

Multiple independence tests for point processes: a permutation Unitary Events approach based on delayed coincidence count

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A permutation
Unitary Events
method

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Introduction of
the Problematic
Problematic

Single testing
Statistical Model
Number of
coincidences

Resampling
approach

Centering issue

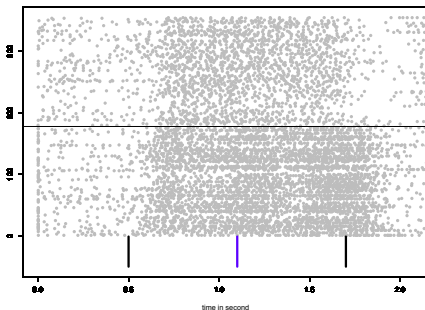
Centered Test
Statistic

Test construction

Multiple tests

Problematic
Simulation study

Conclusion



Global problematic

Synchrony detection?

Notion of coincidence

Neurons fire nearly at the
same time

Model based methods:

- *Unitary Events methods* [Grün (1996), Grün, et al. (1999) or Tuleau-Malot, et al. (2014)].
- *Smoothed JPSTH methods* [Ventura et al. (2005)].

Surrogate data methods:

- *Across time* such as dithering approaches, [Louis et al. (2010)].
- *Across trials* such as the Trial Shuffling [Pipa et al. (2003)].

First step

Test independence on a time window.

Statistical Modeling for Neuronal Activity

Spike trains modeled by point processes on an interval (say $[0, 1]$).

Definition

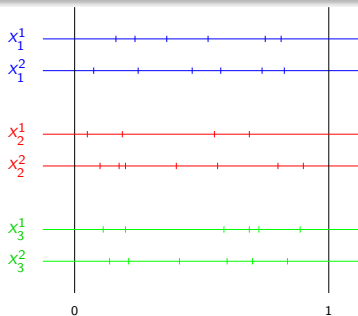
Point process on $[0, 1]$ = random countable set of points in $[0, 1]$.
 \mathcal{X} := the set of almost surely finite point processes on $[0, 1]$.

Example : homogeneous Poisson process with intensity $\lambda > 0$.

↪ In the following, no model assumption for the point processes.

Observation: $\mathbb{X}_n = (X_1, \dots, X_n)$,

where $n = \text{number of trials}$, and $X_i = (X_i^1, X_i^2)$ i.i.d. in \mathcal{X}^2 .



Aim:

Test $(\mathcal{H}_0) : X^1 \perp\!\!\!\perp X^2$ against $(\mathcal{H}_1) : X^1 \not\perp\!\!\!\perp X^2$.

Denote $\mathbb{X}_n^{\perp\!\!\!\perp}$ a sample as above satisfying (\mathcal{H}_0) .

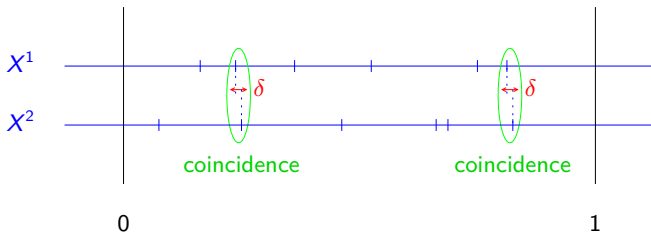
Observation: $\mathbb{X}_n = (X_1, \dots, X_n)$,

where $n =$ number of trials, and $X_i = (X_i^1, X_i^2)$ i.i.d. in \mathcal{X}^2 .

Notion of (delayed) coincidence for point processes

φ_δ^{coinc} counts the number of coincidences between two point processes:

$$\varphi_\delta^{coinc}(X^1, X^2) = \sum_{T \in X^1} \sum_{S \in X^2} \mathbb{1}_{\{|T-S| \leq \delta\}}.$$



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Test statistic based on the total number of delayed coincidences

$$C^{obs} = C(\mathbb{X}_n) = \sum_{i=1}^n \varphi_\delta^{coinc}(X_i^1, X_i^2).$$

General idea

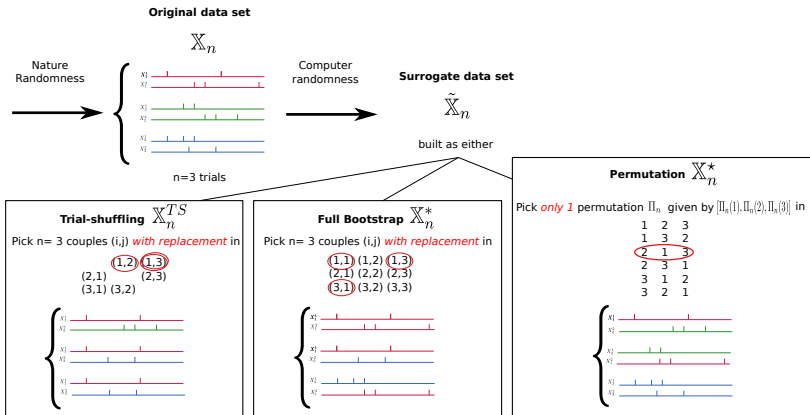
Reject independence when there are **too many** (resp. **too few**) coincidences compared to what is **expected under independence**.

How to recreate the distribution under independence?

Construct a new sample $\tilde{\mathbb{X}}_n$ from the original one, i.e. \mathbb{X}_n , such that

$$\mathcal{L}(C(\tilde{\mathbb{X}}_n) | \mathbb{X}_n) \approx \mathcal{L}(C(\mathbb{X}_n^{\perp})) ,$$

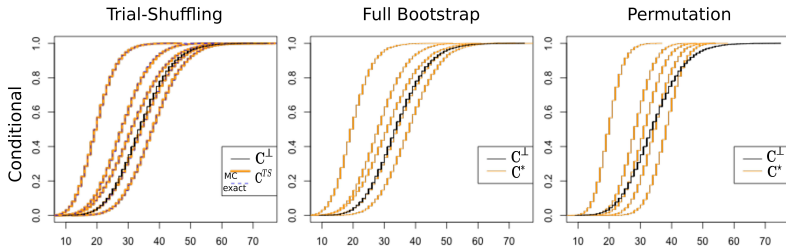
whether \mathbb{X}_n satisfies independence or not.



Unconditional distribution: all possible choices of both *Nature and Computer* randomness

Conditional distribution: 1 fixed original data set (*Nature* randomness), all possible choices of *Computer* randomness

$$\mathcal{L}(C(\tilde{X}_n) | \mathbf{X}_n) \approx \mathcal{L}(C(\mathbf{X}_n^\perp))?$$



Centering issue !!!

In view of the statistical literature, it is not possible to estimate $\mathcal{L}(C(\mathbb{X}_n^{\perp}))$ directly, BUT,

$$\mathcal{L}(C(\tilde{\mathbb{X}}_n) - \mathbb{E}[C(\tilde{\mathbb{X}}_n) | \mathbb{X}_n] | \mathbb{X}_n) \approx \mathcal{L}(C(\mathbb{X}_n^{\perp}) - \mathbb{E}[C(\mathbb{X}_n^{\perp})]).$$

YET, $\mathbb{E}[C(\mathbb{X}_n^{\perp})]$ is unknown...

Centering trick

Let $\hat{C}_0(\mathbb{X}_n) = \frac{1}{n-1} \sum_{i \neq j} \varphi_{\delta}^{coinc}(X_i^1, X_j^2)$, s.t. $\mathbb{E}[\hat{C}_0(\mathbb{X}_n)] = \mathbb{E}[C(\mathbb{X}_n^{\perp})]$,

and let

$$U(\mathbb{X}_n) = C(\mathbb{X}_n) - \hat{C}_0(\mathbb{X}_n).$$

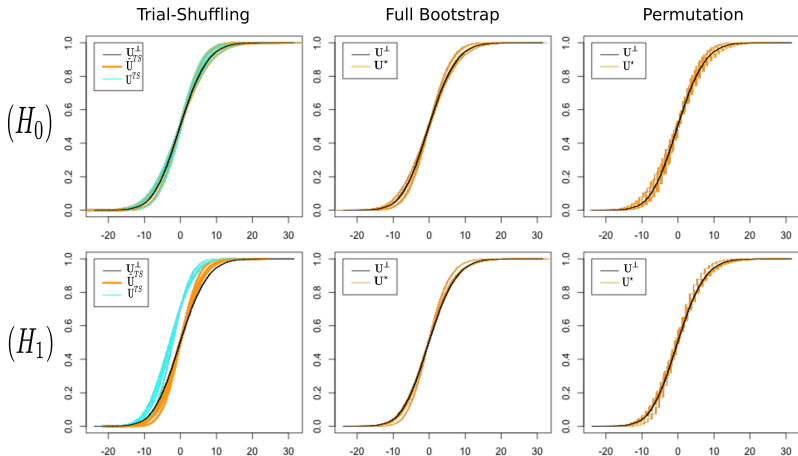
Then

$$\mathcal{L}(U(\tilde{\mathbb{X}}_n) - \mathbb{E}[U(\tilde{\mathbb{X}}_n) | \mathbb{X}_n] | \mathbb{X}_n) \approx \mathcal{L}(U(\mathbb{X}_n^{\perp})).$$

with

$$\mathbb{E}[U(\mathbb{X}_n^{TS}) | \mathbb{X}_n] = -\frac{U(\mathbb{X}_n)}{n}, \text{ and } \begin{cases} \mathbb{E}[U(\mathbb{X}_n^*) | \mathbb{X}_n] = 0, \\ \mathbb{E}[U(\mathbb{X}_n^*) | \mathbb{X}_n] = 0. \end{cases}$$

$$\mathcal{L}(U(\tilde{X}_n) - \mathbb{E}[U(\tilde{X}_n) | \mathbf{X}_n] | \mathbf{X}_n) \approx \mathcal{L}(U(\mathbf{X}_n^\perp))?$$



$$\mathcal{L}(U(\tilde{\mathbf{X}}_n) - \mathbb{E}[U(\tilde{\mathbf{X}}_n) | \mathbf{X}_n] | \mathbf{X}_n) \approx \mathcal{L}(U(\mathbf{X}_n^{\perp}))?$$

Critical value:

$(1 - \alpha)$ -quantile of $\mathcal{L}(U(\tilde{\mathbf{X}}_n) - \mathbb{E}[U(\tilde{\mathbf{X}}_n) | \mathbf{X}_n] | \mathbf{X}_n)$,

\Rightarrow with Monte Carlo approximation.

Trial Shuffling p -values with Monte Carlo approximation:

- Simulate B *Trial Shuffling samples* $\mathbb{X}_n^{TS,1}, \dots, \mathbb{X}_n^{TS,B}$.
- Compute the centered test statistics:

$$\tilde{U}_b^{TS} = U(\mathbb{X}_n^{TS,b}) - \frac{U(\mathbb{X}_n)}{n}.$$

- Define the p -value by

$$\hat{\alpha}^{TS}(\mathbb{X}_n) = \frac{1}{B} \sum_{b=1}^B \mathbb{1}_{\{\tilde{U}_b^{TS} \geq U(\mathbb{X}_n)\}},$$

and reject independence if it is smaller than α .

Full Bootstrap p -values with Monte Carlo approximation:

- Simulate B *Full Bootstrap samples* $\mathbb{X}_n^{*,1}, \dots, \mathbb{X}_n^{*,B}$.
- Compute the centered test statistics:

$$U_b^* = U(\mathbb{X}_n^{*,b}).$$

- Define the p -value by

$$\hat{\alpha}^*(\mathbb{X}_n) = \frac{1}{B} \sum_{b=1}^B \mathbb{1}_{\{U_b^* \geq U(\mathbb{X}_n)\}},$$

and reject independence if it is smaller than α .

Permutation p -values with Monte Carlo approximation:

- Simulate B *permuted samples* $\mathbb{X}_n^{*,1}, \dots, \mathbb{X}_n^{*,B}$.
- Compute the centered test statistics:

$$U_b^* = U(\mathbb{X}_n^{*,b}), \quad \text{and} \quad U_{B+1}^* = U(\mathbb{X}_n).$$

- Define the p -value by [Romano and Wolf (2005)]

$$\hat{\alpha}^*(\mathbb{X}_n) = \frac{1}{B+1} \sum_{b=1}^{B+1} \mathbb{1}_{\{U_b^* \geq U(\mathbb{X}_n)\}},$$

and reject independence if it is smaller than α .

Then, thanks to [Romano and Wolf (2005)],

$$\mathbb{P}_{(\mathcal{H}_0)}(\hat{\alpha}^*(\mathbb{X}_n) \leq \alpha) \leq \alpha,$$

(only for the permutation approach).

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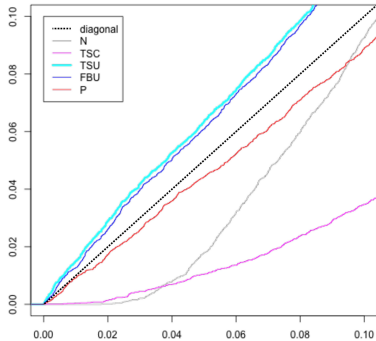
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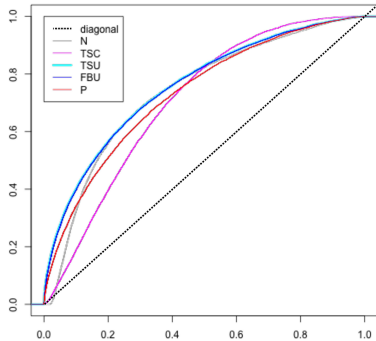
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(H_0)



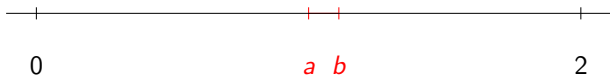
(H_1)



Initial problematic

Detect the synchronizations.

Idea : simultaneously test independence on sliding time windows $[a_k, b_k]$,



$$(\mathcal{H}_{0,k}) : X^1 \perp\!\!\!\perp X^2 \text{ on } [a_k, b_k] \quad (\mathcal{H}_{0,k}) : X^1 \not\perp\!\!\!\perp X^2 \text{ on } [a_k, b_k].$$

Aim:

Control the m tests at a global level α .

⚠ The errors accumulate !

↔ Benjamini and Hochberg multiple testing procedure to control the False Discovery Rate (1995).

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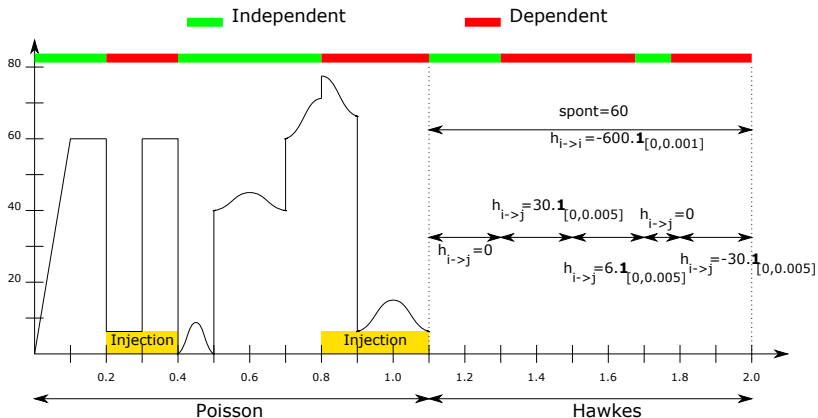
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A: Description of Experiment 1

- $n = 50$,
- δ varies in $\{0.001, 0.002, \dots, 0.04\}$,
- $B = 10000$ steps in the Monte Carlo approximation of the quantiles,
- $m = 191$ simultaneous tests.

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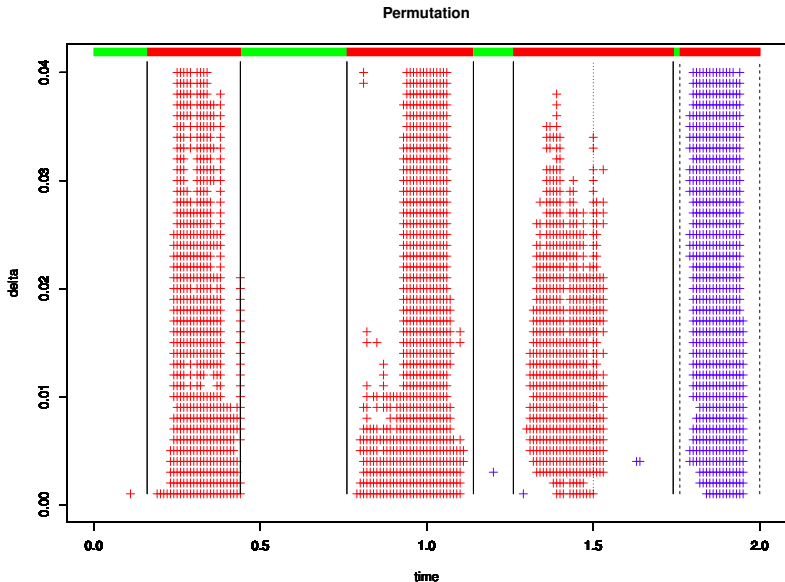
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Conclusions and perspectives

- Centering when applying bootstrap-based methods.
- The permutation approach is more reliable.
- Asymptotic theoretical results for full bootstrap and permutation approaches.
- Non-asymptotic results for the permutation tests?
- Choice of δ for the notion of coincidences?
- More than two neurons?



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