Statistics in Neuroscience

By: David Ye Mentor: Ethan Ancell

The Experiment

- Classical conditioning on mice
 - o Neutral stimulus: two different tones
 - $\circ~$ Unconditioned stimulus: food and shock
- Question of Interest
 - Does classical conditioning influence neuron activity?
- 2-Photon Calcium Imaging
 - New tech for looking at calcium levels in neurons (calcium presence signifies neuron firing)
 - The variable dF/F measures calcium presence

CONDITIONING

Pavlov's Dog Experiment



Hypothesis Testing

- In this experiment, we want to see if neuron activity changes after an event occurred (i.e. food is given/tone is played)
- Null Hypothesis: the mean dF/F is the same in the pre-event and postevent windows
- Alternative Hypothesis: the mean dF/F is different in the pre-event and post-event windows

We'll focus on pre/post food windows:







Statistical Analysis:

- Two sample t-test
- Permutation Distribution based Approaches:
 - Permutation Test
 - Uniform Wrapping
 - K-Chunking
 - Criss-Cross with Uniform Wrapping

Naive Approach: Two Sample t-Test

- Well known method for testing differences in means
- Assumption for t-test:
 - Observed dF/F in both pre-food and post-food windows must be obtained via a random sample
- Random Sample
 - A sequence of independent and identically distributed dF/F



p-value = 3.358 * 10⁻⁸

p-value is invalid because assumptions are violated (the t-statistic may follow some unknown distribution)

Finding another approach...

- Can't use t-distribution so we need another way to obtain p-values
- We will use a **restricted randomization scheme** to approximate the tstatistic under the null hypothesis of no mean neuron difference
- Randomization is a powerful way to approximate unknown distributions
- We will first explore unrestricted randomization and think about ways to restrict randomization

Approach #1: Permutation Test

- 1. Calculate the t-statistic for the pre-food and post-food window
- 2. Repeatedly shuffle the dF/F values in pre-food and post-food windows and repeat step 1. at each iteration
- 3. Obtain p-value by counting the number of t-statistics as or more extreme than our initial t-statistic



Assumptions for Permutation Tests

- Exchangeability
 - Sequence of dF/F is exchangeable if any permutation of the sequence has the same joint probability distribution
- Check Assumption of Exchangeability



 Intuition: neurons tend to activate/deactivate gradually rather than jump volatilely between active and inactive states

Exchangeability Assumption Violated

Approach #2: Uniform Wrapping

60.

40 -



- 1. Calculate the t-statistic for the pre-food and post-food window
- 2. Select a uniformly random time point between the pre/post food window
- 3. Push sequence forward until the selected index is the endpoint and move data pushed out of bounds to the beginning of the sequence and repeat step 1.
- 4. Repeat steps 2. and 3. on the original data

Uniform Wrapping Distribution

5. Obtain p-value by counting the number of t-statistics as or more extreme than our initial t-statistic



p-value = 2(3/1000) = 0.006



Uniform Wrapping Pros and Cons

• Pros:

- Random wrapping destroys the association between neural activity and the time of events (this is a way to approximate the null distribution of the t-statistic)
- Autocorrelation between time points is mostly preserved: this mostly preserves the joint distribution of the data

• Cons:

- No theoretical basis* (just a clever idea to approximate the null distribution)
- Limited number of permutations (only 250 possible permutations)
 - Image of data under uniform wrapping does not capture the full spectrum of an unresponsive neuron
- Overrepresentation of neural traces with peaks if neuron portrait has a peak

• Next approach:

 K-Chunking: Many more possible permutations of data to draw a null distribution from

*Uniform Wrapping, K-Chunking, Criss-Cross with Uniform Wrapping all have no theoretical basis

Approach #3: k-Chunking

- 1. Calculate the t-statistic for the pre-food and post-food window
- 2. Break data into *k* equally spaced intervals
- 3. Repeatedly shuffle the intervals and repeat step 1. at each iteration
- 4. Obtain p-value by counting the number of t-statistics as or more extreme than our initial t-statistic



K-Chunking Pros and Cons

• Pros:

- most of the autocorrelation structure is preserved, only broken up at the edges of the chunks
- Much larger palette to draw from to approximate the null distribution
- Cons:
 - Overrepresentation of neural traces with peaks if neuron portrait has a peak
 - No theoretical basis* (just a clever idea to approximate the null distribution)
- Next approach:
 - Criss-Cross with Uniform Wrapping: less likely to overrepresent peaks

*Uniform Wrapping, K-Chunking, Criss-Cross with Uniform Wrapping all have no theoretical basis

Approach #4: Criss-Cross with Uniform Wrapping

post-food

pre-food

- Standardize every neuron activity 1.
- Calculate the t-statistic for the pre-food and post-food window 2.
- Randomly select two trials of the neuron of interest and combine the pre-food windows 3. from both trials
- Repeatedly perform uniform wrapping with combined pre-food windows 4.
- 5. Repeat steps 3. and 4. many times

Time Points

6. Obtain p-value by counting the number of t-statistics as or more extreme than our initial t-statistic

pre-food (a

pre-food (b)





Approach #4: Criss-Cross with Uniform Wrapping

- 1. Standardize every neuron activity
- 2. Calculate the t-statistic for the pre-food and post-food window
- 3. Randomly select two trials of the neuron of interest and combine the pre-food windows from both trials
- 4. Repeatedly perform uniform wrapping with combined pre-food windows
- 5. Repeat steps 2. and 3. many times
- 6. Obtain p-value by counting the number of t-statistics as or more extreme than our initial t-statistic



Criss-Cross with Uniform Wrapping Pros and Cons

• Pros:

- autocorrelation between time points is mostly preserved
- large palette to draw from to approximate the null distribution
- does not overrepresent neural traces with peaks if neuron portrait has a peak

• Cons:

• No theoretical basis* (just a clever idea to approximate the null distribution)

*Uniform Wrapping, K-Chunking, Criss-Cross with Uniform Wrapping all have no theoretical basis

P-Value Comparison Table (orange – significant at 95% confidence level)

		•	<u> </u>	0	, , , , , , , , , , , , , , , , , , , ,
t-Test	Permutation Test	Uniform Wrapping	K-Chunking	Criss-Cross with U.W.	Portrait
5.438 * 10 ⁻⁷⁸	0	4.2 * 10 ⁻³	0	0	
-2.019 * 10 ⁻⁵¹	-0	-4.8 * 10 ⁻³	-9.6 * 10 ⁻²	-2.801 * 10 ⁻²	Neuron Activity Portrait
-1.596 * 10 ⁻³¹	-0	-0.424	-1.006 * 10 ⁻¹	-1.026 * 10 ⁻¹	Neuron Activity Portrait

P-Value Comparison Table (orange – significant at 95% confidence level)

				,	
t-Test	Permutation Test	Uniform Wrapping	K-Chunking	Criss-Cross with U.W.	Portrait
3.002 * 10 ⁻²	3.06 * 10 ⁻²	8.53 * 10 ⁻¹	5.07 * 10 ⁻¹	7.581 * 10 ⁻¹	Neuron Activity Portrait.
-1.302 * 10 ⁻⁹	-0	-4.0 * 10 ⁻³	-0	-4.214 * 10 ⁻¹	Neuron Activity Portrait
-2.759 * 10 ⁻²⁵	-0	-2.994 * 10 ⁻¹	-8.980 * 10 ⁻²	-3.327 * 10 ⁻²	Neuron Activity Portrait

Unsupervised ML Approach:

- Spectral Clustering with Dynamic Time Warping
 - A k-means clustering technique based on the Laplacian matrix of a similarity matrix built from the dynamic time warpping distance metric



Discussions

- Is there a time series approach to answering the question "does classical conditioning influence neuron activity"?
- Is there an unsupervised learning approach?
 - Possible approach to try is spectral clustering approach with DTW
- Is there any theoretical basis to the tests being used?
- Is there a better approach than comparing means of pre/post event windows?



Thank You!