (2008) Lecture Notes in Computer Science, vol 5286, 96-114
* Schrader, Grün, Diesmann, Gerstein (2008) J Neurophysiol 100(4):2165-2176
* Shimazaki, Amari, Brown, Grün (2009) IEEE ICASSP, 3501-3504
* Louis, Borgelt, Grün (2010) Neural Networks 23: 705–712
* Staude, Rotter, Grün (2010) J Comput Neurosci. doi:10.1007/s10827-009-0195-x
* Staude, Grün, Rotter (2010) Front Comput Neurosci 4:16. doi:10.3389/fncom.2010.00016
* Berger, Borgelt, Louis, Morrison, Grün (2010) Computat Intell Neurosci Vol. 2010, Article ID 439648, DOI:10.1155/2010/439648
* Shimazaki, Amari, Brown, Grün (2012) Plos Comput Biology 8(3):e1002385
* Gerstein, Wiliams, Diesmann, Grün, Trengove (2012) J Neurosci Meth 206(1):54-64
* Picado-Muiño, Borgelt, Berger, Gerstein, Grün (2013) Front Neuroinform doi: 10.3389/fninf.2013.00009
* Torre, Picado-Muiño, Denker, Borgelt, Grün (2013) Front Comput Neurosci doi: 10.3389/fncom.2013.00132

Pairwise Analysis

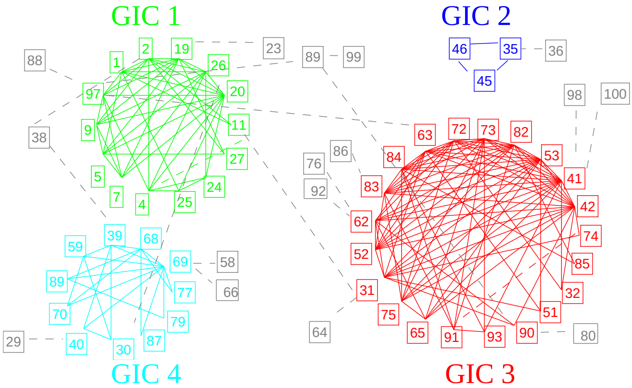




- Cat visual cortex, 10X10 electrode grid, 400μm distance
- 83 multi-unit activities (MUAs)
- Pairwise cross-correlation analysis; significance by surrogates
- Identify cliques of mutually correlated pairs

* Berger, Warren, Normann, Arieli, Grün (2007) Neurocomputing

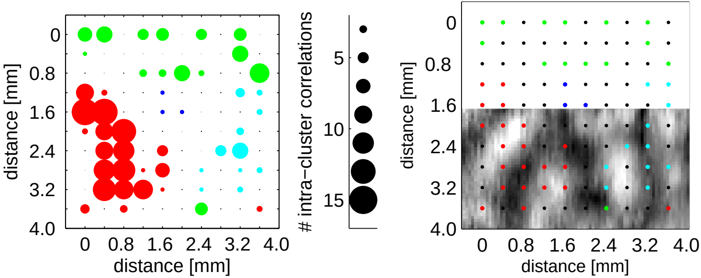
Clusters of Correlated Neurons



- Huge nr of cliques that overlap
- On minimal criteria graph decomposes in small number of distinct clusters

* Berger, Warren, Normann, Arieli, Grün (2007) Neurocomputing

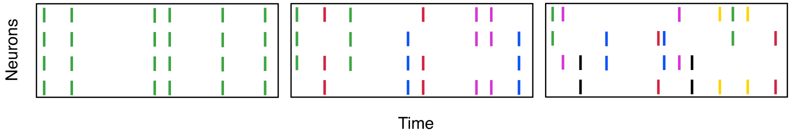
Clusters in Cortical Space



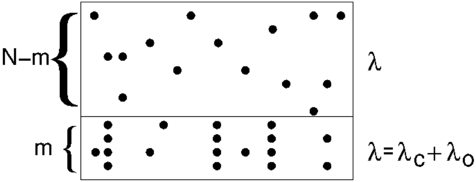
- Clusters of correlated spiking also cluster in cortical space
- Spatial scale corresponds to areas of orientation tuning

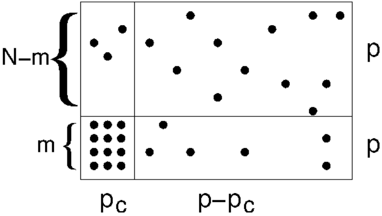
* Berger, Warren, Normann, Arieli, Grün (2007)

Presence of Higher-Order Correlations?



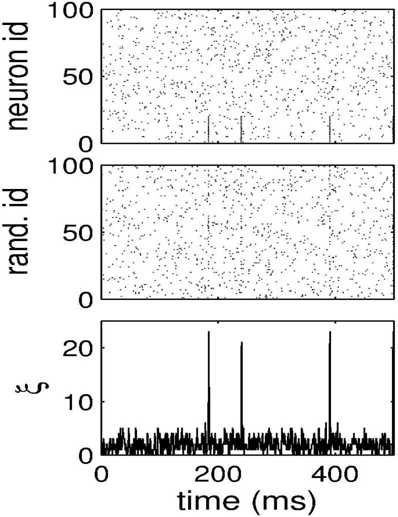
Stochastic Model





* Grün, Abeles, Diesmann (2008) Lecture Notes
* Louis, Borgelt, Grün (2010) Neural Networks

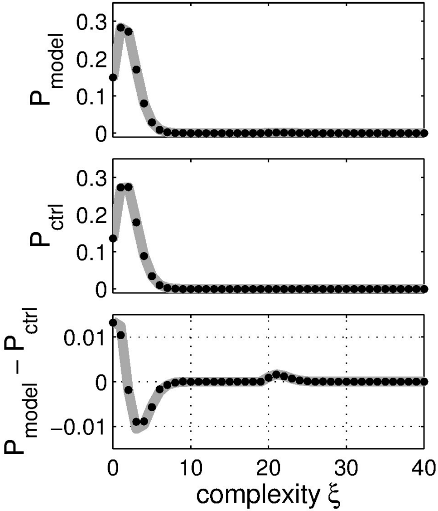
Complexity Distribution



- Population histogram → distribution
- Correlated spiking expressed by high spike counts

* Grün, Abeles, Diesmann (2008) Lecture Notes
* Louis, Borgelt, Grün (2010) Neural Networks

Complexity Distribution

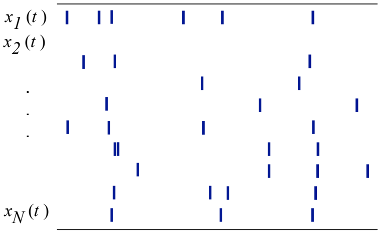


- Population histogram → distribution
- Correlated spiking expressed by high spike counts
- Difference of distributions indicates presence of correlation

* Grün, Abeles, Diesmann (2008) Lecture Notes

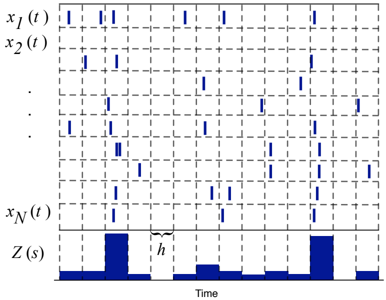
* Louis, Borgelt, Grün (2010) Neural Networks

Inference of HOC



- Population histogram, i.e. sum of spikes per bin h: $Z(s) = \sum_{i=1}^{N} X_i(s)$
- Drawback: individual patterns not resolved
- Correlated spiking expressed by high counts

Inference of HOC



- Population histogram, i.e. sum of spikes per bin h: $Z(s) = \sum_{i=1}^{N} X_i(s)$
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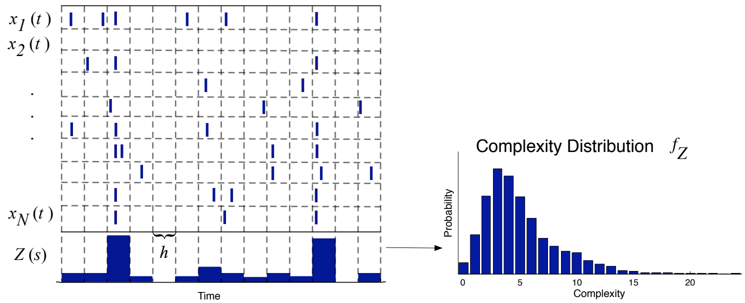
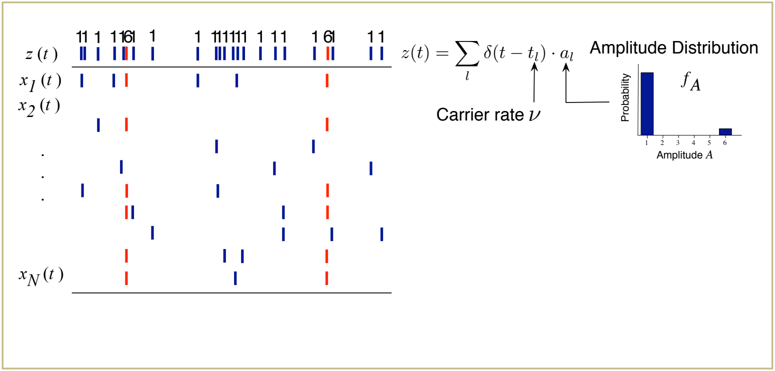
Measurement



- Complexity distribution: distribution of spike counts $Z(s)$
- High counts by presence of correlation expected to distort distribution
- Use cumulants $\kappa_m[Z]$ to quantify shape of complexity distribution

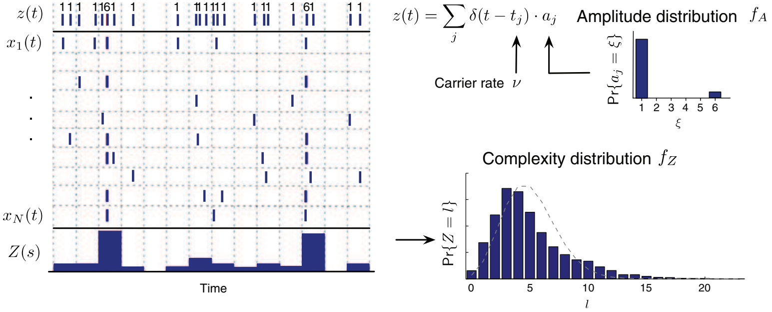
JÜLICH FORSCHUNGSZENTRUM

Model



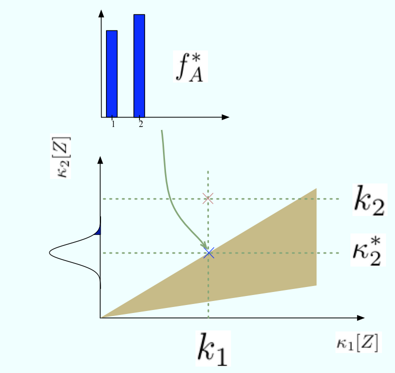
- Compound Poisson process (CPP): spikes copied from hidden process in child processes
- Amplitude distribution f_A defines correlation structure

Relate Measurement and Model



- Cumulants of CPP model: $\kappa_m[Y_l] = f_A(l)\nu$ in bins of h, for all m
- Observable cumulants of complexity distribution relate to unobservable amplitude distribution as $\kappa_m[Z] = \mu_m[A]\nu h$

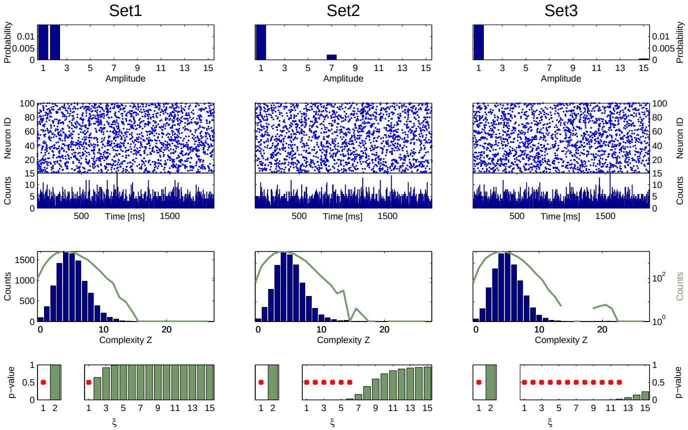
Significance Test



- Significance of measured cumulant $\kappa_m[Z]$ by comparison to $\kappa_m[\nu, f_A, \xi_m]$ based on model
- Null-hypothesis $H_0^{m,\xi}$: correlation of order m are compatible with the assumption that there are no correlations beyond order ξ
- Rejecting $H_0^{m,\xi}$ implies that $\xi + 1$ is a lower bound for the correlation order
- Using cumulants of only order m yield reliable results

* Staude, Rotter, Grün (2010) J Comput Neurosci, 29 (1-2): 327–350

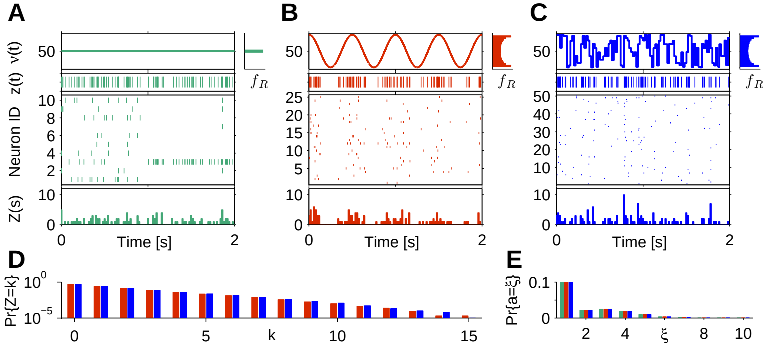
Examples



30 correlated, 70 independent; Set1: $\xi_{in} = 2$, Set2: $\xi_{in} = 7$, Set3: $\xi_{in} = 15$.

$T = 100$ sec, $\lambda = 10\,\mathrm{Hz}$, $h = 5\,\mathrm{ms}$, Pairwise correlation $c = 0.01$

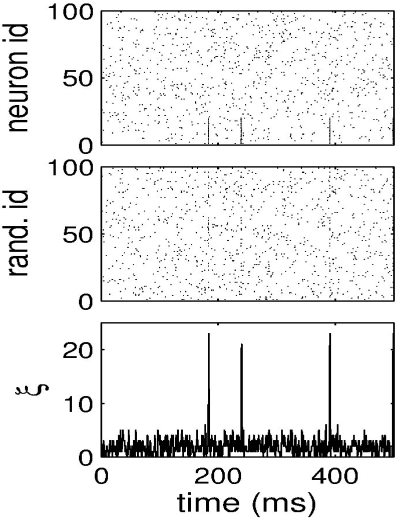
Non-Stationary Firing Rates



- Non-stationary carrier rate incorporated in the model
- Specific distribution types (symmetric, uniform) allow analytical expression of cumulants

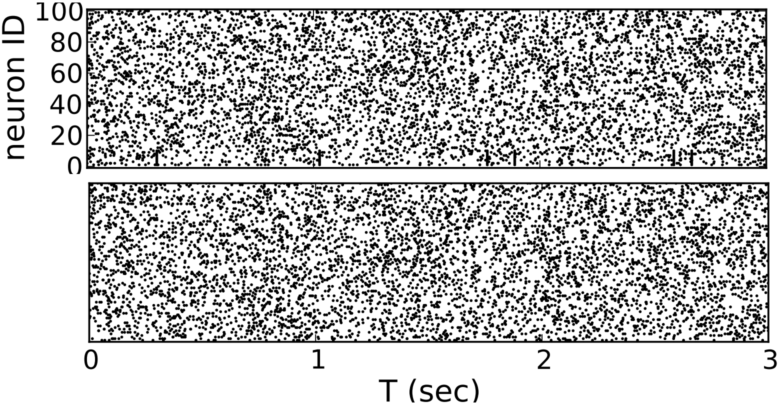
* Staude, Grün, Rotter (2010) Front Comput Neuroscience

Introduction



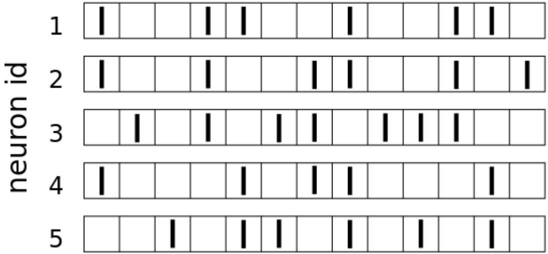
- Back to synchrony
- Massively parallel spike trains
- **Goal: find presence of excess synchrony and identify pattern composition**

Uncover Neurons involved in Synchrony Patterns



* Torre et al (2013) Front Comput Neurosci

Earlier suggested: Accretion Method



* Gerstein et al (1978) Brain Research 140(1): 43–62

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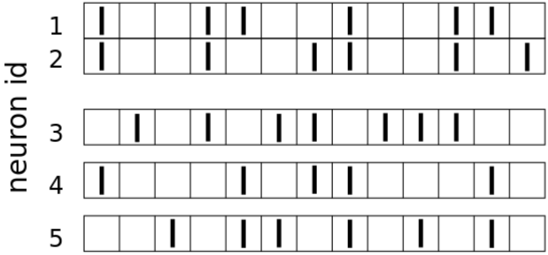

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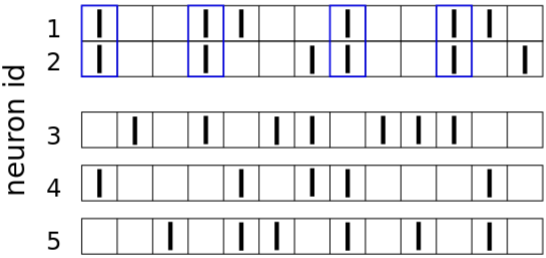

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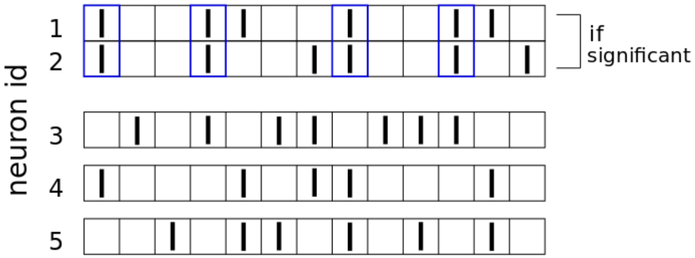

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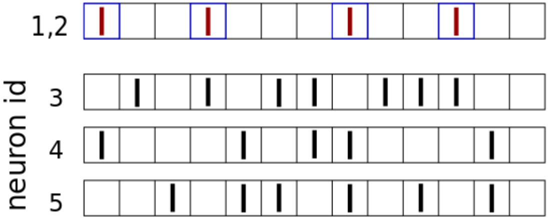

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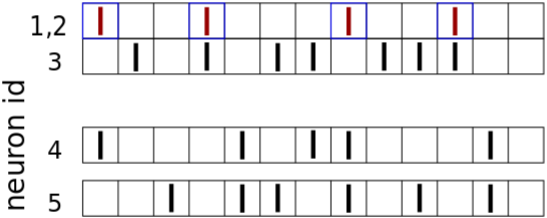

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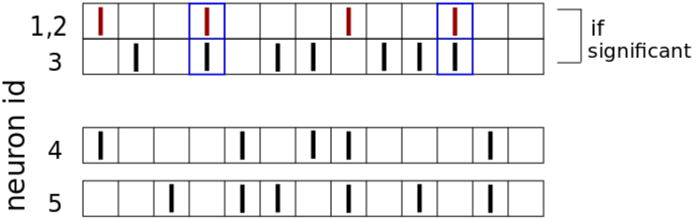

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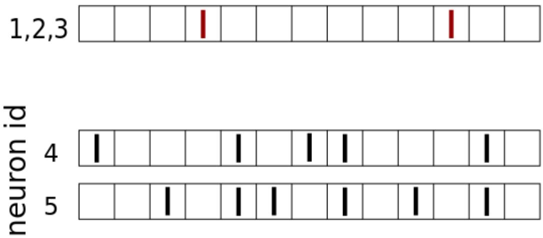

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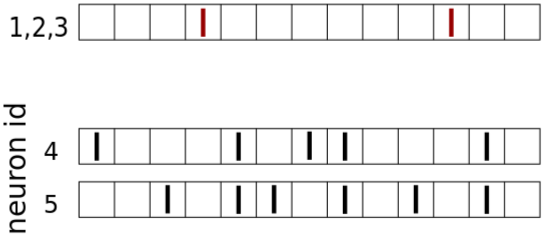

* Gerstein et al (1978) Brain Research 140(1): 43–62

Disadvantages:

- Start with any pair combination → Redundant, sequences analyzed
- Numerically expensive → limited branching factor → assemblies may be missed

Idea: Make use of Frequent Itemset Mining (FIM)

mathematics	market basket analysis	spike train analysis
item	product	neuron
item base	set of products	set of neurons
transaction *id*	customer	time bin
transaction	set of products bought by a customer	set of neurons firing in a time bin
frequent item set	set of products frequently bought together	set of neurons frequently firing together

- Developed for market basket analysis (e.g. Borgelt (2012) Wiley Interdisciplinary Reviews (WIREs), doi:10.1002/widm.1074)
- Fast and efficient algorithms available
- Searches for **sets** instead of **sequences**

* Picado-Muino et al (2013) Front Neuroinformatics

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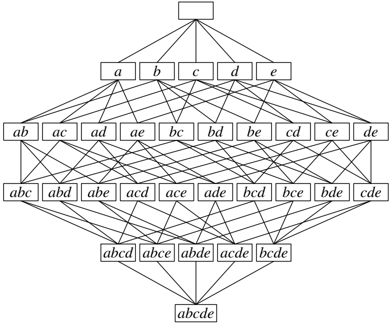

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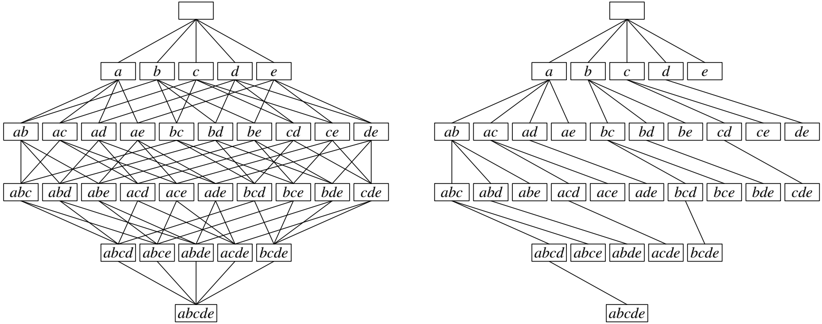

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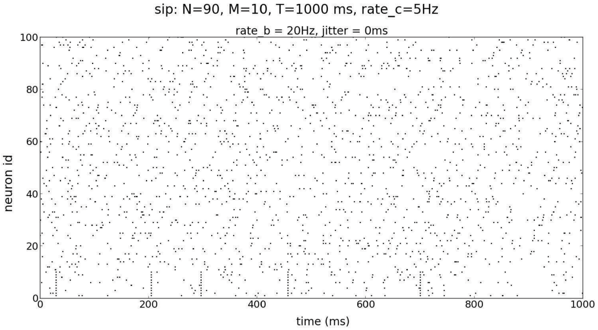
* Picado-Muino et al (2013) Front Neuroinformatics

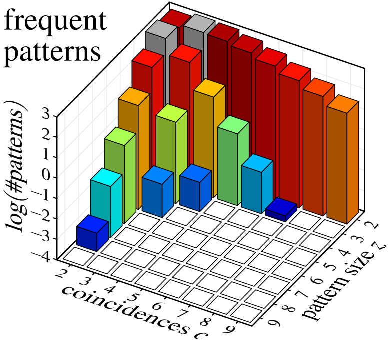
Data Model



- Modified single interaction process (SIP) model (Kuhn et al, 2003)
- 100 neurons, independent Poisson
- Synchronous events inserted in subset of neurons (2-10)
- Background rate of inserted neurons reduced by coincidence rate

* Picado-Muino et al (2013); * Torre et al (2013)

How to Evaluate Significance of Patterns?

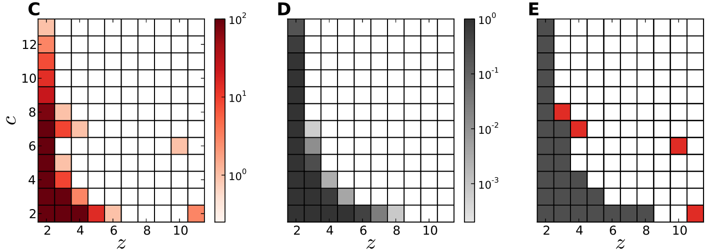


- Many frequent item sets, even in independent data
- Issue: Multiple testing

→ Pool patterns of same signature:
number of occurrences c, pattern size z

* Picado-Muino et al (2013); * Torre et al (2013)

Pattern Spectrum Filtering



F

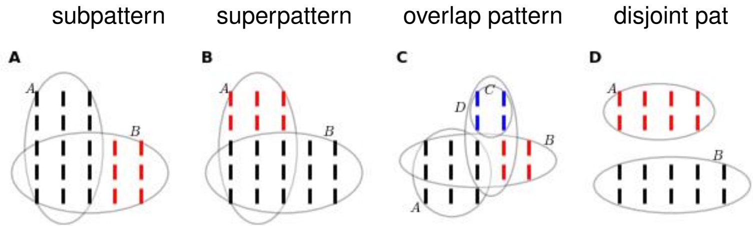
(1,2,3,4,5,6,7,8,9,10,80): 2
(1,2,3,4,5,6,7,8,9,10,24): 2
(4,6,9,10): 7

(1,2,3,4,5,6,7,8,9,10,28): 2
(1,2,3,4,5,6,7,8,9,10): 6
(4,6,10): 8

- C: Pattern spectrum of correlated data (100 neurons, 6 injected synchronous events in 10 neurons)
- D: p-value spectrum by **surrogates**, $\alpha = 0.01$, Bonferroni corrected
- E: Significance spectrum, red: significant pattern (listed)
- Detected, but also FPs!

* Torre et al (2013)

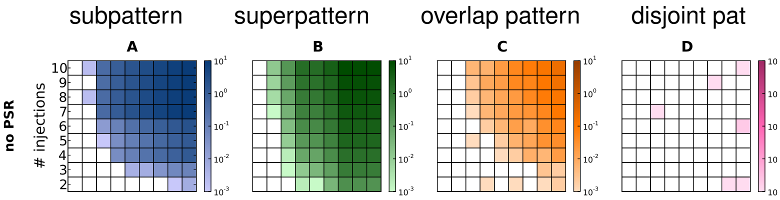
But: Special FPs



- Assembly pattern (black) may by chance coincide with background spikes (A-C)

* Torre et al (2013)

But: Special FPs

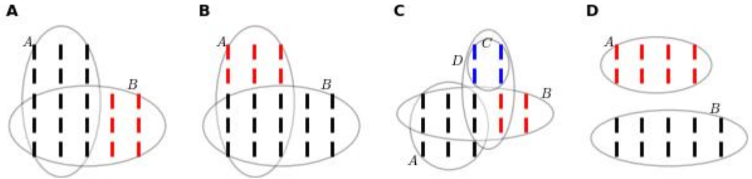


- Assembly pattern (black) may by chance coincide with background spikes (A-C)
- Mostly subset and superset FPs !
- The larger the pattern size and the more injections, the larger the FPs

* Torre et al (2013)

Remove FPs by Pattern Set Reduction

subpattern superpattern overlap pattern disjoint pat

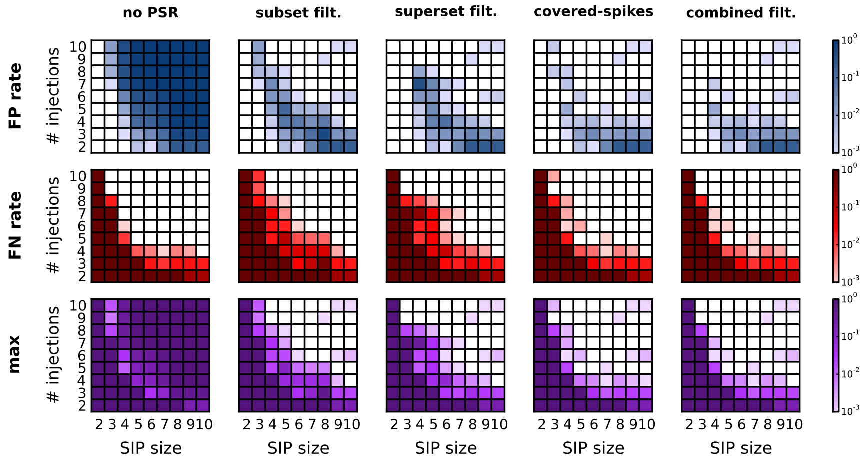


Additional tests:

- Subset filtering: test if B given A is significant, i.e. test only $c_B - c_A$ excess occurrences of B
- Superset filtering: test if A given B is significant, i.e. test $\mid A \mid - \mid B \mid$ excess items of A
- Combined subset and superset filtering removes overlapping patterns
- Disjoint chance patterns basically do not occur

* Torre et al (2013)

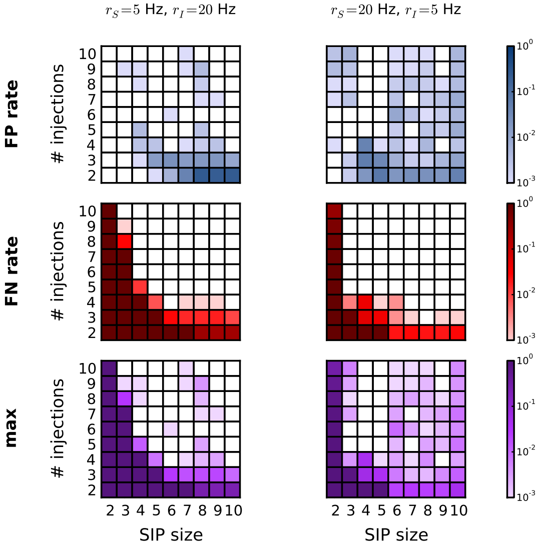
SPADE - Performance



- Overall performance measured by the maximum of FN and FP

* Torre et al (2013)

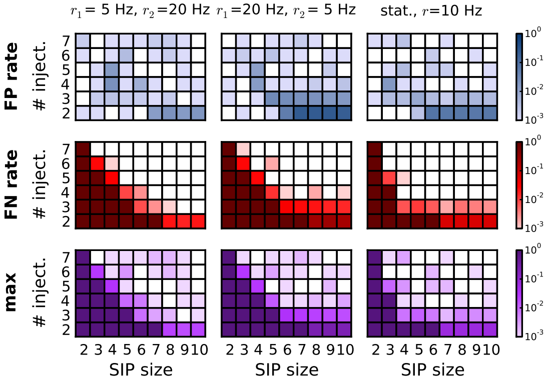
Heterogeneous Firing Rates



- SIP neurons either of lower (left) or higher (right) firing rate than the independent neurons
- Detection border defined by firing rates

* Torre et al (2013)

Non-stationary Rates



- Homogeneous firing rates across neurons
- Firing rate changes from r_1 to r_2 at $0.5 \cdot 3$ sec
- Injections only in the first period

* Torre et al (2013)

Discussion

- Correlation analysis for identification of interaction in the network
- Excess spike patterns indicate transiently active assemblies
- Avoid false positives by incorporating statistical features of neuronal data
- Multiple pairwise analysis: no conclusion on higher-order correlation
- Assembly activity expected to be expressed as higher-order correlation
- Massively parallel spike data: explosion of parameters, new methods developed
- Analytical treatment difficult $\rightarrow$ surrogates
- Avoid FPs by proper choice of surrogates
- Test and calibrate analysis methods using simulated data of known ground truth

Analysis Methods at Hand

Model	looks at	+	-
CCH	pairwise correlations	• delayed correlations • fast	• requires large samples
Unitary Event Analysis	pairwise correlations	• time-resolved	• only synchrony
Complexity distribution	population correlation	• simple and fast • scalable	• only synchrony • not time-resolved
CuBIC	population correlation	• analytical ($\Rightarrow$ fast) • scalable • deals with (standard) non-stationary rates	• only synchrony • not time-resolved • needs long data • only analytical
SPADE	neural assemblies	• any HOC • time-resolved	• only synchrony • supra-linear scaling
WORMS	neural assemblies	• spatio-temporal patterns	• specific to synfire chain detection

Numerical Implementation

Chapter 20

Practically Trivial Parallel Data Processing in a Neuroscience Laboratory

Michael Denker, Bernd Wiebelt, Denny Fliegner, Markus Diesmann, and Abigail Morrison

* In: Analysis of parallel spike trains. Eds. Grün & Rotter, Springer, 2010

- Surrogates are numerically expensive $\rightarrow$ Parallelization
- Avoid license problems by either compiling Matlab code, or use Python
- Distribute on cluster
- Make use of e.g. queueing systems and code generation for easy parallelization

JÜLICH FORSCHUNGSZENTRUM

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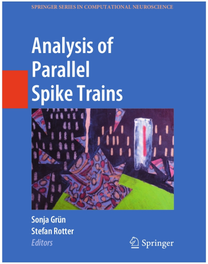
and many collaborators!

Helmholtz Portfolio Theme SMHB Supercomputing and Modeling for the Human Brain

Human Brain Project

SPP 1665

Literature



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