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PSTH, STA, Linear filters

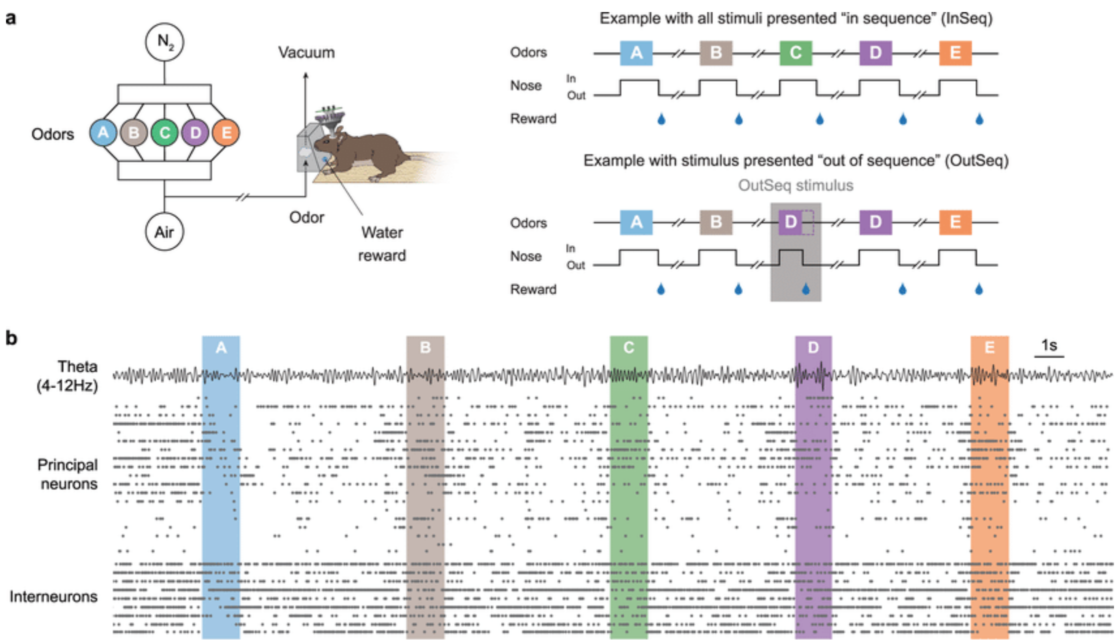
Encoding

A major question in neuroscience concerns the translation of a stimulus or an event to neural activity.

We can relate the events as two types, as a time point onset or as a continuous input.

Class exercise:

in the following figure, what are the discrete event onsets?



(Adopted from Shahbaba et al. 2022)

Given a stimulus and a spike train, we can ask two questions:

- At what duration the **neuron** responded to the **stimulus**?
  PSTH can assist in answering this question.
- What is the **stimulus** which the **neuron** responds to?
  STA can assist in answering this question.

In any case, to study relations between stimulus and neural response we need to align between two signals, but the signal to align with need to be chosen.

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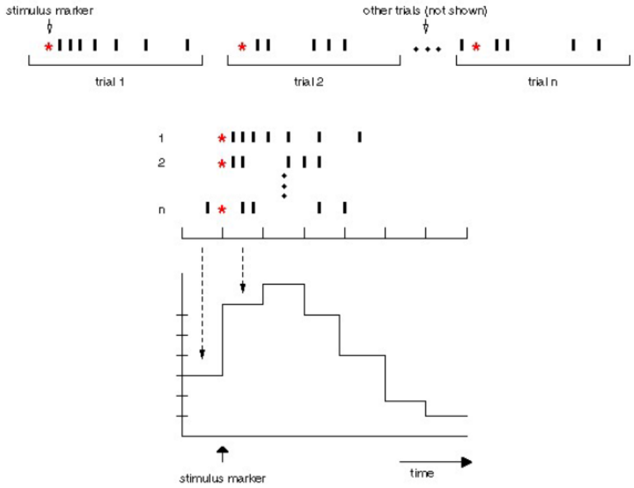
PSTH

PSTH is an acronym for **P**eri-**s**timulus **t**ime **h**istogram, a histogram to provide information about neural activity (for example spikes) in response to a certain event.

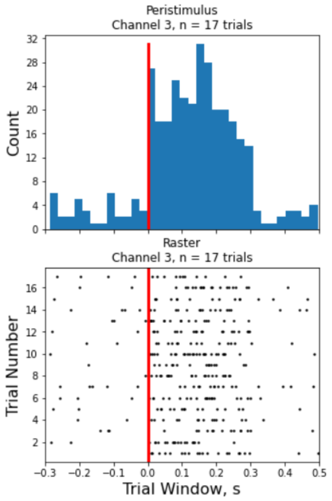
How to compute a PSTH?

A. Align the neural activity to the same onsets for a chosen duration T.
   - We can align the onset to any time in T
B. Divide the duration T to bins, for example even sizes Δt.
C. Count the number of spikes in each bin at each event-aligned vector.
D. Normalize the values to probability or firing rate (by dividing to Δt).

Example for PSTH calculation:



PSTH and raster plot:



Class discussion:

A. Why not calculating firing rate and aligning it to the onset?
B. What information does a raster plot provides in addition to PSTH?

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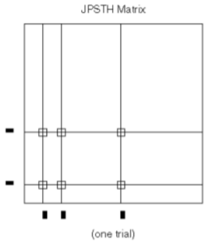
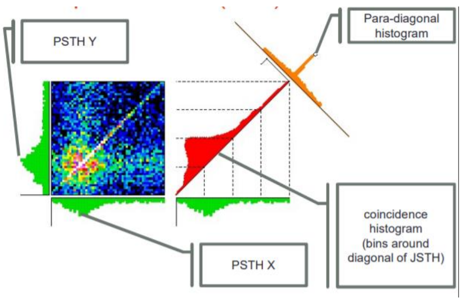
JPSTH: when we want information about co-activations of more than one neuron to a specific event, we use a JPSTH. The method for creating this matrix is **different** from the one of simple PSTH, and is a 3D histogram:

- For each trial:
    - Aligning the spike trains of each neuron to the same onset
    - Any couple of spike aligned time of each neuron represents an index in the matrix to assign with 1. Example:



- Normalizing the matrix to joint probability matrix or rate.

Example for JPSTH:

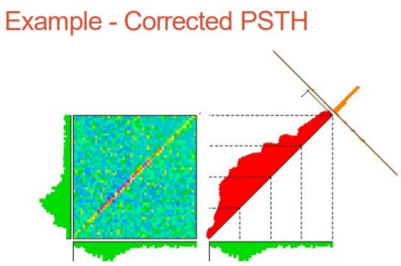


Shift Predictor:

A basic method for creating shuffling data by which JPSTH can be used to indicate the relationship between the two neurons. To create the shift predictor we shuffle the pairs of trials of each neuron (originally by shifting a trial from one neuron).

Important notes:

- When using shift predictor, we must notice not to count twice the same shuffled couple.
- Shift predictor must be used when normalization is to probability or rate.



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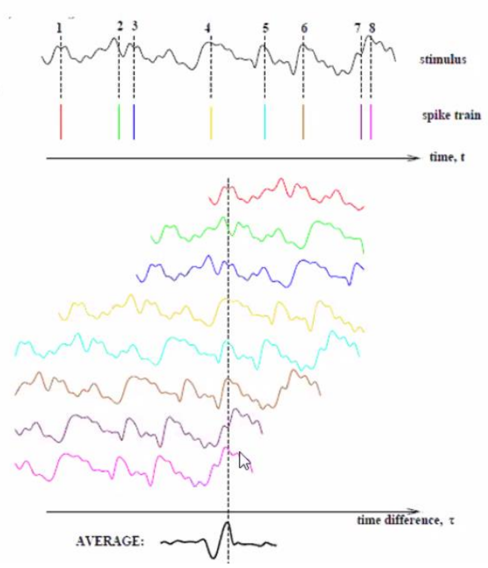
Class discussion:

A. What does the diagonal represents? And the para-diagonal?
B. What does a cluster somewhere in JPSTH represents?
C. What other figures can be used to complete information such as variability of the data?
D. Does the JPSTH necessarily indicates connection of the two neurons to the event? (global activation, excitation or inhibition between the neurons)

STA

As previously mentioned, PSTH is a one direction method by which neural data is aligned to stimulus onset and the neural activity is tested. To characterize the stimulus to which a neuron responds to, we need to align stimulus to the spiking activity. STA is a very simplified method to do it by aligning continuous stimulation to each single spike while assuming for simplicity that the firing of one spike represents response. Note that we can also align to other events as onsets such as firing rate change, highest correlation between neurons and others. This is why STA is a method in the reverse correlation family.

Example to STA:



Class discussion:

A. Given the above example, does the neuron responds to excitatory or inhibitory input?
B. Why do we use such a long stimulus which changes in time?
C. Does the given duration of the average is best for this neuron?
D. What is missing? (variance for example)

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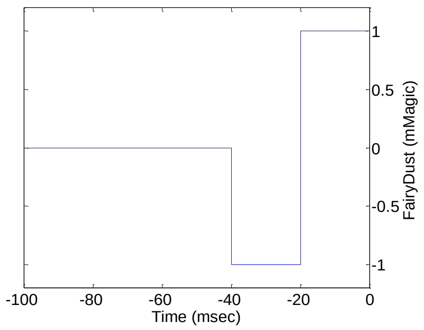
Class exercise:

The fairy's 7th sense receptors respond to the appearance of fairy dust (measured in mMagic units) according to the following reverse correlation. Which of the following input A(t) will lead to maximal changes in the neuronal activity?



A. Constant level of fairy dust (A=100).
B. Wave of fairy dust, $A(t)=100*\sin(25*t*2\pi)$.
C. Wave of fairy dust, $A(t)=100*\sin(50*t*2\pi)$.
D. Wave of fairy dust, $A(t)=100+50*\sin(25*t*2\pi)$.
E. Wave of fairy dust, $A(t)=100+50*\sin(50*t*2\pi)$.

Solution:

In the reverse correlation, we see that the averaged activity is 0, and therefore answers A, D and E are irrelevant. The difference between B and C is the frequency. In the reverse correlation the cycle time is 40 ms, therefore the frequency is 25 Hz (2.5 cycles in 100 ms). Therefore, answer B is the correct one.

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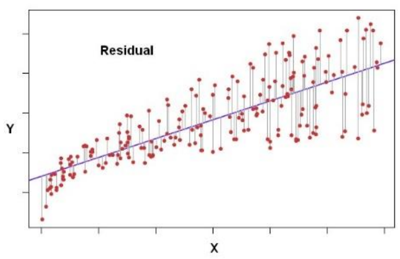
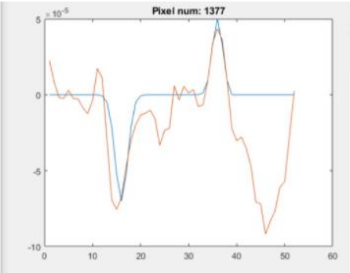
From characterization to models

Given that we've characterized stimulating input for a given neuron, we would like to use it as a model to the neuron's behavior. To evaluate any model, we use an error function which describes for a given set of parameters how good is our model. Commonly, root mean square error (RMSE, aka residuals) is a useful tool for this evaluation:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(Model_i - Actual_i)^2}{N}} \qquad N - number\ of\ measurements$$

Two examples:





Linear kernels: A common model that we use assumes that the change in the firing rate of a neuron can be predicted by the stimulus function convolved causally with another function- which is the linear kernel:

$$r_{model} = r_0 + D(t) * s(t)$$

$$r_{model} = r_0 + \int_0^\infty D(\tau)s(t-\tau)dt$$

r_0- Baseline firing rate, $s(t)$- stimulus function, $D(t)$-Kernel.

How to compute the kernel? Since we assume the kernel is a function and not a set of parameters, we can't find it by optimization solely. For this reason, we tend to perform a complementary experiment in which we stimulate the neuron using a white noise. In linear approximations we get for the full recording:

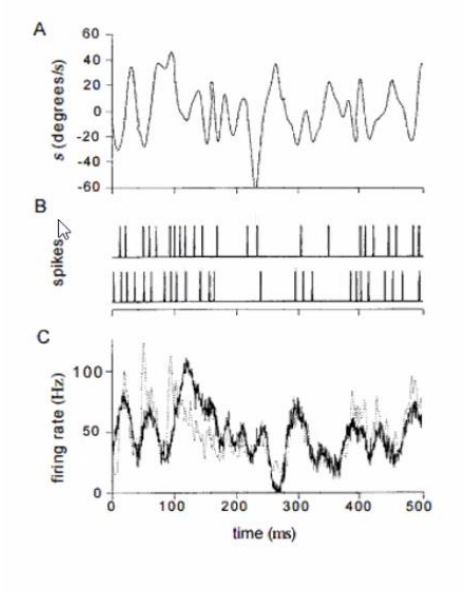
$$D(t) = \frac{\langle r \rangle \cdot STA(t)}{\sigma_s^2}$$

$\langle r \rangle$- averaged firing rate, $STA(t)$- reverse correlation of the white noise in relation to the spikes, σ_s^2- the variance of the white noise.

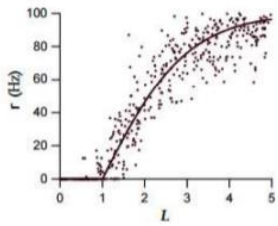
Practically to compute a linear filter:

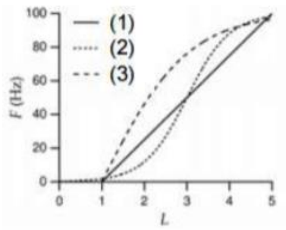
- Creating a white noise stimulus for a given σ
- Computing the STA to the white noise
- Normalizing the STA to firing rate

Example for linear kernel:



Adding a static non-linearity: To compensate the over-simplifying assumption of linearity, a next step in the model is commonly to add static non-linearity to the neuron which represents the phenomena of saturation and thresholdings in the neuron:





The most used function to represent this static non-linearity are:

1. Rectifier: $F^{+}(L) = \max(threshold, L)$
2. Sigmoid: $F(L) = \frac{r_{max}}{1+e^{F^{+}(L_{\frac{1}{2}}-L)}}$ when $L_{\frac{1}{2}}$ is the value of half of L
3. Hyperbola: $F(L) = r_{max}\left[\tanh\left(F^{+}(L-L_0)\right)\right]_{+}$

To summarize the scheme of a basic model: