# A primer on: Spectral power analyses

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## Getting to know you

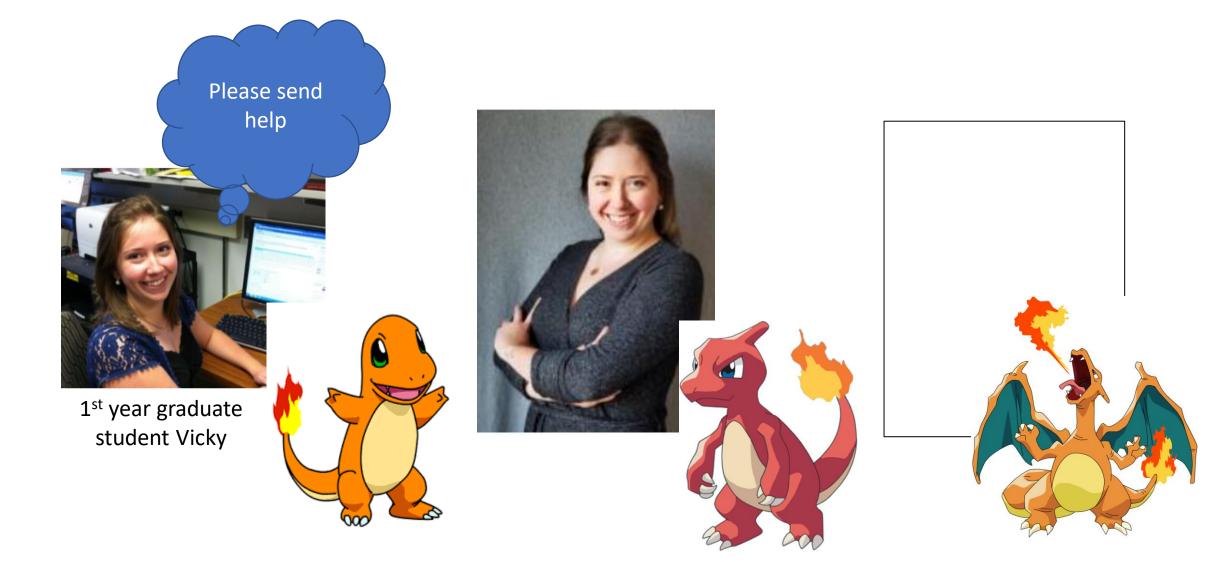
#### Already covered:

- Pre-processing
- ERPs 🗸
- Fast Fourier transform

Please pull out 3 pieces of paper and a pen/pencil:

- -> this will be relevant later for understanding the code
- -> Not a lame ice-breaker

# Getting to know you



### Topics we will cover:

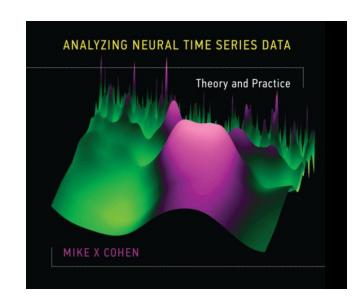
- 1. Where the heck do I start?
- 2. Overview of analysis pipeline
- 3. Time-varying signals as a collection of sinewaves
- 4. What is power?
- 5. Types of spectral analyses
- 6. Notes (baseline correction and stats)

Note: we will not have the time to cover what's under the hood. I will note important terms for you to look up in blue boxes.

#### 1. Where the heck do I start?

#### These analyses are hard!

- 1. Find a group:
  - Hacky hour,
  - PSY 7150:0000 Current topics in psychology (Dr. Wessel)
- 2. Find a mentor
- 3. Cohen's materials
  - Book
  - Youtube channel



#### A note on nomenclature

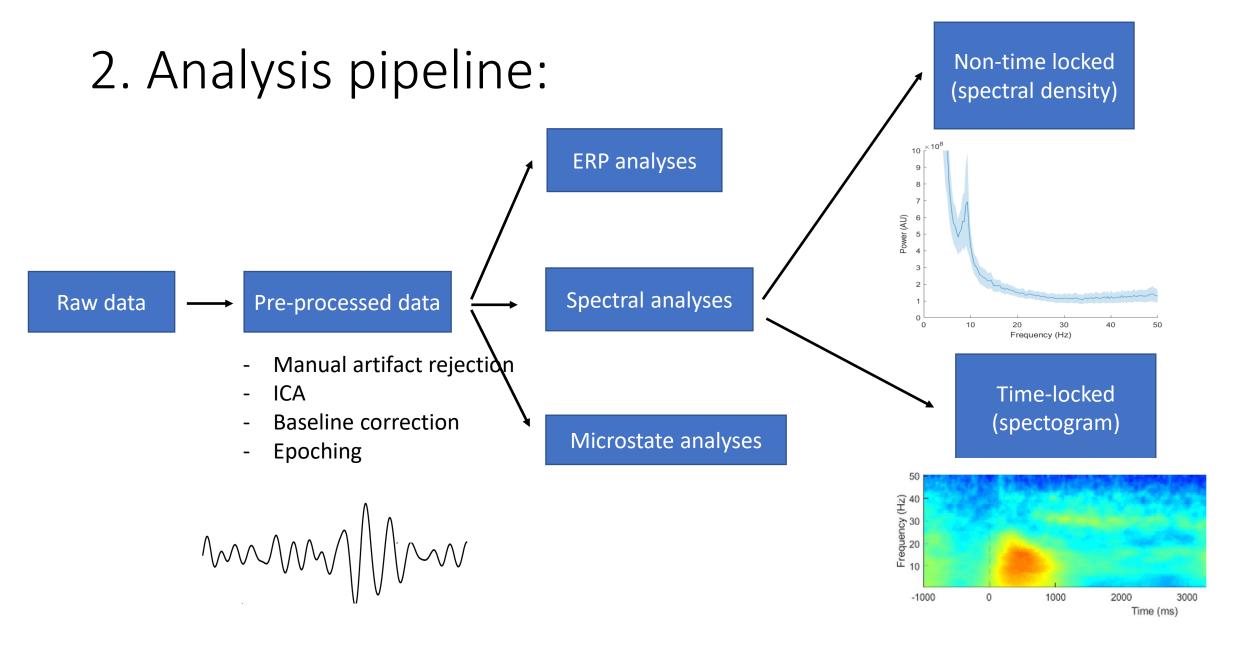
I'm trying to do LFP analyses in rats. Why do I keep getting told I need to learn about EEG?

It's all the same type of signal:

- EEG
- LFP
- Intra-cranial recordings

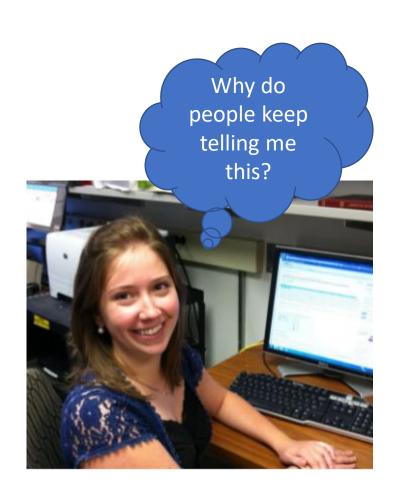
Brain signals that vary across time: it's all time-series data

#### 2. Analysis pipeline: -100 +300 — Standard cue **ERP** analyses Unexp. visual cue Unexp. auditory cue TARGET p < .00044 Spectral analyses Pre-processed data Raw data Manual artifact rejection **ICA** Baseline correction Microstate analyses **Epoching**



Muller Ewald Unpublished

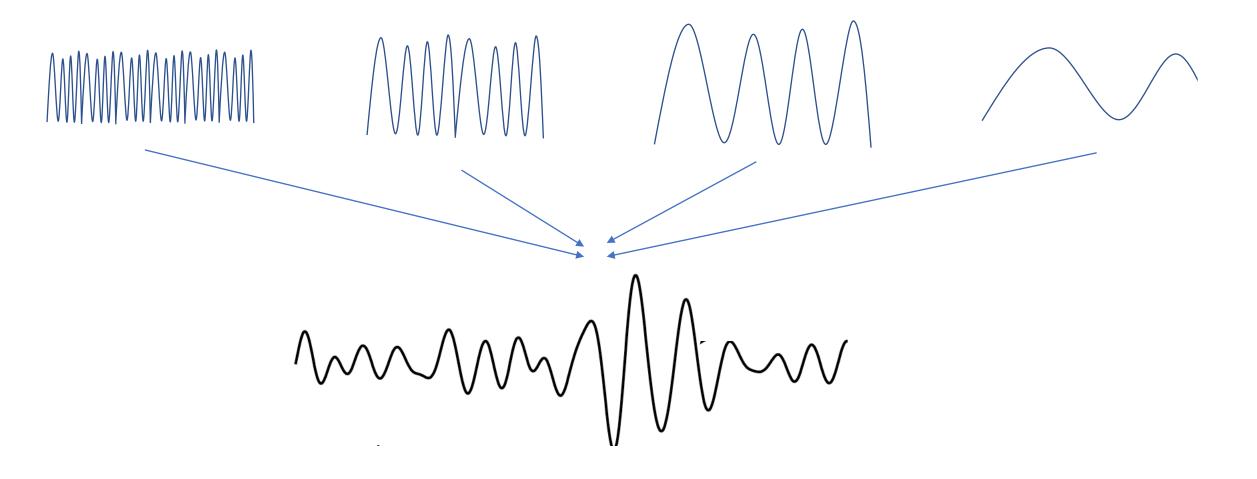
# 3. Time-varying signals as a collection of sinewaves



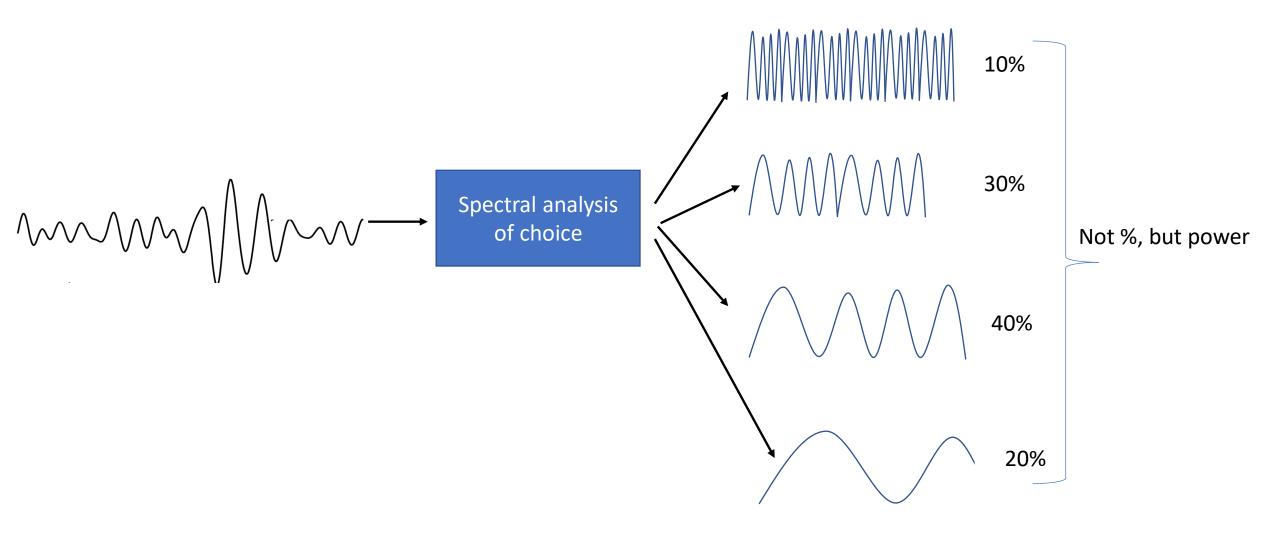
- Because it's literally the most important thing.
- All spectral analyses are based on this principle.
- Spectral analysis: figuring out which sinewaves make up the signal and how much each sinewave contributes to the signal.

# Any time-varying signal can be expressed as a collection of sinewaves

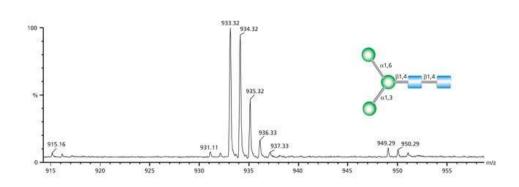
Pretend these are perfect sinewaves



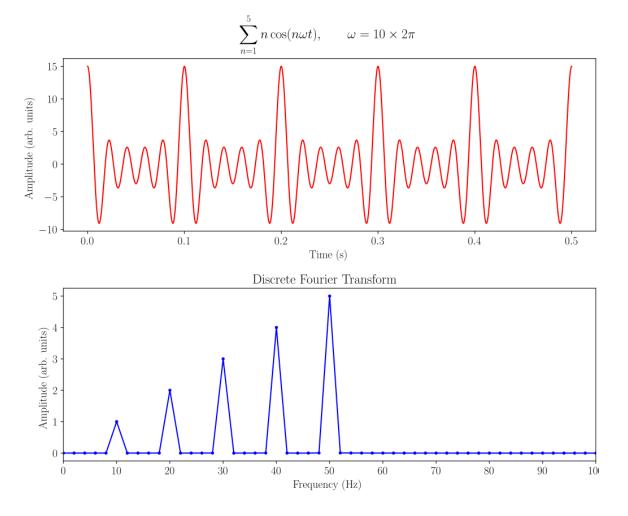
# Any time-varying signal can be expressed as a collection of sinewayes



# Any time-varying signal can be expressed as a collection of sinewayes



Think of spectral analyses as mass spec, but for time-series data.



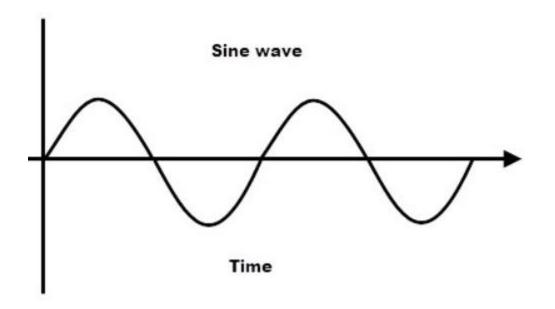
# Takeaway

Any time-varying signal can be expressed as a collection of sinewayes.

A spectral analysis breaks an EEG signal down into it's component sinewaves (and tells you how much of each is present).

This is relevant to neuroscientists because different oscillations (frequencies of sinewaves) are related to different neural processes.

# 4. What is power?



- 1. Amplitude how high?
- Frequency how often/how fast?
- 3. Phase when/at what degree?



# What is power?



- 1. Amplitude and power are related how strong?
- 2. Frequency how often?
- 3. Phase when?

### Different explanations of what power is:

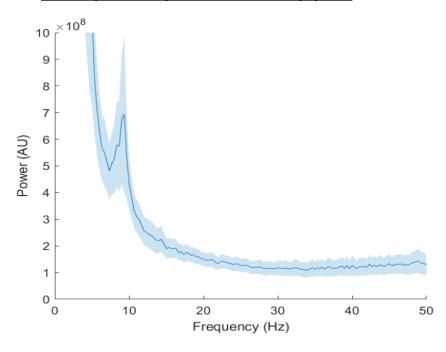
<u>Level 1</u> – power is a property of a wave that tells you how prevalent that wave is in your signal.

<u>Level 2</u> - power is the covariance between two signals.

<u>Level 3</u> – power is the mapping of two vectors across time.

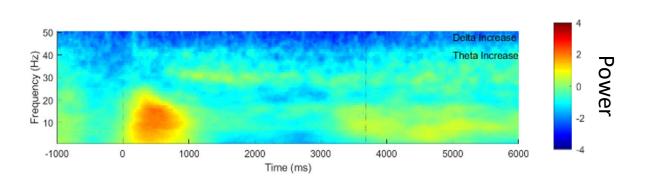
# Level 1 – power is a property of a wave that tells you how prevalent that wave is in your signal

Example 1: Spectral density plot



Peak between 7 - 10 Hz represents high power in those frequencies.

**Example 2: Spectrogram** 

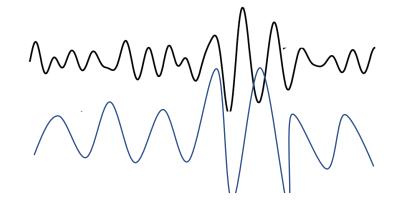


Orange shading from 0 to 1000 ms represents high power in frequencies 0 - 20 Hz.

# Level 2 – power is the covariance between two signals

Signal 1 = EEG signal

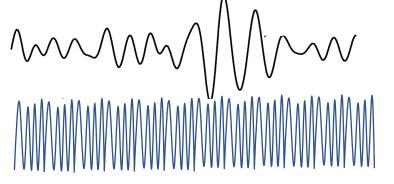
Signal 2 = a sinewave



High covariance = high power

Signal 1 = EEG signal

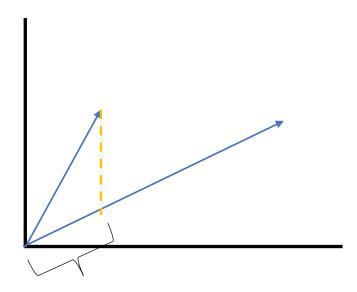
Signal 2 = a different sinewave



Low covariance = low power

How do I mathematically figure out the covariance between two vectors? This is where the dot product and convolution come in.

# Level 3 – Mapping between two vectors across time



Dot product/projection

Vector 1 = your EEG data Vector 2 = a wave/wavelet

$$a \cdot b = \Sigma_{a_i \ b_i = a_1 b_1 + a_2 b_2} \dots$$
 Dot product equation across timepoints

### Different explanations of what power is:

<u>Level 1</u> – power is a property of a wave that tells you how prevalent that wave is in your signal.

<u>Level 2</u> - power is the covariance between two signals.

<u>Level 3</u> – power is the mapping of two vectors across time.

<u>Level 4</u> – complex numbers!

# 5. Types of spectral analyses

#### A. Non time-locked

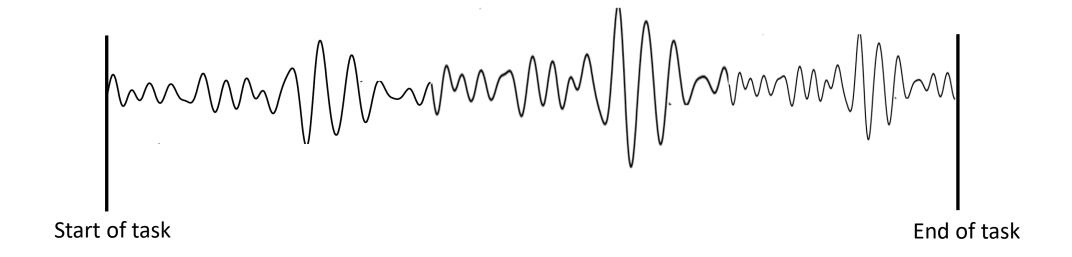
Fast Fourier transform

#### **B.** Time locked

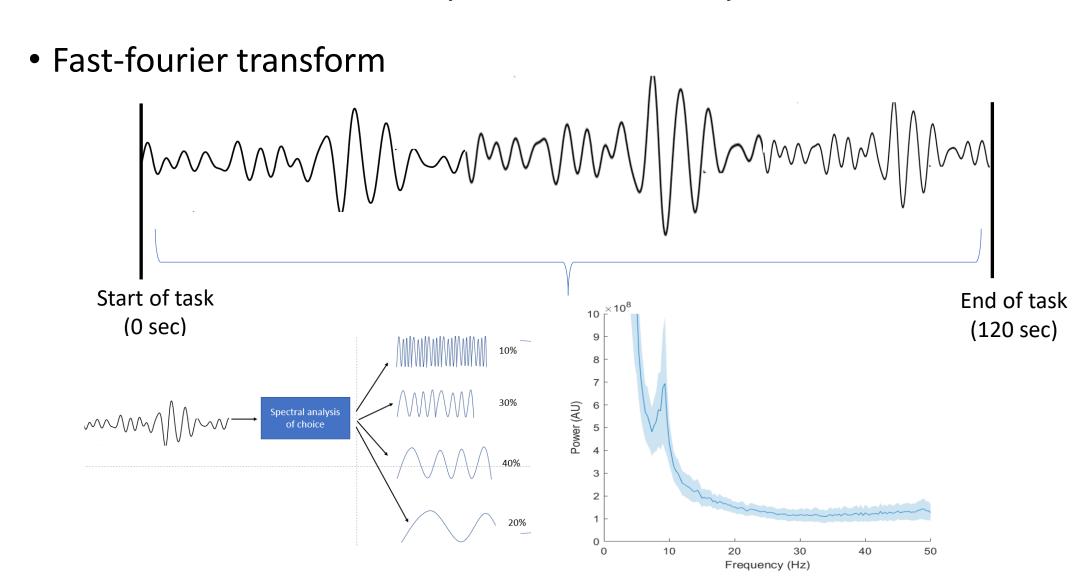
- Short term fast Fourier transform
- Hilbert transform
- Morlet wavelets

### Non-time locked spectral analyses

Fast Fourier transform



## Non-time locked spectral analyses



Fast Fourier transform: what the code looks like (in theory)

```
%% Load in the data for one subject
load(subjData);
%% Do the fft
for frequencyRUN = 0:maxFreq
      subjData % grab subject data
      sinewave %make a sinewave at this frequency that is the same size
             as the subject's data
      fftCoefficient = dot (subjData, sinewave) % get the dot product between
                                 the subject's data and your sinewave
      store fftCoefficient
end
```

#### Fast Fourier transform: what the code looks like (in theory)

```
%% Load in the data for one subject
load(subjData);
%% Do the fft
for frequencyRUN = 0:maxFreq
       subjData % grab subject data
       sinewave %make a sinewave at this freque
               as the subject's data
       fftCoefficient = dot (subjData, sinewave) % 2 6 the subject's d 2 4
                                                                                     en
       store fftCoefficient
end
                                                              10
                                                                   Frequency (Hz)
```

# Non-time locked spectral analyses

Fast Fourier transform

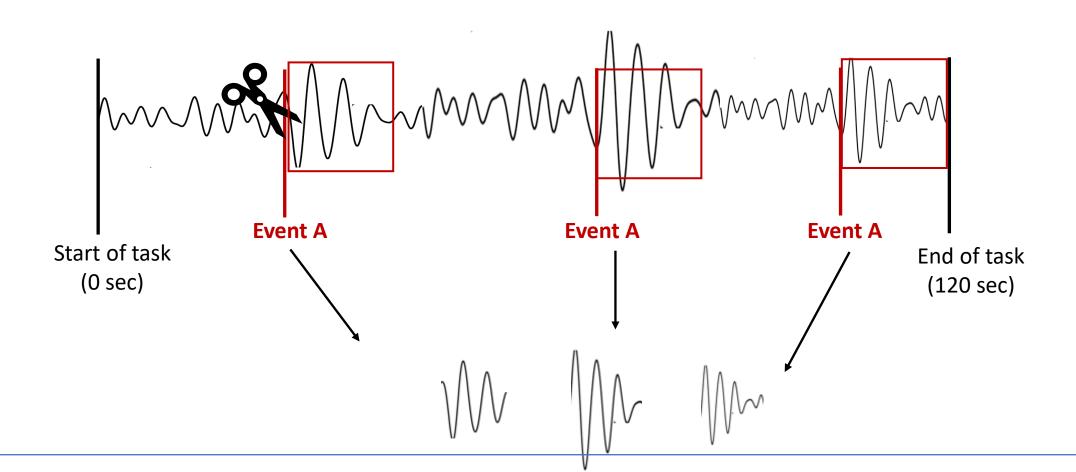


Biggest downside: it's not time-locked

- 1. It's a great place to start
- Easier to code. Doesn't involve as many event time stamps
- 2. Great for looking at gross-level differences between conditions
- 3. Great if you don't have time-stamps/events
  - e.g. resting-state analysis

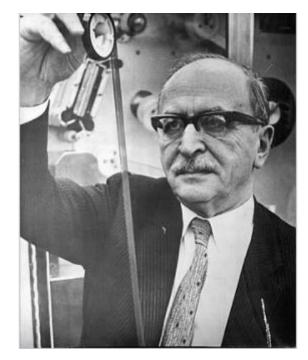
# Note: you can get more precise with your data when using the fft

What if I want to use the FFT to compare general power levels in my data in the baseline vs the post-event period?



# Time-locked spectral analyses

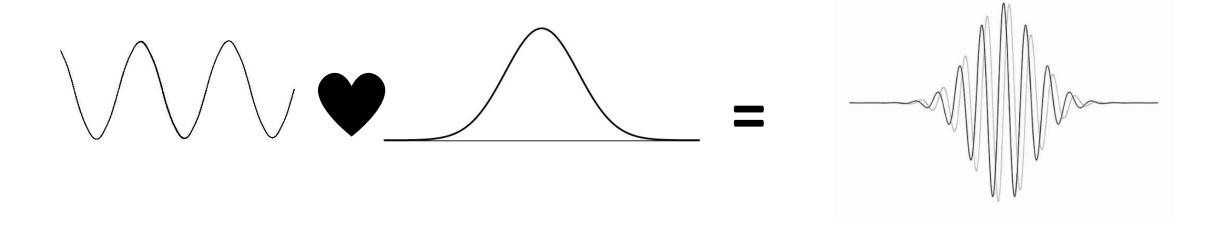
- 1. Short-term fast Fourier transform
- 2. Hilbert transform
- 3. Morlet Wavelets



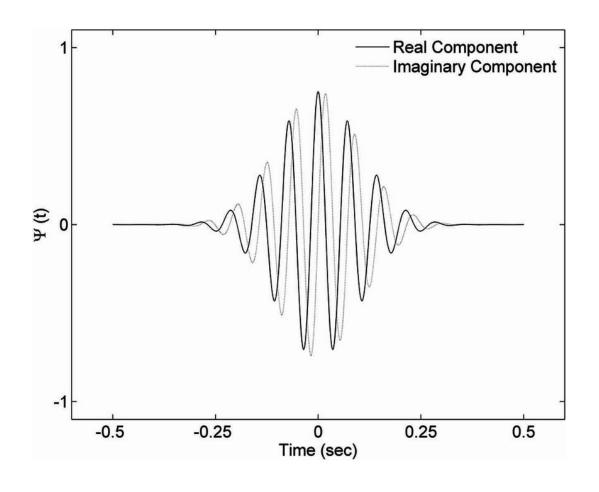
Gabor: professor of physics

#### Morlet wavelet method

• A Morlet wavelet is a sinewave mixed with a gaussian curve



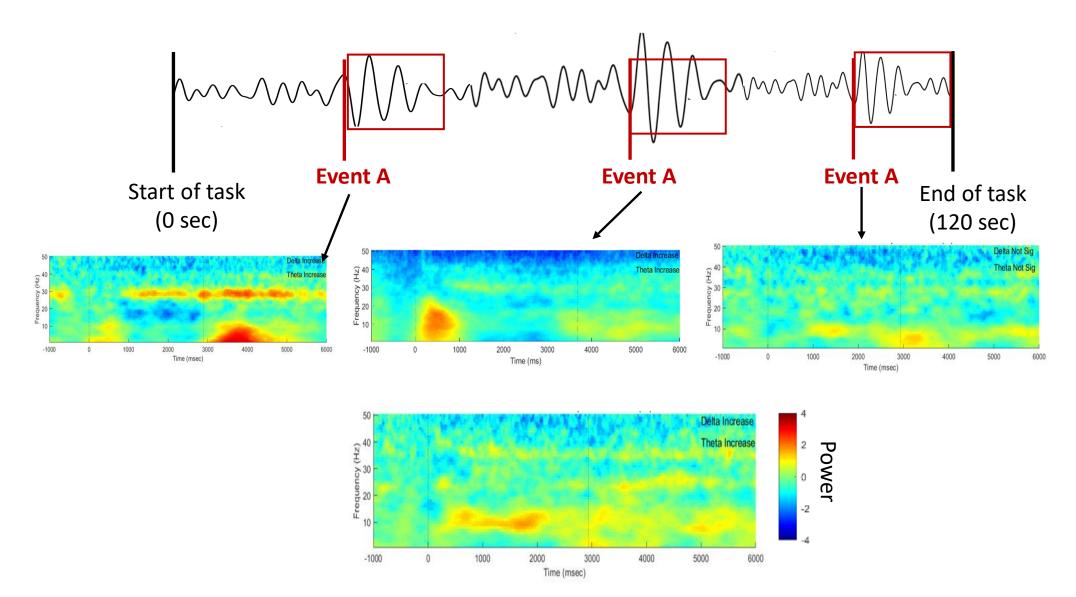
#### Morlet wavelet method



- Because your wavelet varies in time, you can now look at how your signal varies in time
- You can now time/eventlock

Morlet wavelets have a real and an imaginary component. This is important.

#### Morlet wavelet method



for subjectRUN = 1:maxSubjects % Load in the data for one subject
 data = load(subjData);

```
for subjectRUN = 1:maxSubjects % Load in the data for one subject
     data = load(subjData);
     %% Convolve
     for trialRUN = 1:maxTrials % Grab data from a single trial
          dataTrial = data(one trial); % grab data from one trial
```

end

dataAverageTrials = nanmean(dataTrialX ,3); % Average across trials
end

```
for subjectRUN = 1:maxSubjects % Load in the data for one subject
        data = load(subjData);
        %% Convolve
        for trialRUN = 1:maxTrials % Grab data from a single trial
                dataTrial = data(one trial); % grab data from one trial
                for waveletRUN = 1: maxWavelets % Convolve your signal with wavelets at your
                                                        frequencies of interest
                end
```

end
dataAverageTrials = nanmean(dataTrialX ,3); % Average across trials
end

dataTrialX = cat(3, dataTrialX, dataTrialY);

```
for subjectRUN = 1:maxSubjects % Load in the data for one subject
        data = load(subjData);
        %% Convolve
        for trialRUN = 1:maxTrials % Grab data from a single trial
                 dataTrial = data(one trial); % grab data from one trial
                for waveletRUN = 1: maxWavelets % Convolve your signal with wavelets at your frequencies of interest
                         dataTrial singleWavelet = convolve(dataTrial, wavelet);
                         dataTrialY = vertcat(dataTrialY, dataTrial singleWavelet );
                 end
                 dataTrialX = cat(3, dataTrialX, dataTrialY);
        end
dataAverageTrials = nanmean(dataTrialX,3); % Average across trials
end
```

```
for subjectRUN = 1:maxSubjects % Load in the data for one subject
        data = load(subjData);
        %% Convolve
        for trialRUN = 1:maxTrials % Grab data from a single trial
                dataTrial = data(one trial); % grab data from one trial
                for waveletRUN = 1: maxWavelets % Convolve your signal with wavelets at your
                                                        frequencies of interest
                        dataTrial_singleWavelet = convolve(dataTrial, wavelet)
                        dataTrialY = vertcat(dataTrialY, dataTrial singleWavelet)
                end
                dataTrialX = cat(3, dataTrialX, dataTrialY)
        end
dataAverageTrials = nanmean(dataTrialX,3); % Average across trials
```

end

Note: this is not the actual computation we do because this would be too slow. Look up the convolution theorem.

# Morlet wavelet method: what the code looks like (in theory)

- 1. Load in a subject
- 2. Convolve data from each trial
- 3. Average data across trials
- 4. Save averaged data in a matrix

Subject-level analyses: Covered in previous slide

- 5. Average data across all subjects
- 6. Run stats
- 7. Make figure

### 5. Notes

- a. Baseline correction
- b. Stats

### A. Baseline correction

- 1. No baseline correction
- 2. Baseline correction

Please consider baseline-correcting.

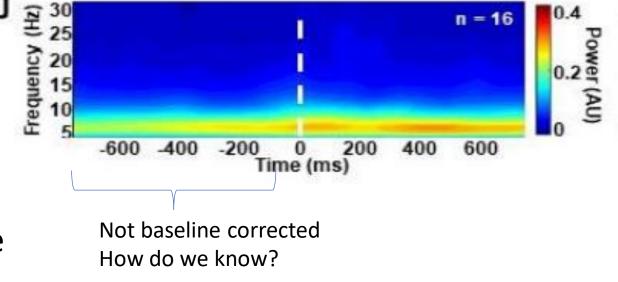
You can miss interesting aspects of the data (especially at higher frequencies) when you don't baseline correct

### A. Baseline correction

- 1. No baseline correction
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Please consider baseline-correcting.

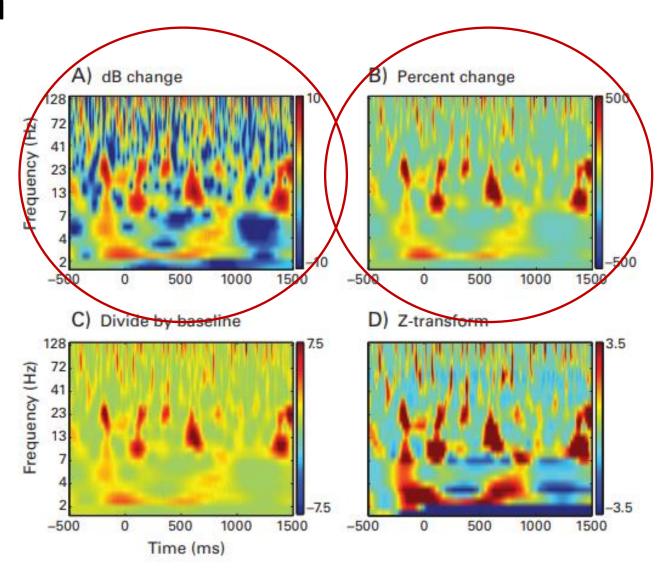
You can miss interesting aspects of the data (especially at higher frequencies) when you don't baseline correct.



Baseline correction

#### 2. Baseline correction

- dB change
- % change
- Divide by baseline
- Z-transform



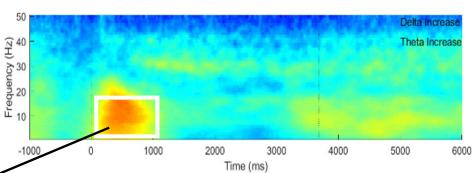
- 1. Average across ROI and compare
  - Only do if you have a very strong a-priori hypothesis
- 2. Sample-by-sample t-test
  - Preferred -> honors the resolution of the data
  - Don't forget to correct for multiple comparisons (Bonferroni, Bonferroni-Holm, FDR, cluster-based)

1. Average across ROI and compare

#### **Condition 1**

Subject	Averaged value
1	2.5

#### Subject 1

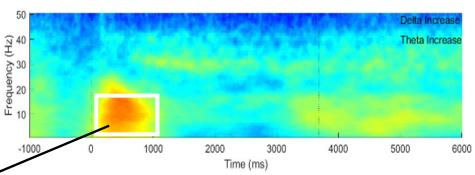


1. Average across ROI and compare

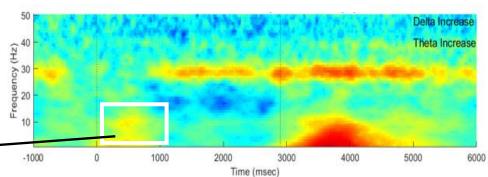
#### **Condition 1**

Subject	Averaged value
1	2.5
2	1
3	1.5

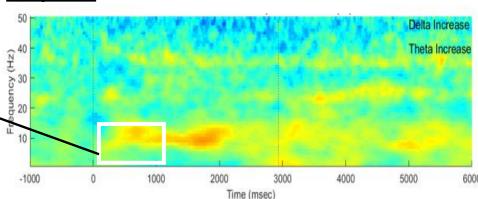
#### Subject 1



#### Subject 2



#### Subject 3



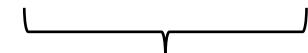
## 1. Average across ROI and compare

#### **Condition 1**

Subject	Averaged value
1	2.5
2	1
3	1.5

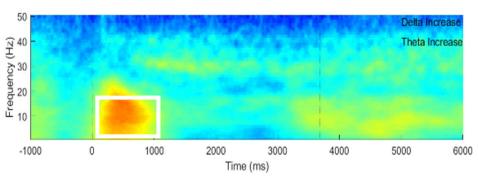
#### **Condition 2**

Subject	Averaged value
1	5
2	7
3	2.5

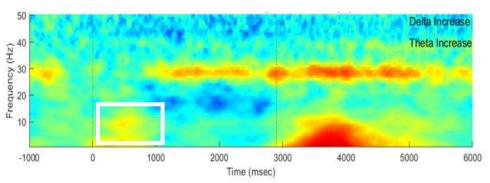


(Non-parametric) t-test

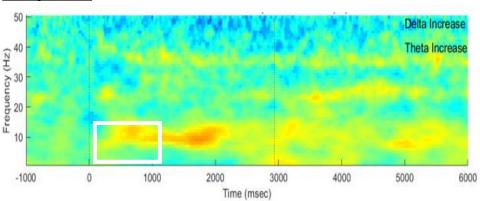
#### Subject 1



#### Subject 2

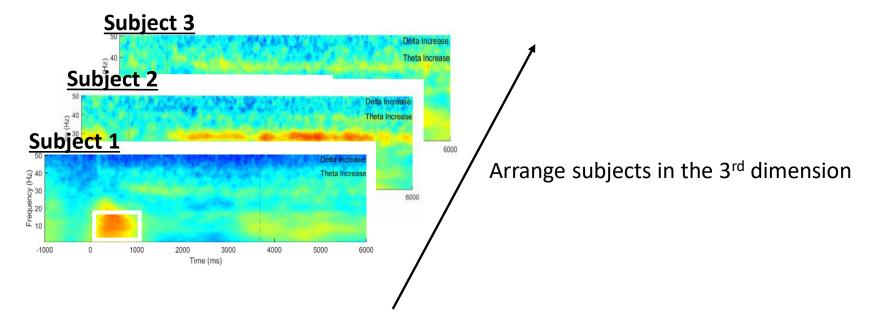


#### Subject 3



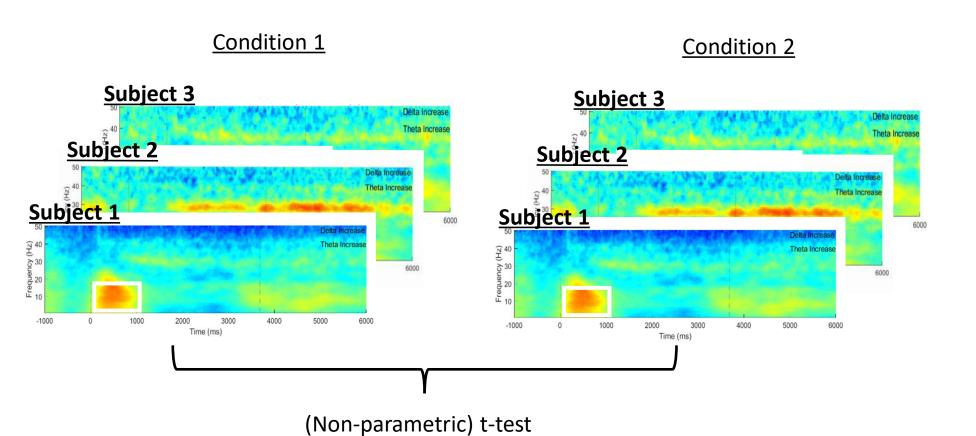
### 2. Sample-by-sample t-test



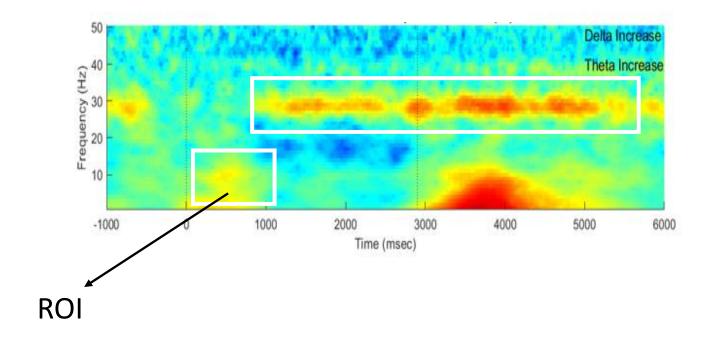


2. Sample-by-sample t-test

[~,p] = ttest(condition1, condition2, 'Dim', 3);



- Beware of getting off-track based on what a spectrogram looks like.
- Stick to the stats.



### 1. Where the heck do I start?

### These analyses are hard!

Anyone can borrow some code and run an analysis. Being able to understand what you are doing and troubleshoot problems is where the real work begins.

- 1. Find a group:
  - Hacky hour,
  - PSY 7150:0000 Current topics in psychology (Dr. Wessel)
- 2. Find a mentor
- 3. Cohen's materials
  - Book
  - Youtube channel

