

# The variation of spike time.

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- └ Motivation.

## Spike trains.

# A



## B

[illegible]

C

[illegible]

D

[illegible]

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## Rate coding.

Adrian and Zotterman (1926)

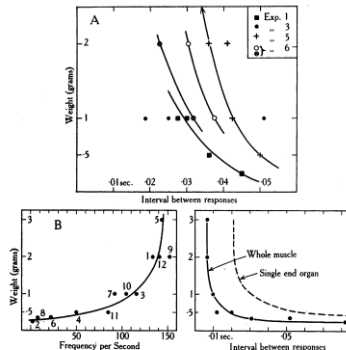


Fig. 5. *A.* Relation between stimulus and period of rhythmic responses in different experiments.

*B.* Exp. 9, 17° C. Relation between stimulus and frequency of response, muscle intact.

*C.* Exp. 9, 17° C. Relation between stimulus and interval between responses for intact muscle. Hypothetical curve for single end-organ.

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## Temporal coding.



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## Coding.

What is the precision of temporal spiking?

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# Analog noise.



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## Digital signal noise.



1011100101

## Digital noise.

1011100101

1011100001

1011100101

1011110101

1011100101

1010100101

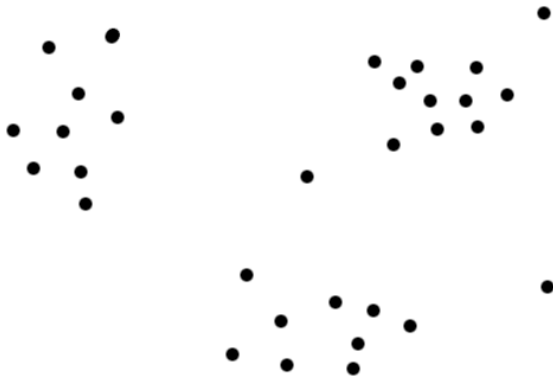
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## Cluster noise.



## Spike trains: two sorts of noise.

Two sorts of noise:

- *Unreliability*: variations in spike count.
- *Jitter*: variations in spike time.

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## Spike trains.

# A



## B

[illegible]

C

[illegible]

D

[illegible]

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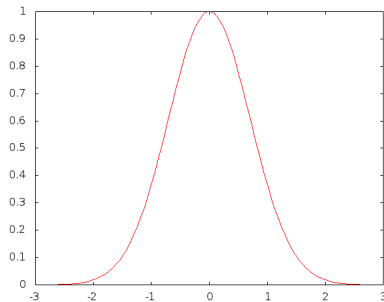
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# Goal

Our purpose here is to check what the distribution of jitter is.

## What is the distribution of jitter.



Surely it must be Gaußian? Isn't everything?

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[illegible][illegible][illegible]

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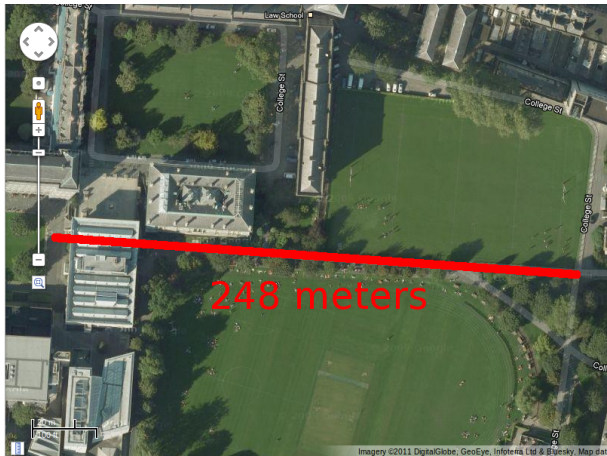
## How do we pair up spikes?

Idea: use a spike train metric!

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└ Metrics

Metrics measure distances.

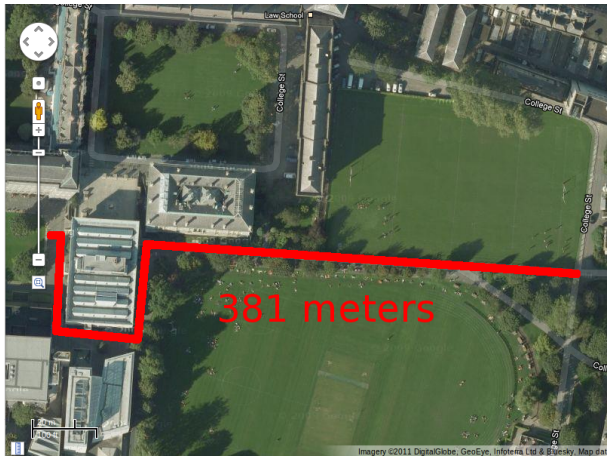




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└ Metrics

Metrics measure distances.



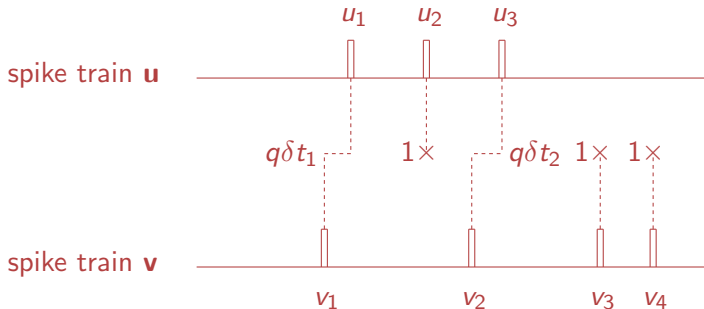
## The Victor-Purpura metric.

Edit one spike train in to the other:

1. Insertion of a spike with a cost of one.
2. Deletion of a spike with a cost of one.
3. Moving a spike a distance  $\delta t$  costs  $q|\delta t|$ .

The distance is the cost of the cheapest edit.

## The Victor-Purpura metric.



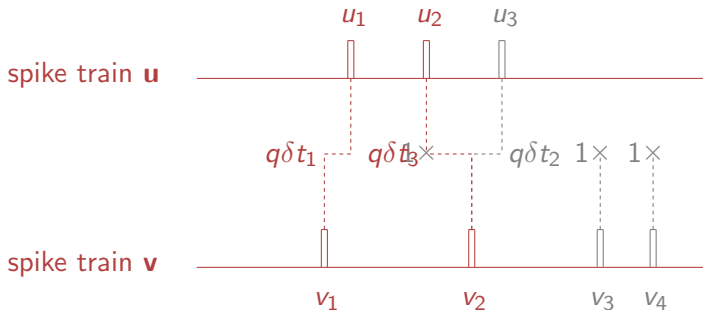
$$d = 3 + q(\delta t_1 + \delta t_2)$$

## About the metric.

- This is a good metric: this can be evaluated using metric clustering.
- $q$  is a time scale thought to indicate the temporal percision of spiking.  $q|\delta t| < 2$ .

## Victor-Purpura metric: algorithm.

Define  $G_{ij}$  as the distance between the truncated spike trains with the first  $i$  spikes in  $\mathbf{u}$  and the first  $j$  spikes in  $\mathbf{v}$ .



$$G_{22} = q(\delta t_1 + \delta t_2)$$

## Victor-Purpura metric: algorithm.

New  $G_{ij}$ 's are calculated iteratively.

$$G_{i,0} = i \text{ and } G_{0,j} = j.$$

and

$$G_{i,j} = \min \{ G_{i-1,j-1} + q|u_i - v_j|, G_{i-1,j} + 1, G_{i,j-1} + 1 \}.$$

	0	1	2	3
0	0	1	2	3
1	1	$q\delta t_1$	$1 + q\delta t_1$	$2 + q\delta t_1$
2	2	$1 + q\delta t_1$	$q(\delta t_1 + \delta t_3)$	$1 + q(\delta t_1 + \delta t_2)$
3	3	$2 + q\delta t_1$	$1 + q(\delta t_1 + \delta t_3)$	$2 + q(\delta t_1 + \delta t_2)$
4	4	$3 + q\delta t_1$	$2 + q(\delta t_1 + \delta t_3)$	$3 + q(\delta t_1 + \delta t_2)$

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└ Calculating jitter.

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Idea.

Why not use the Victor-Purpura metric to pair up spikes?

Follow the arrows.

	0	1	2	3
0	0	1	2	3
1	1	$q\delta t_1$	$1 + q\delta t_1$	$2 + q\delta t_1$
2	2	$1 + q\delta t_1$	$q(\delta t_1 + \delta t_3)$	$1 + q(\delta t_1 + \delta t_2)$
3	3	$2 + q\delta t_1$	$1 + q(\delta t_1 + \delta t_3)$	$2 + q(\delta t_1 + \delta t_2)$
4	4	$3 + q\delta t_1$	$2 + q(\delta t_1 + \delta t_3)$	$3 + q(\delta t_1 + \delta t_2)$

	0	1	2	3
0	0	1	2	3
1	1	↖	←	←
2	2	↑	↖	↖
3	3	↑	↑	↑
4	4	↑	↑	↑

	0	1	2	3
0	0	1	2	3
1	1	↖	←	
2	2			↖
3	3			↑
4	4			↑



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└ Calculating jitter.

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Now pick up the jitter.

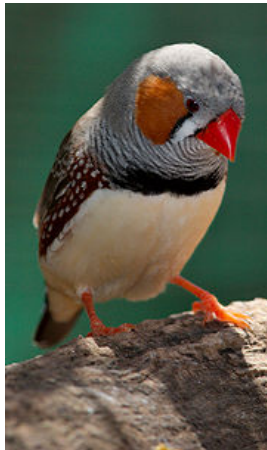
Record the  $\delta t$ 's corresponding to the diagonal arrows ↖.

## Thanks to the Theunissen lab.

The algorithm has been tested using the large extracellular zebra finch dataset made available on the Collaborative Research in Computational Neuroscience database by the Frederic Theunissen laboratory at UC Berkeley.

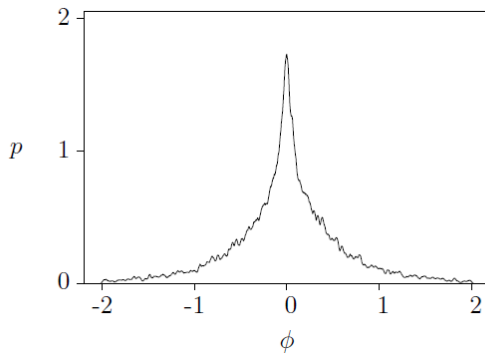
<http://crcns.org/data-sets/aa/aa-2>

## The zebra finch.



Typically 20 songs played 10 times each for 449 cells.

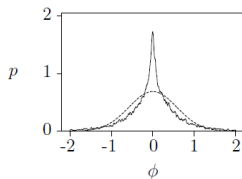
## The jitter distribution



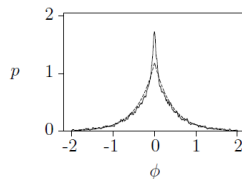
$$\phi = q\delta t$$

## The jitter distributions - fitting

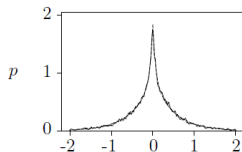
A



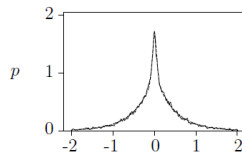
B



C



D



**A:** Gauß, **B:** Laplace, **C:** hyper-Laplace and **D:** hyper-Gauß.

## The hyper-Laplace distribution

Best modelled by a hyper-Laplace distribution

$$p(\phi) = \begin{cases} \frac{1}{Z} \left[ \frac{p_1}{2b_1} \exp\left(-\frac{|\phi|}{b_1}\right) + \frac{p_2}{2b_2} \exp\left(-\frac{|\phi|}{b_2}\right) \right] & |\phi| \leq 2 \\ 0 & \text{otherwise} \end{cases}$$

with

$$Z = \frac{p_1}{2} [1 - \exp(-2/b_1)] + \frac{p_2}{2} [1 - \exp(-2/b_2)]$$

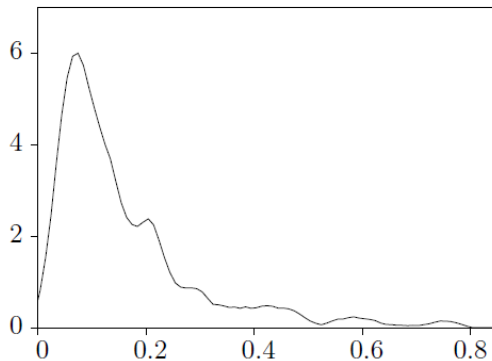
and

$$\phi = q\delta t$$

## Anderson-Darling test.

- The proposition that the jitter distribution is **Gaussian** can be ruled out with significance greater than 99% percent for all the cells.
- **Laplace** distribution fails the Anderson-Darling test with significance 95% for all but five of the 449 cells.
- For the **hyper-Laplace** only for 65 of the 449 cells can the hypothesis be rejected with significance 95%.
- The test only rejects the best-fit **hyper-Gauss** distribution 84 times at significance 95%.

## The jitter time scale.





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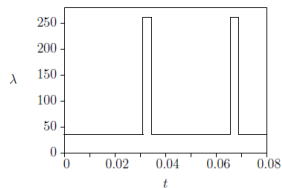
└ Results

## The Laplace distribution.

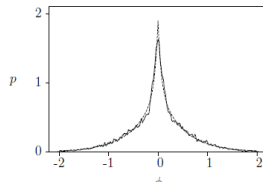


## Telegraph neurons.

A



B



May be time to think some more about firing rates.

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└ Results

Thanks!

