

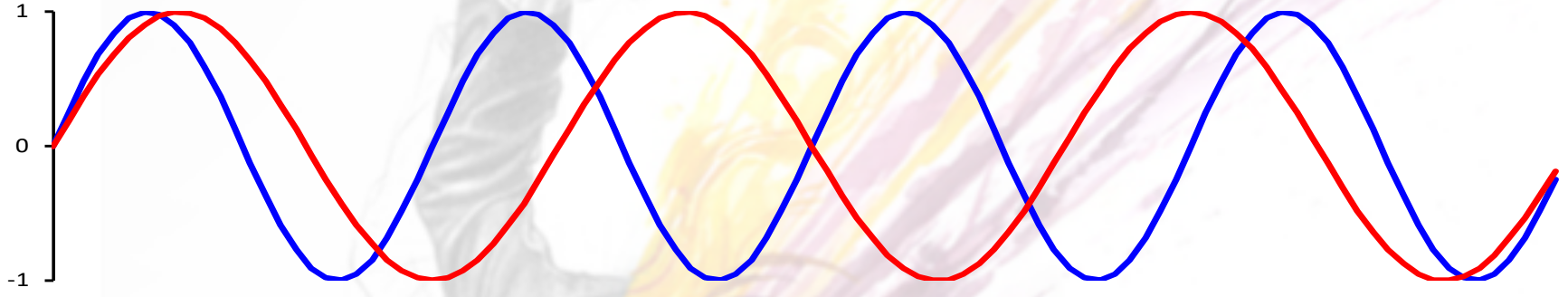
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Key Background Issues

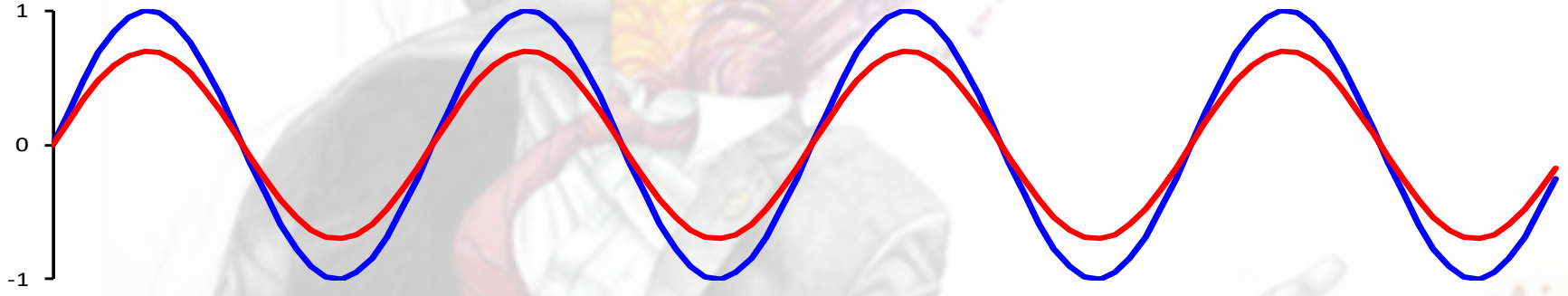
Fourier Analysis & Fundamental Principle #1



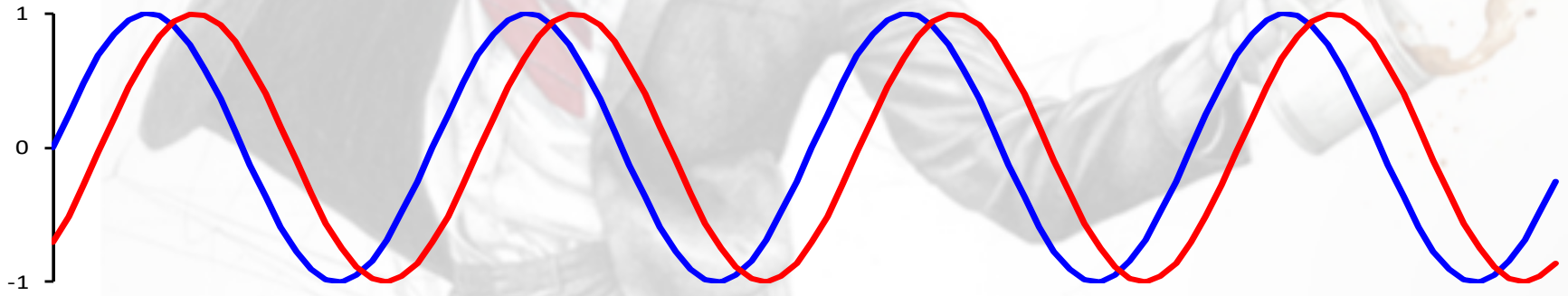
Different
Frequencies



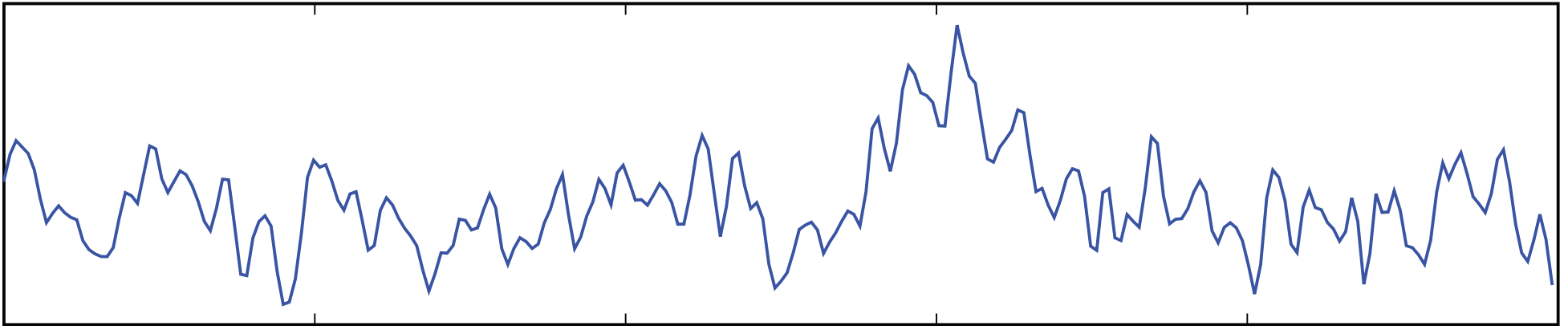
Different
Amplitudes



Different
Phases



Raw EEG



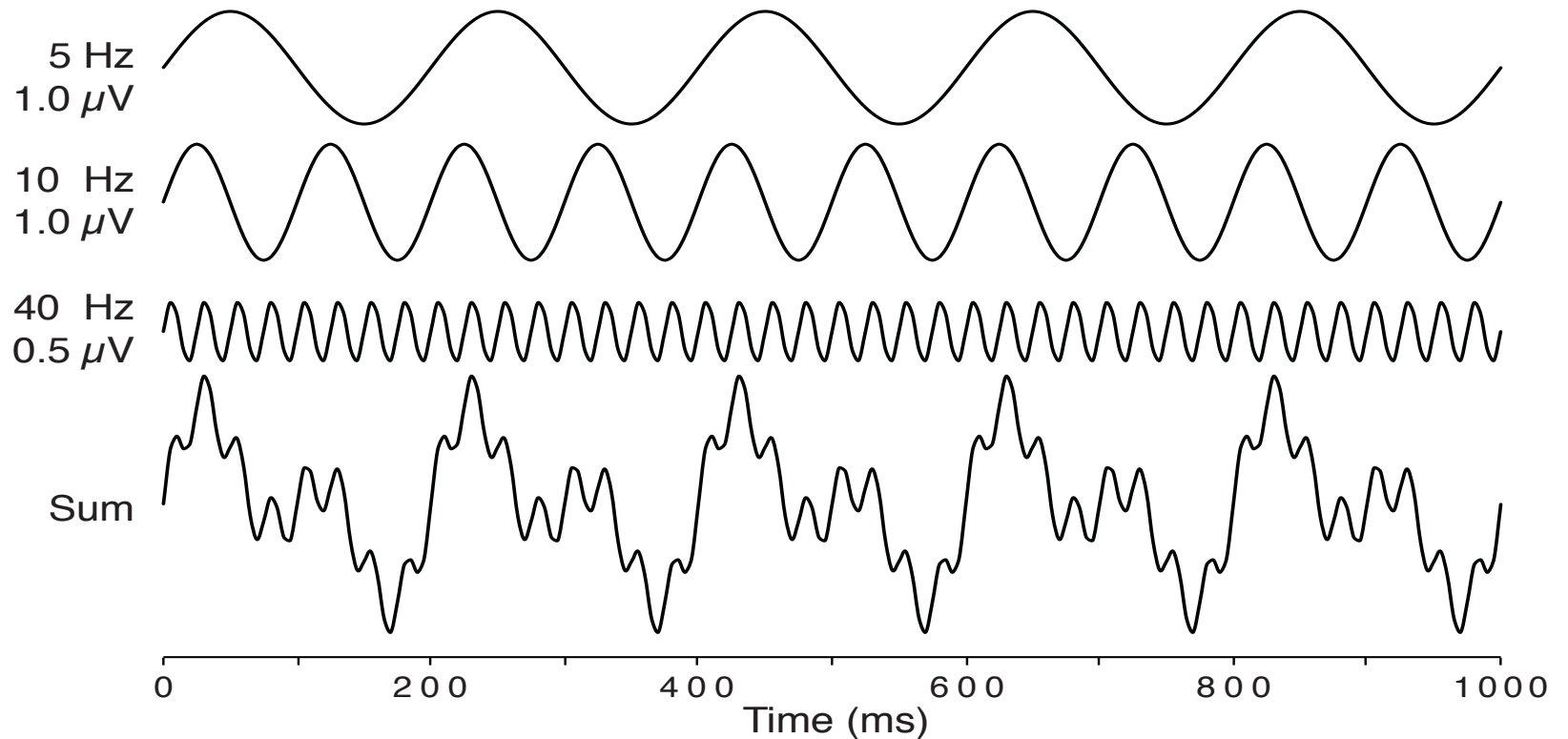
An EEG or ERP waveform can be decomposed into a set of sinusoids of different frequencies, phases, and amplitudes.

You could perfectly reproduce this entire waveform by summing together a set of sinusoids.



Joseph Fourier

Fourier Analysis

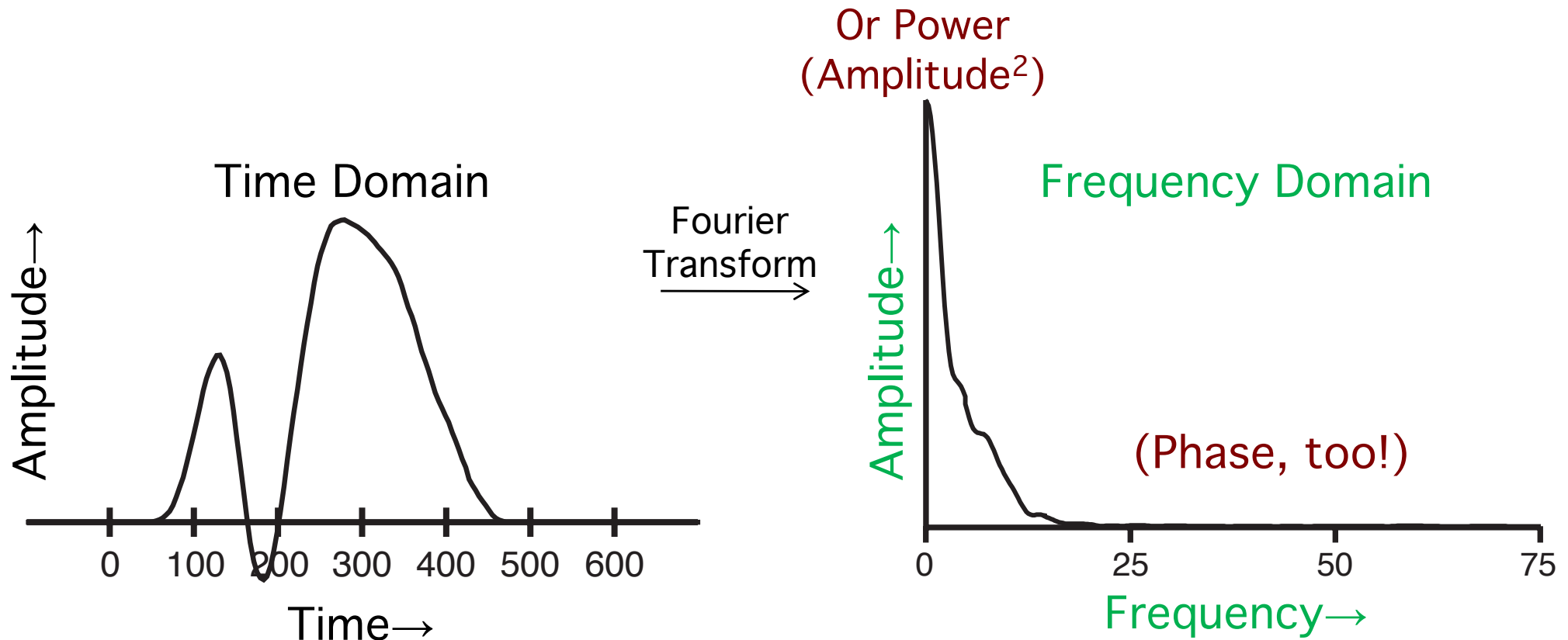


ANY waveform, no matter how complex, can be recreated by summing together a set of sinusoids. The Fourier transform tells you the amplitudes, phases, and frequencies of the sinusoids you would need to reconstruct a given complex waveform.

Fourier Analysis

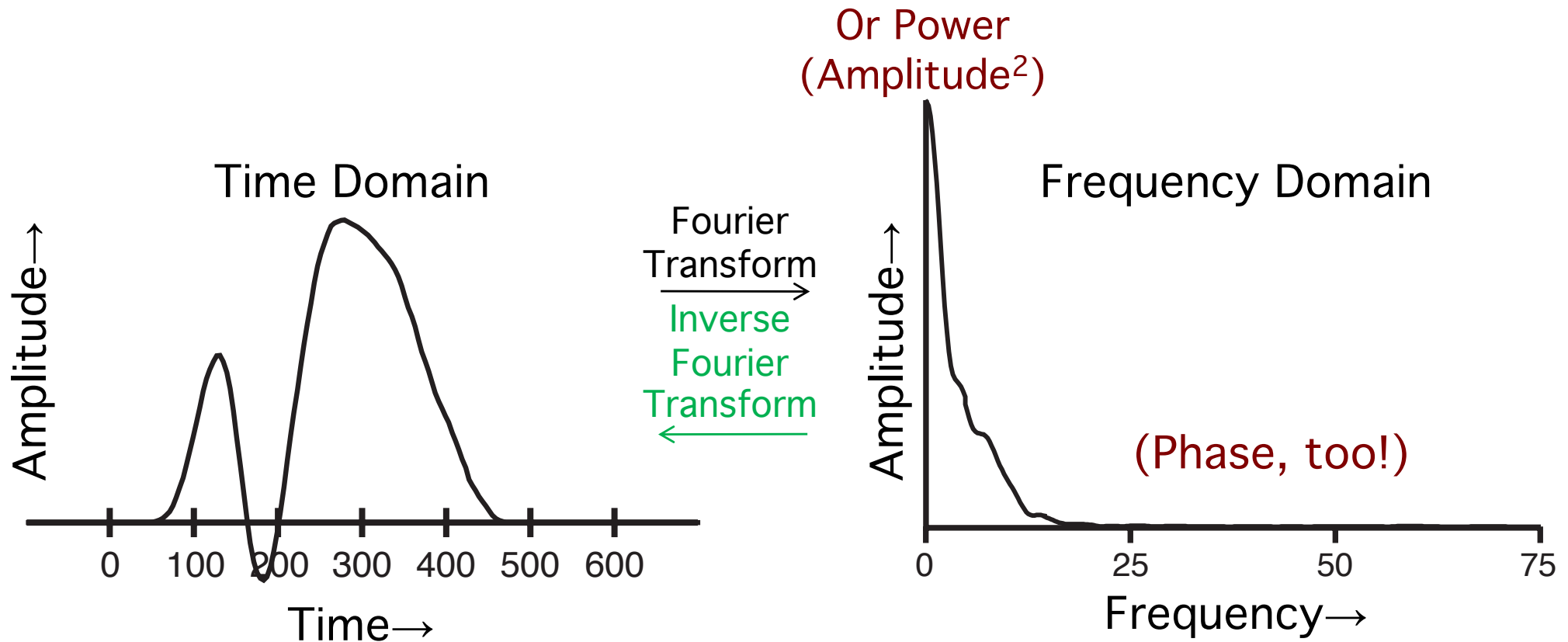
The Fourier transform shows the amplitudes and phases of the sinusoids that we'd need to sum together to recreate our original ERP waveform.

(Phase is not usually shown.)



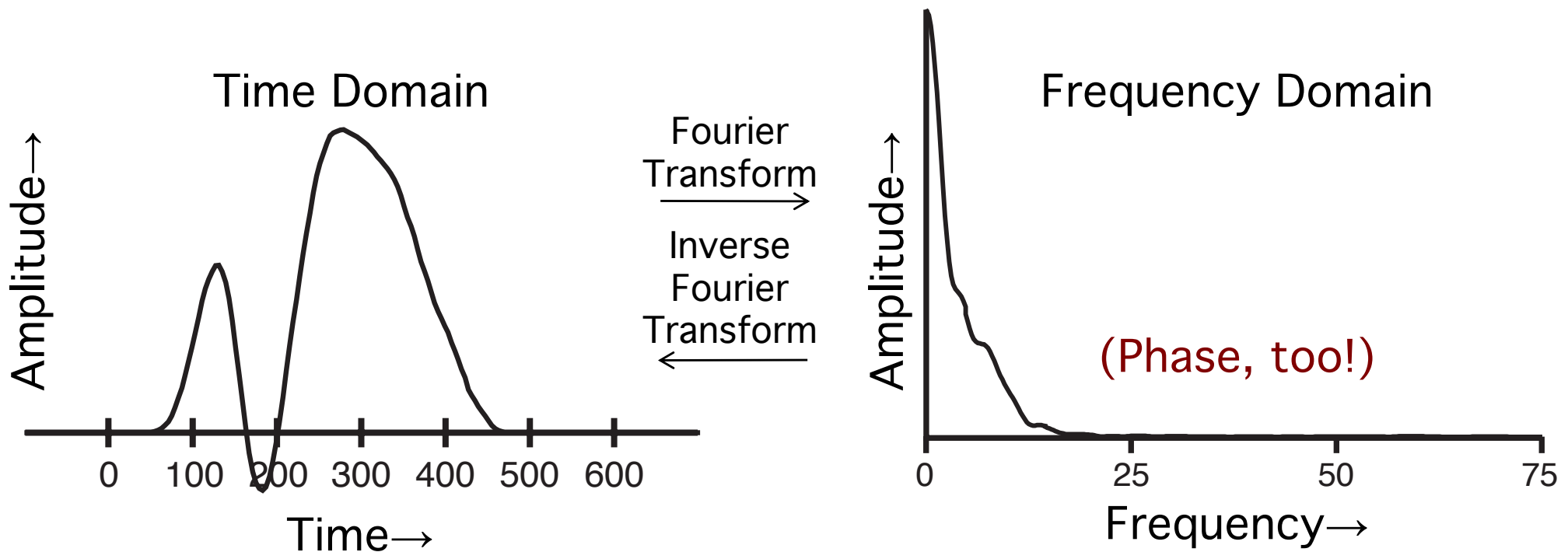
Fourier Analysis

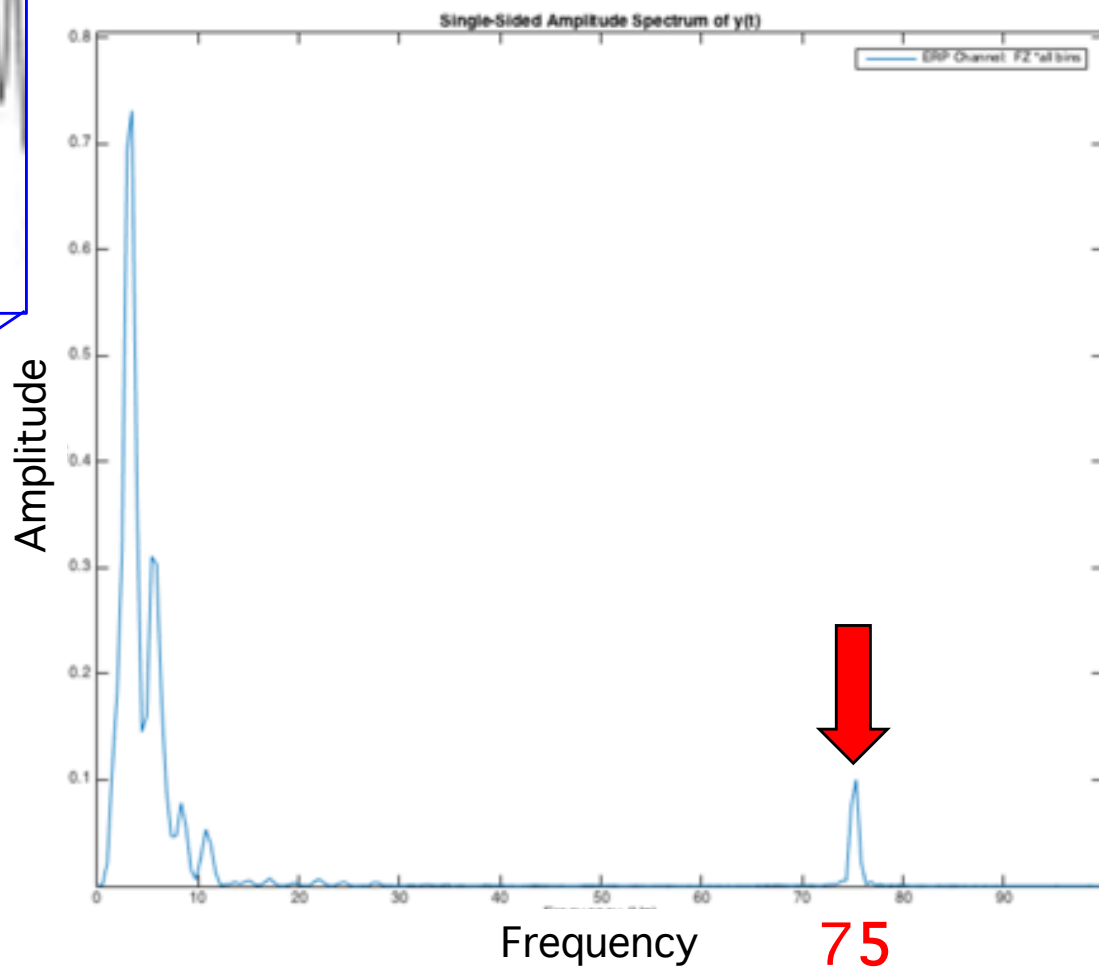
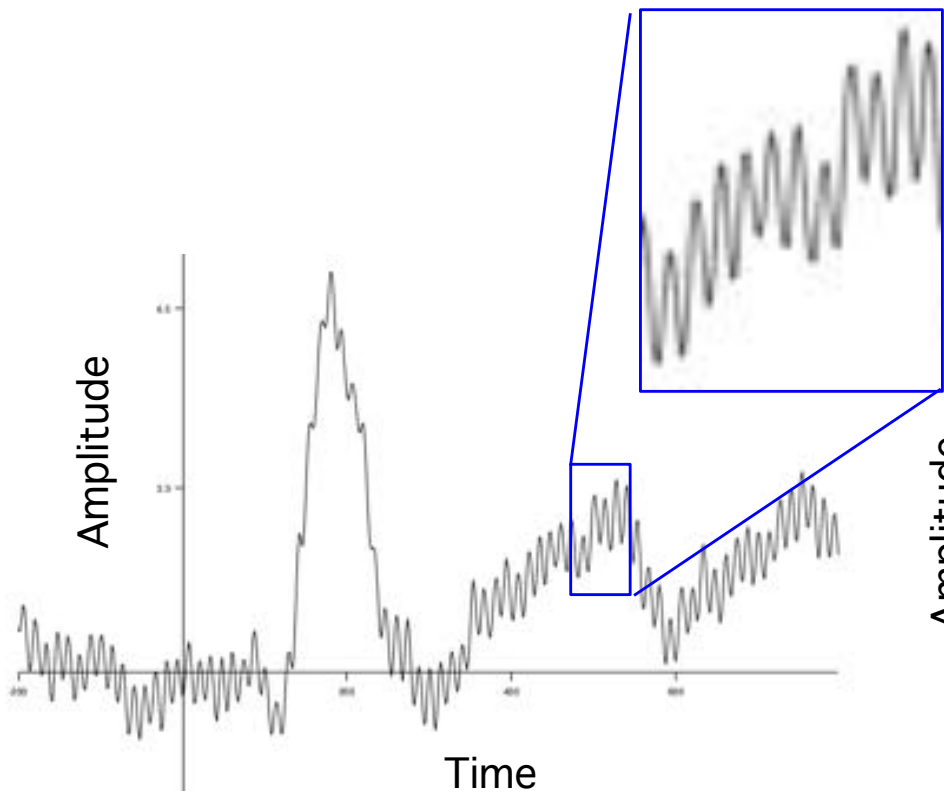
The inverse Fourier transform simply sums together the sinusoids shown in the Frequency Domain plot to recreate the original Time Domain waveform.



Fourier Analysis

Any time-domain waveform has a unique frequency-domain equivalent. There is one and only one set of sinusoids that can perfectly recreate the original waveform. You need only one amplitude and phase for each frequency.





Fundamental Principle #1

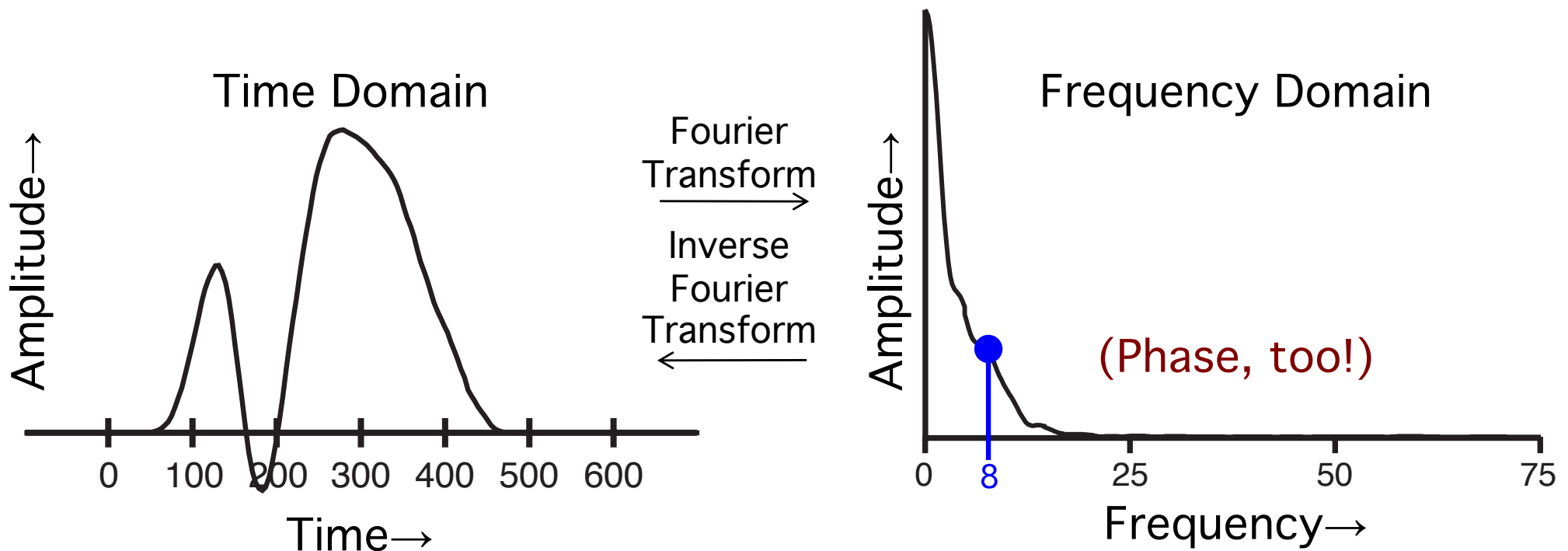
- Power at a frequency in a Fourier transform does not mean that an oscillation was present at that frequency
- Power at a frequency means that a sinusoid at that frequency, when added to other sinusoids at other frequencies, can create an equivalent waveform

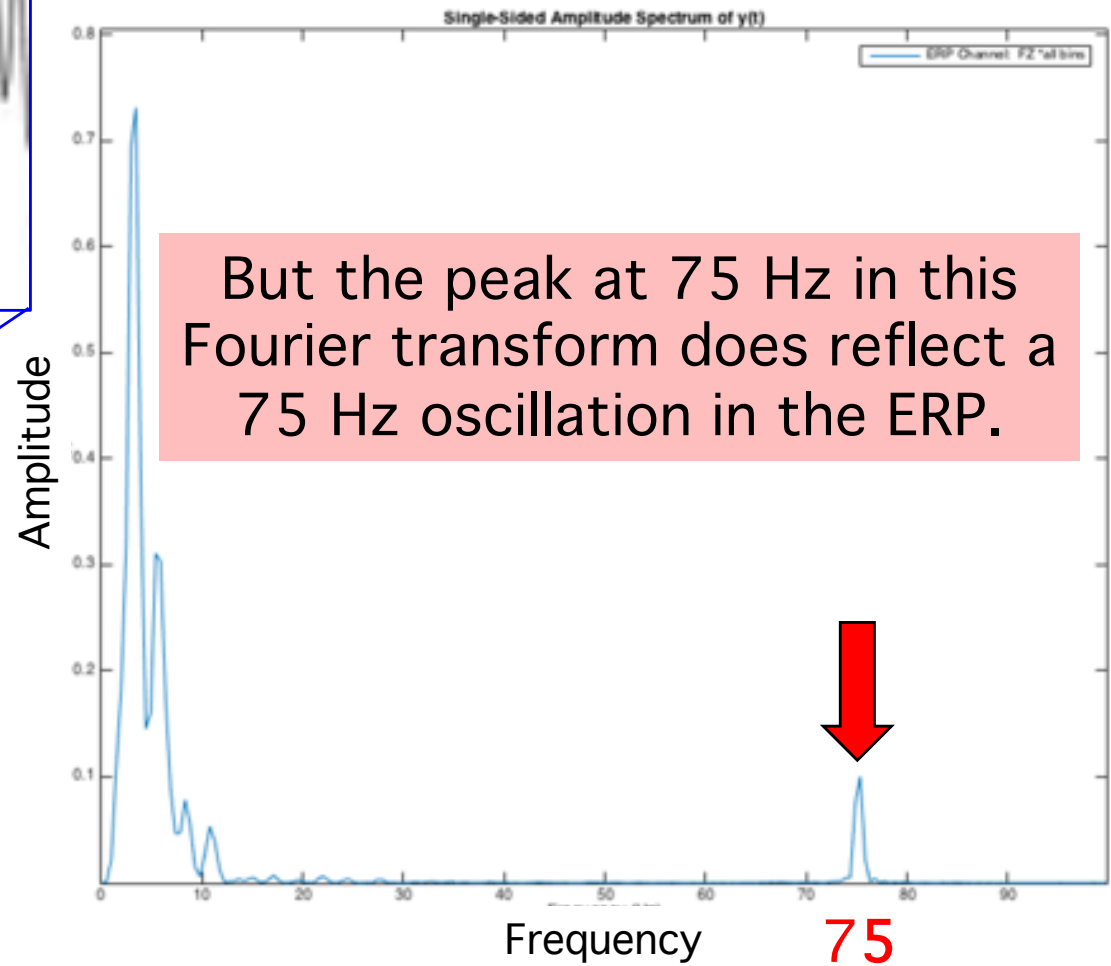
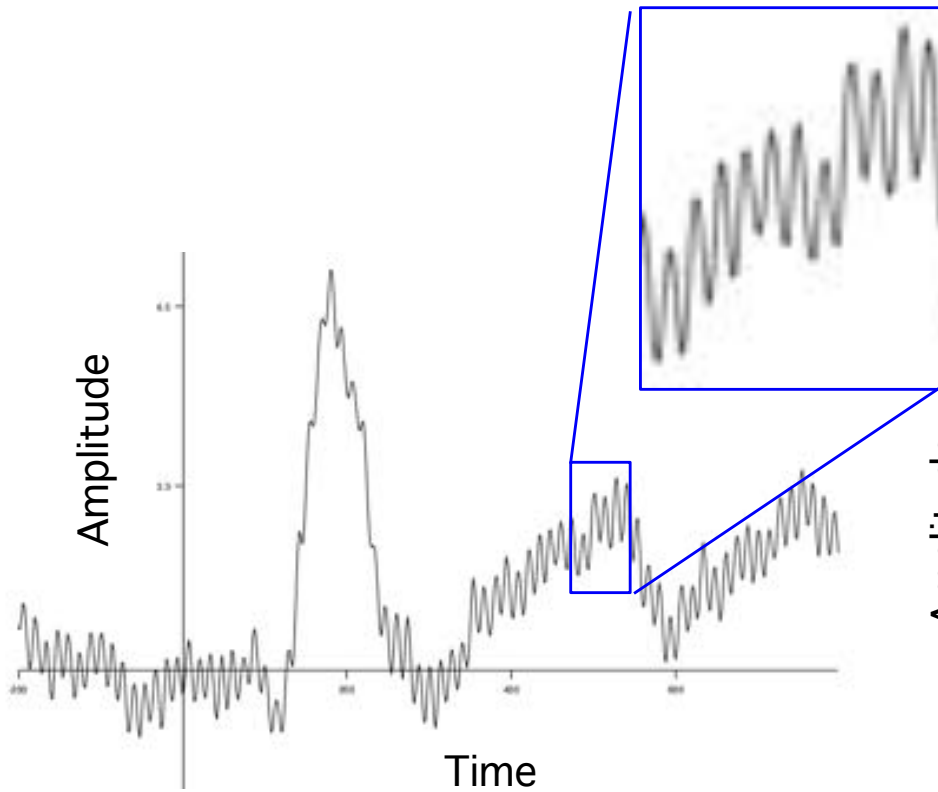
It does not mean that the biological signal consists of the sum of these sinusoids

Fundamental Principle #1

ANY time-domain waveform has a unique frequency-domain equivalent.

The fact that we have a certain amplitude at 8 Hz in the Fourier transform doesn't mean that there are 8 Hz oscillations in the ERP





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Key Background Issues

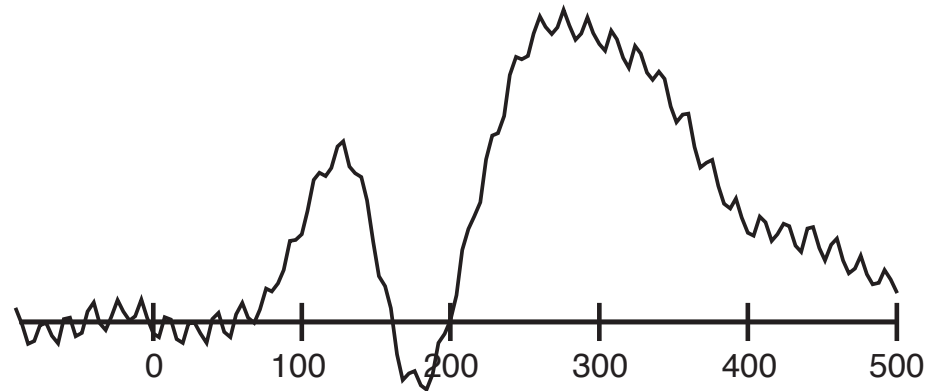
Filtering



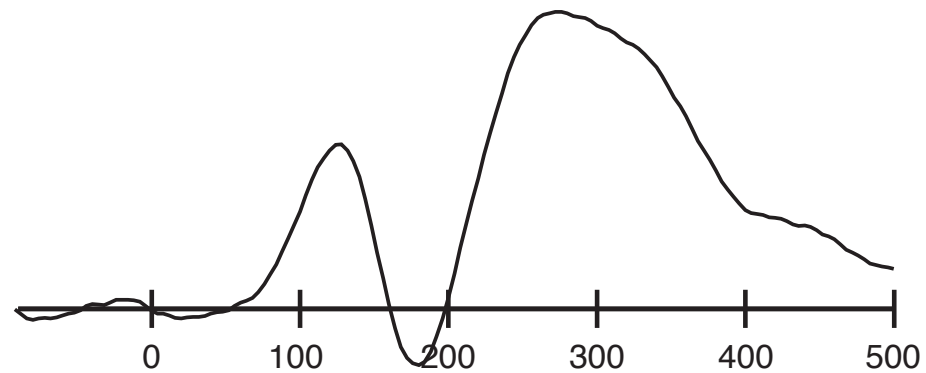
4 Classes of Filters

- Low-pass filter
 - Remove high frequencies, pass low frequencies

ERP,
Unfiltered



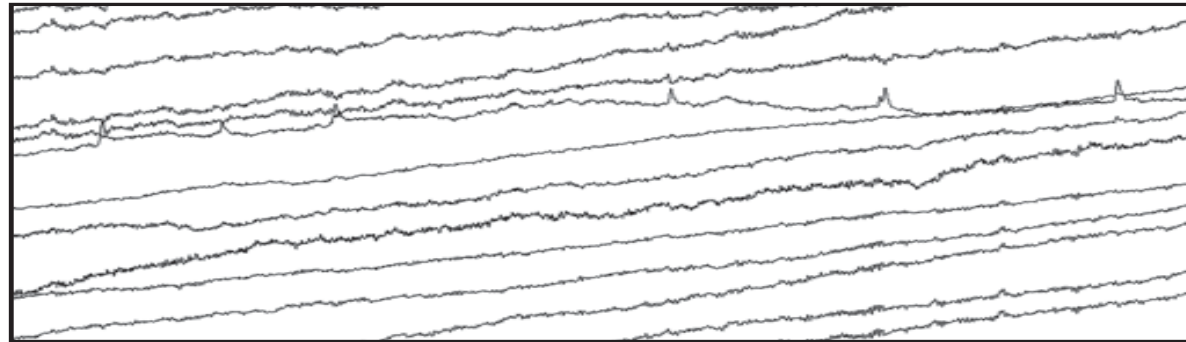
ERP,
Low-pass
Filtered
@ 30 Hz



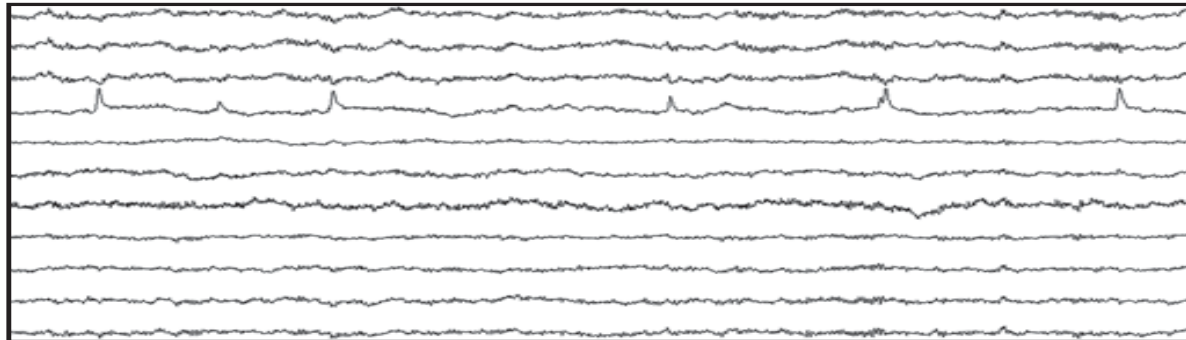
4 Classes of Filters

- Low-pass filter
 - Remove high frequencies, pass low frequencies
- High-pass filter
 - Remove low frequencies, pass high frequencies

EEG
Unfiltered



EEG
Filtered
@ 0.1Hz

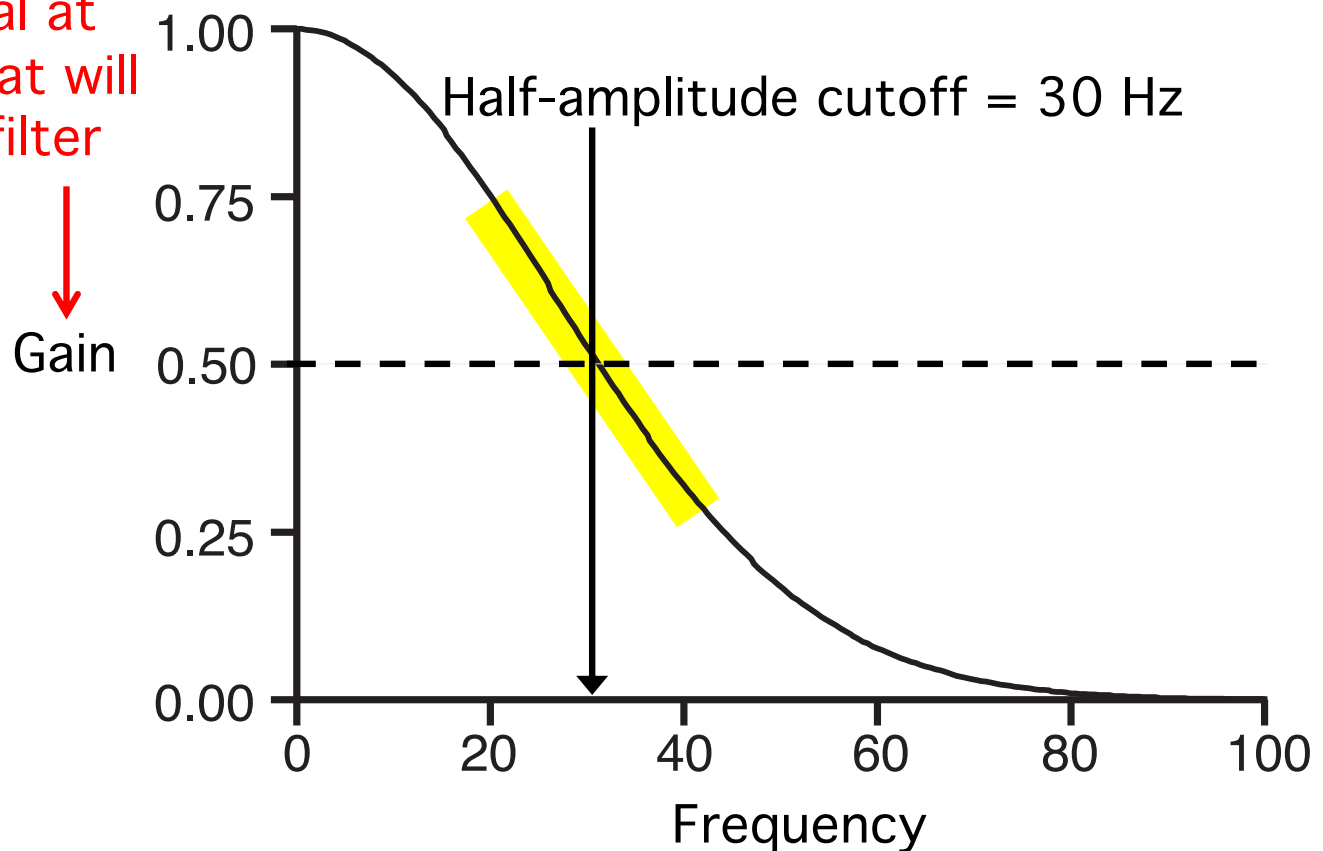


4 Classes of Filters

- Low-pass filter
 - Remove high frequencies, pass low frequencies
- High-pass filter
 - Remove low frequencies, pass high frequencies
- Band-pass filter
 - Remove low and high frequencies, pass intermediate band
 - Same as sequential application of low-pass and high-pass filters
- Notch filter
 - Remove narrow band of frequencies (e.g., 50 Hz or 60 Hz)

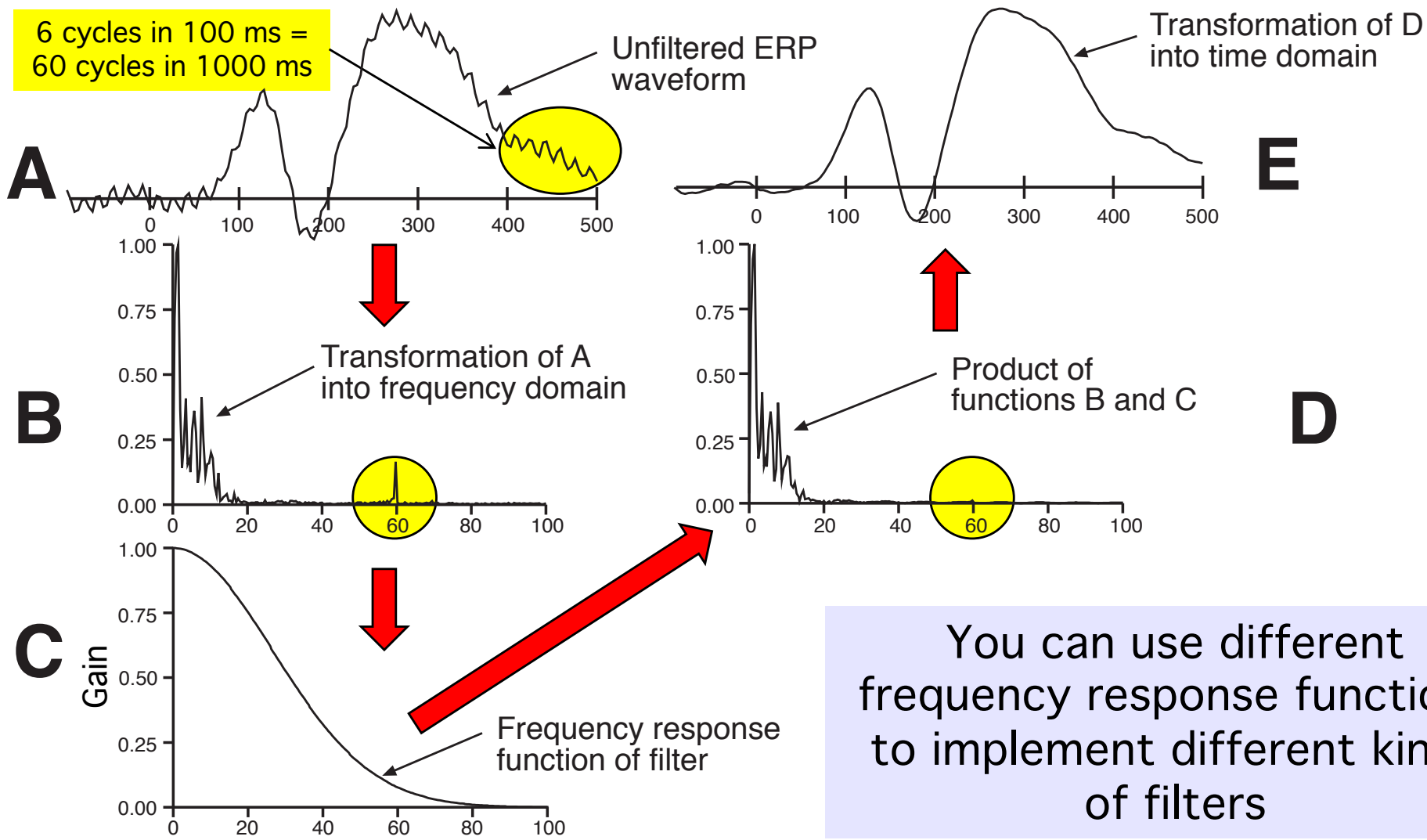
Frequency Response Function

Proportion of signal at each frequency that will pass through the filter



Gain: Multiplication factor for adjusting the amplitude of each frequency

Rolloff: Slope of the filter at its steepest point (dB/octave)



You can use different frequency response functions to implement different kinds of filters

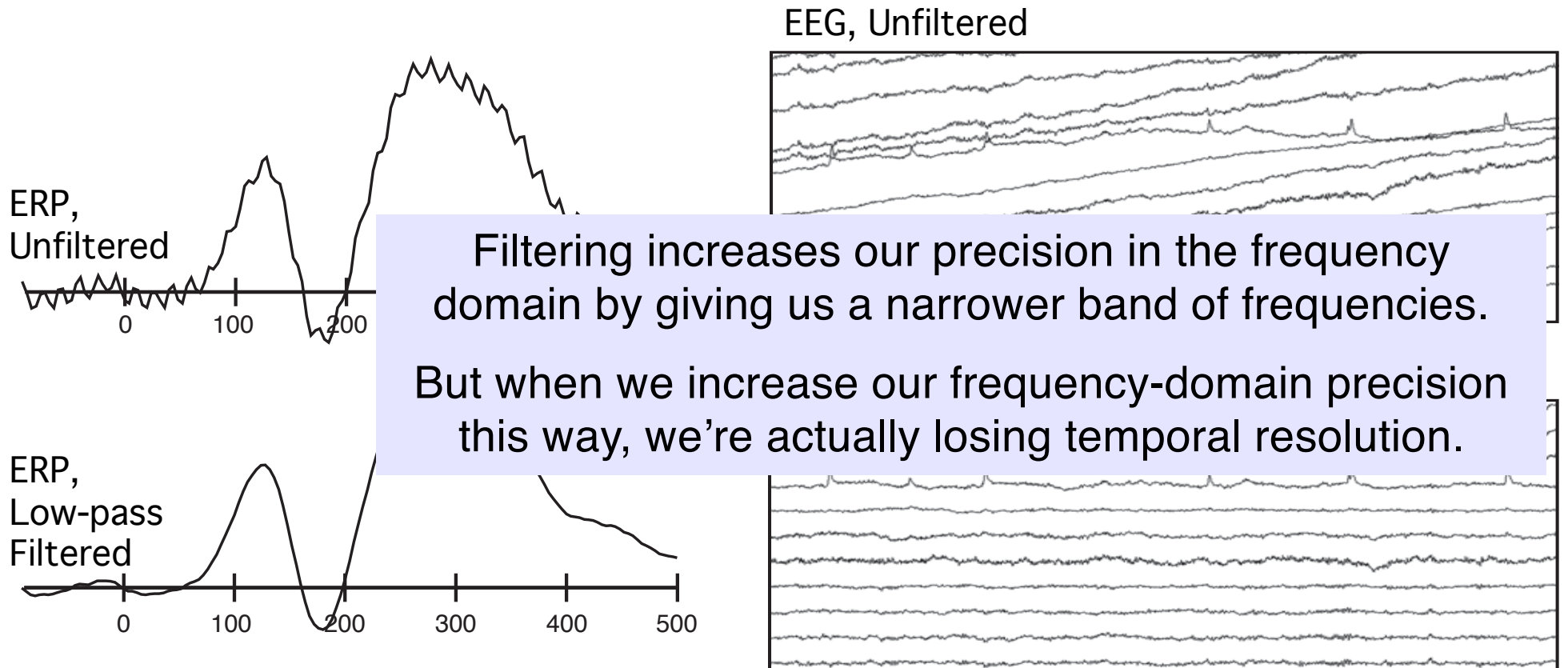
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Key Background Issues

Fundamental Principle #2

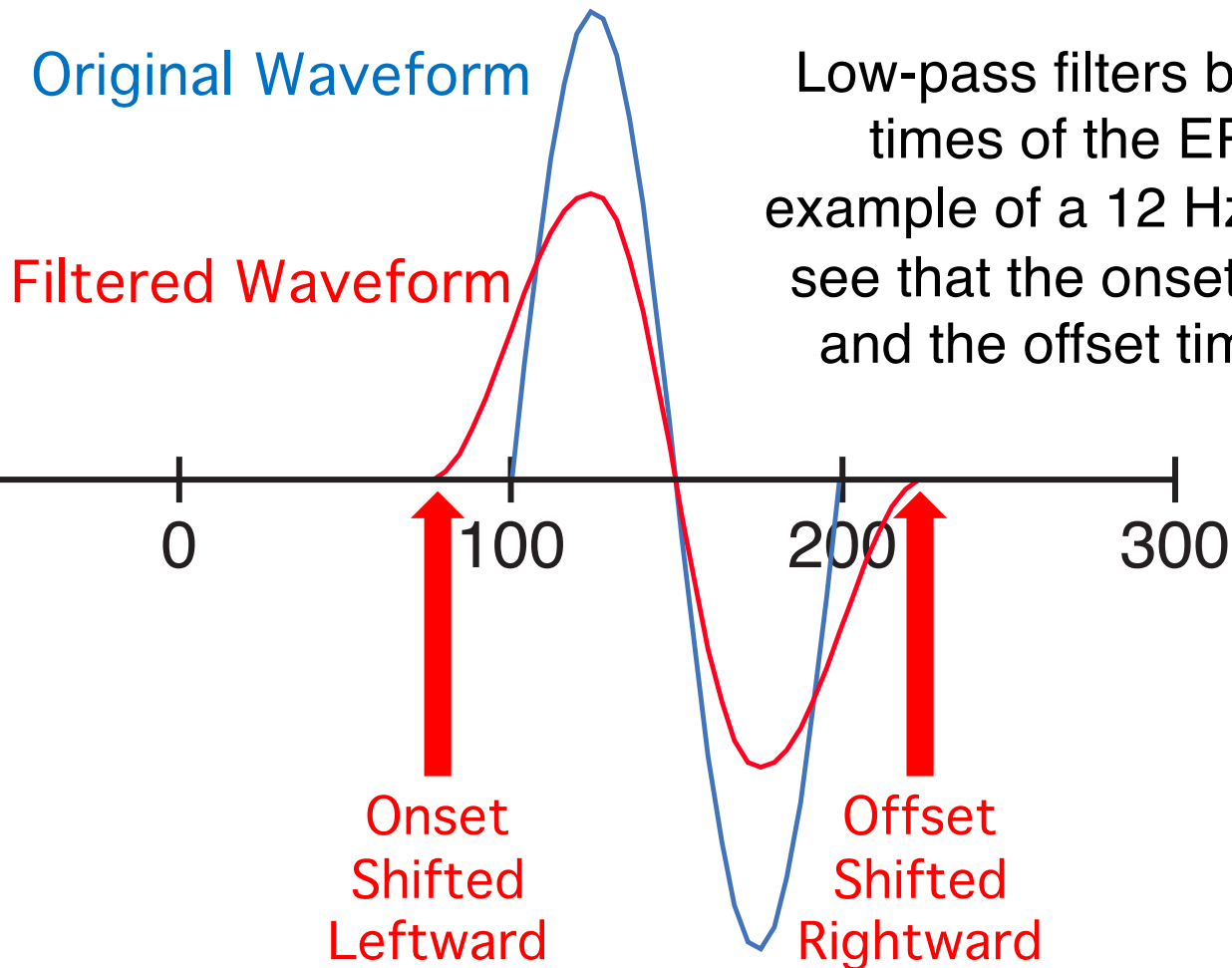


Filters are a form of controlled distortion



Fundamental Principle #2: Precision in the frequency domain is inversely related to precision in the time domain

Low-pass filter distortion



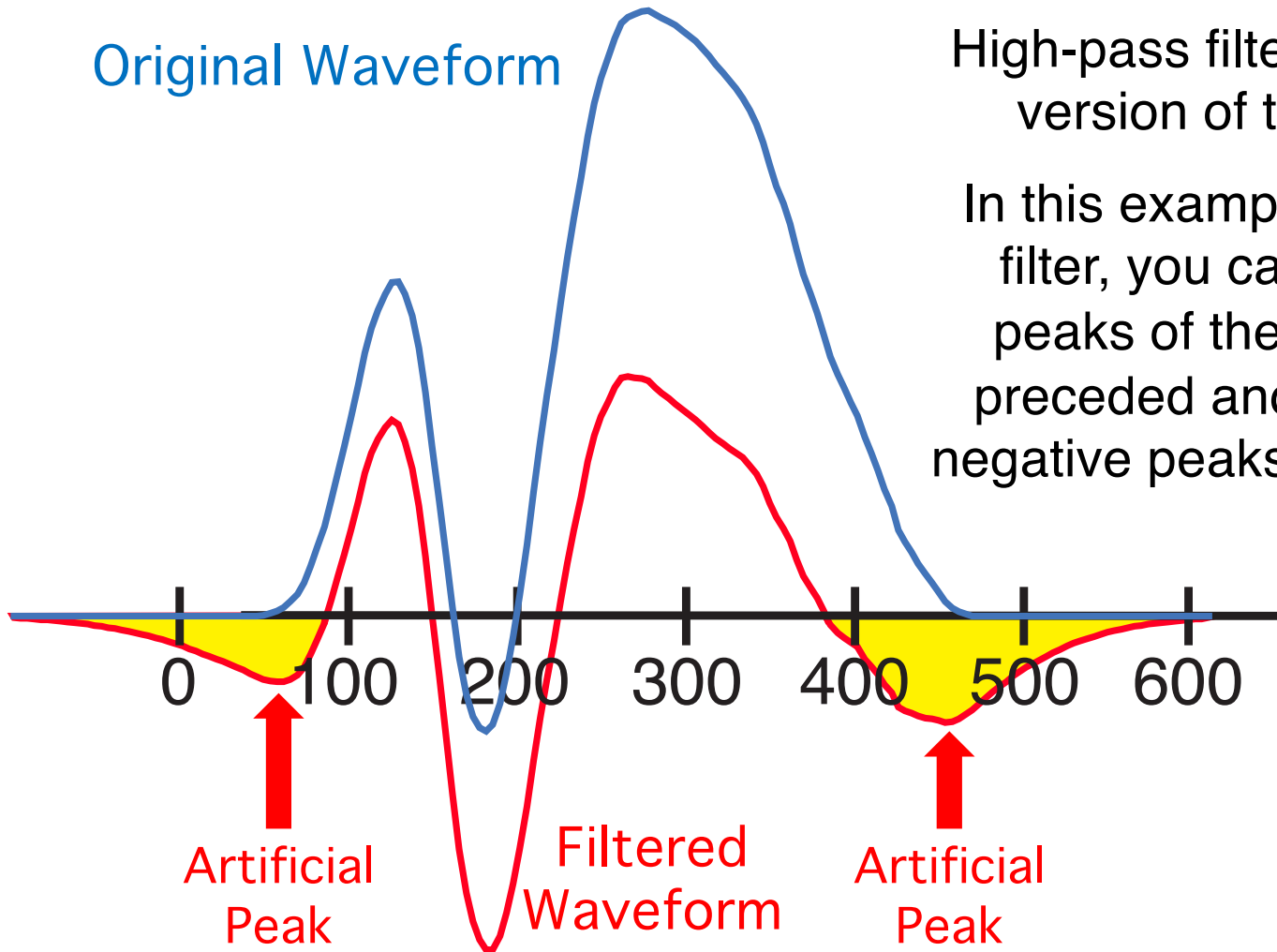
Low-pass filters blur the onset and offset times of the ERP waveform. In this example of a 12 Hz low-pass filter, you can see that the onset time is shifted leftward and the offset time is shifted rightward.

High-pass filter distortion

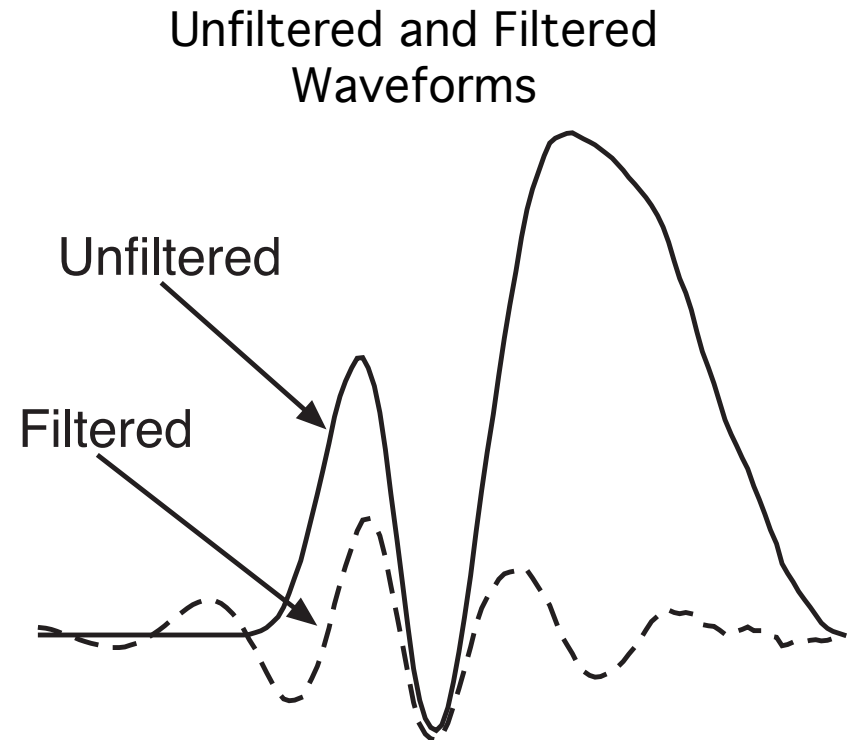
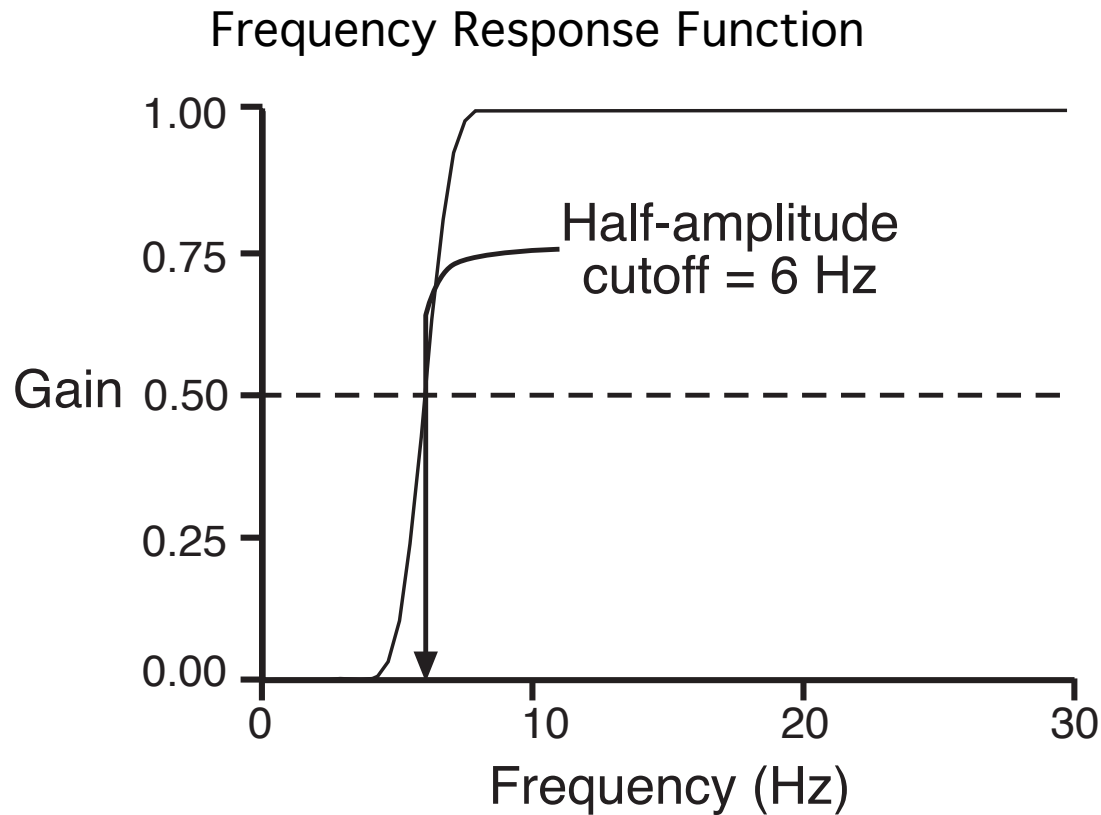
Original Waveform

High-pass filters subtract out a blurred version of the original waveform.

In this example of a 2.5 Hz high-pass filter, you can see that the positive peaks of the original waveform are preceded and followed by artifactual negative peaks in the filtered waveform.



Sharp Rolloffs and Oscillations



A frequency response function with a very steep slope induces artifactual oscillations in the data.



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How inappropriate high-pass filters can produce artifactual effects and incorrect conclusions in ERP studies of language and cognition

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^aDepartment of Linguistics, Beckman Institute for Advanced Science and Technology, Neuroscience Program, University of Illinois at Urbana-Champaign, Urbana, Illinois, USA

^bDepartment of Hispanic and Italian Studies, Department of Psychology, University of Illinois at Chicago, Chicago, Illinois, USA

^cDepartment of Psychology, Center for Mind and Brain, University of California Davis, Davis, California, USA



Darren Tanner



Kara Morgan-Short

Recommendations

for cognitive research in adults

	High-pass cutoff	Low-pass cutoff
Don't worry	≤ 0.1 Hz	≥ 20 Hz
Worry a little	0.1-0.5 Hz	10-20 Hz
Worry a lot*	> 0.5 Hz	< 10 Hz

*Especially when slope is > 12 dB/octave

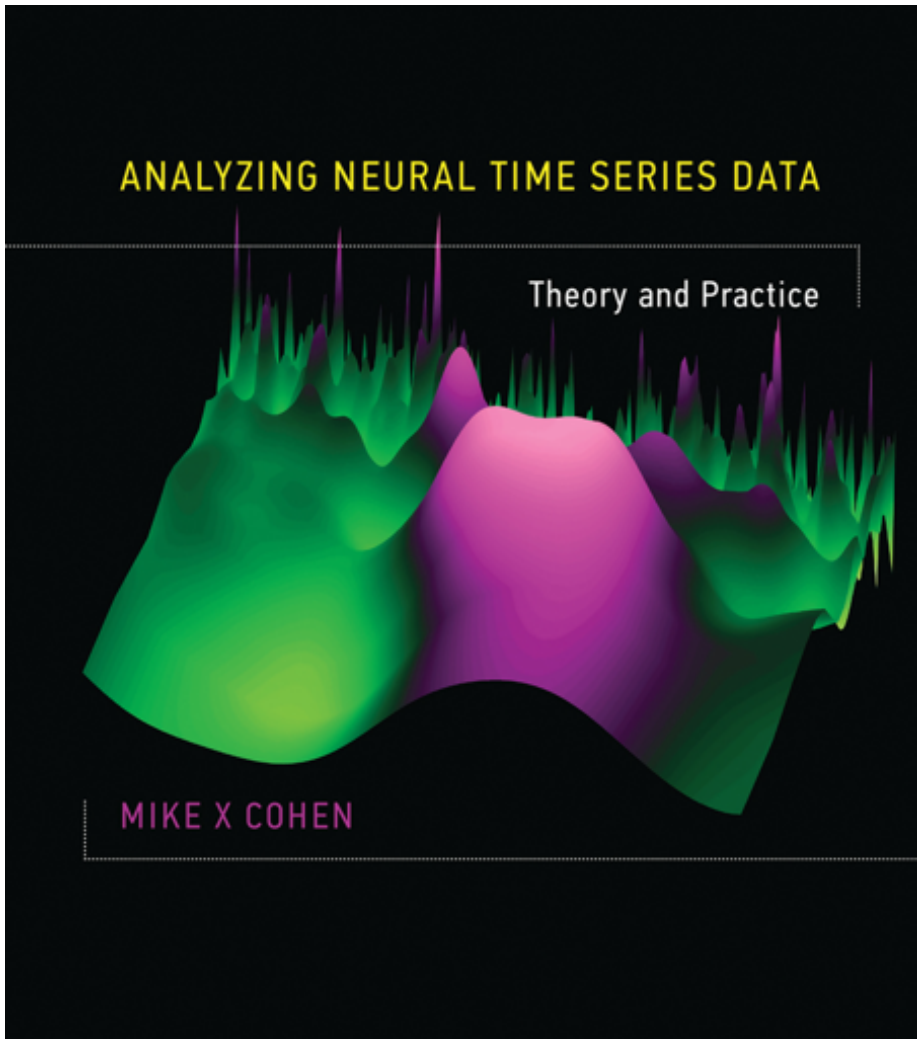
When you're reading an ERP paper, one of the first things you should look at is the filter settings. If they're in the red range, the filters may have distorted the data so badly that the conclusions are invalid.

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Key Background Issues

Time-Frequency Analysis

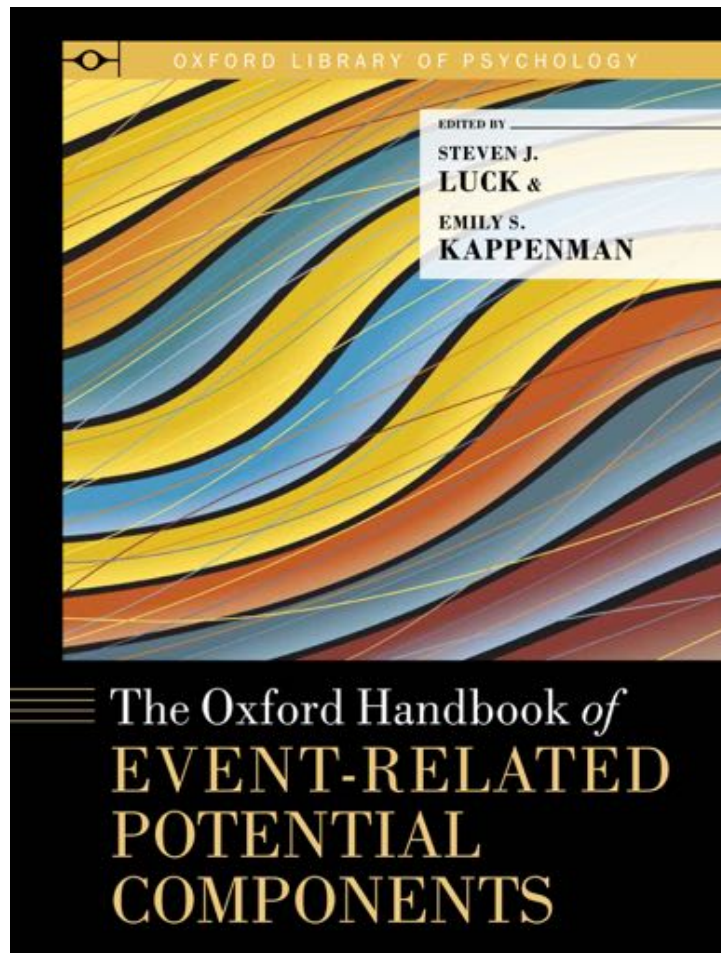




<http://mitpress.mit.edu/books/analyzing-neural-time-series-data>

The image shows a website landing page with a blue background. The main heading is 'Analyzing neural time series data' in white, bold, sans-serif font. Below it is a paragraph of text: '40+ hours of video lectures that supplement my book "Analyzing Neural Time Series Analysis."'. There are two buttons: 'WEBSITE VERSION' and 'YOUTUBE VERSION', both in white, all-caps, sans-serif font. Below this is another heading: 'Solved challenges in neural time series analysis' in white, bold, sans-serif font. Below that is another paragraph of text: 'This is a follow-up to the above course. It presents additional and more advanced material that will help you bring your neuroscience time series analysis skills to the next level.' At the bottom is a button labeled 'LEARN MORE' in white, all-caps, sans-serif font.

<https://www.mikexcohen.com/#courses>



CHAPTER

2

Beyond ERPs: Oscillatory Neuronal Dynamics

Marcel Bastiaansen, Ali Mazaheri, and Ole Jensen

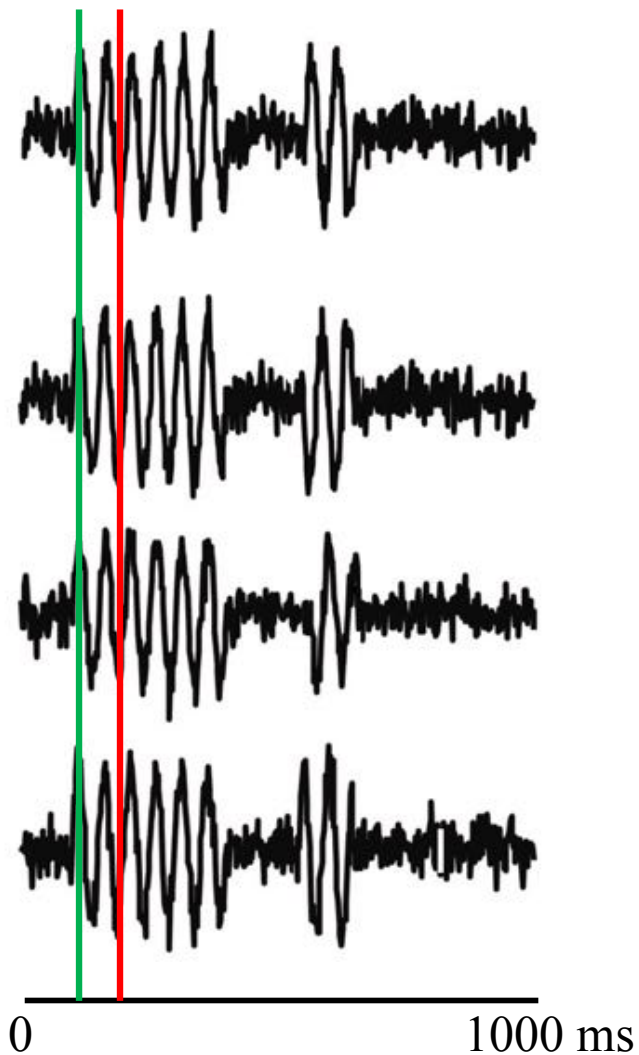
Abstract

The event-related potential (ERP) approach has provided a wealth of fine-grained information about the time course and the neural basis of cognitive processing events. However, in the 1980s and 1990s, an increasing number of researchers began to realize that an ERP only represents a certain part of the event-related electroencephalographic (EEG) signal. This chapter focuses on another aspect of event-related EEG activity: oscillatory EEG activity. There exists a meaningful relationship between oscillatory neuronal dynamics, on the one hand, and a wide range of cognitive processes, on the other hand. Given that the analysis of oscillatory dynamics extracts information from the EEG/magnetoencephalographic (EEG/MEG) signal that is largely lost with the traditional time-locked averaging of single trials used in the ERP approach, studying the dynamic oscillatory patterns in the EEG/MEG is at least a useful addition to the traditional ERP approach.

Keywords: ERP, oscillatory EEG activity, EEG oscillations, cognitive processes, oscillatory dynamics

Bastiaansen, M., Mazaheri, A., & Jensen, O. (2012). Beyond ERPs: Oscillatory neuronal dynamics. In S. J. Luck & E. S. Kappenman (Eds.), *The Oxford Handbook of ERP Components* (pp. 31–49). Oxford University Press.

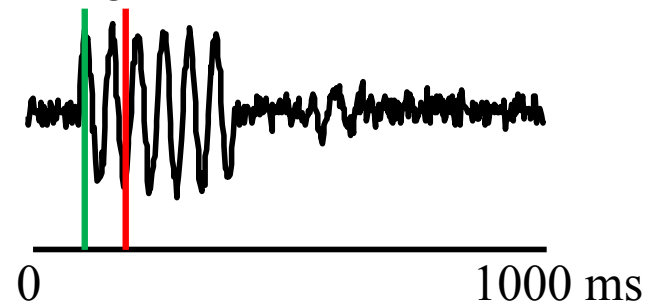
Single-Trial EEG Epochs



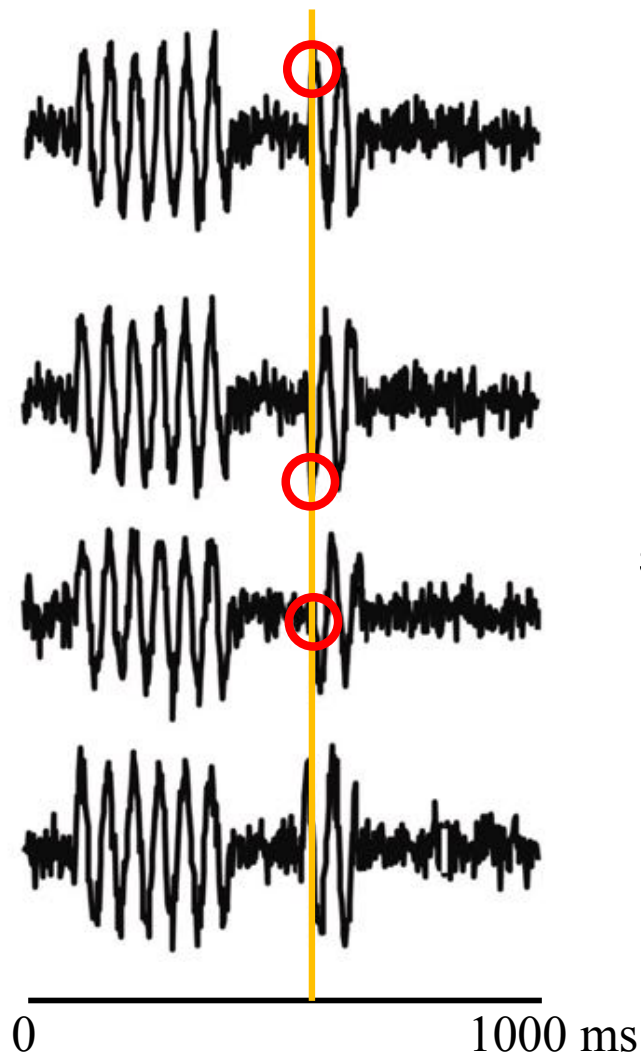
On each trial, the stimulus elicits two alpha-band bursts. The first burst is phase-locked to the stimulus. On every trial, we get positive peaks at consistent times and negative peaks at consistent times.

When we average the trials together, we can see the alpha burst in the average, with the same positive and negative peaks.

Average of Single-Trial EEG Epochs



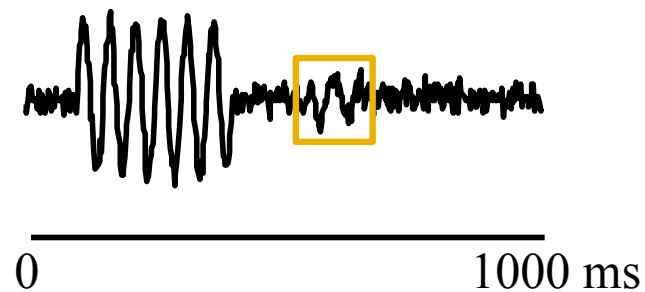
Single-Trial EEG Epochs



The second alpha burst doesn't have a consistent phase from trial to trial. Where we have a positive peak in the first epoch, we have a negative peak in the second, and no peak at all in the third.

These oscillations therefore cancel out in the average, which makes it look as if there was no stimulus-related brain activity during this period.

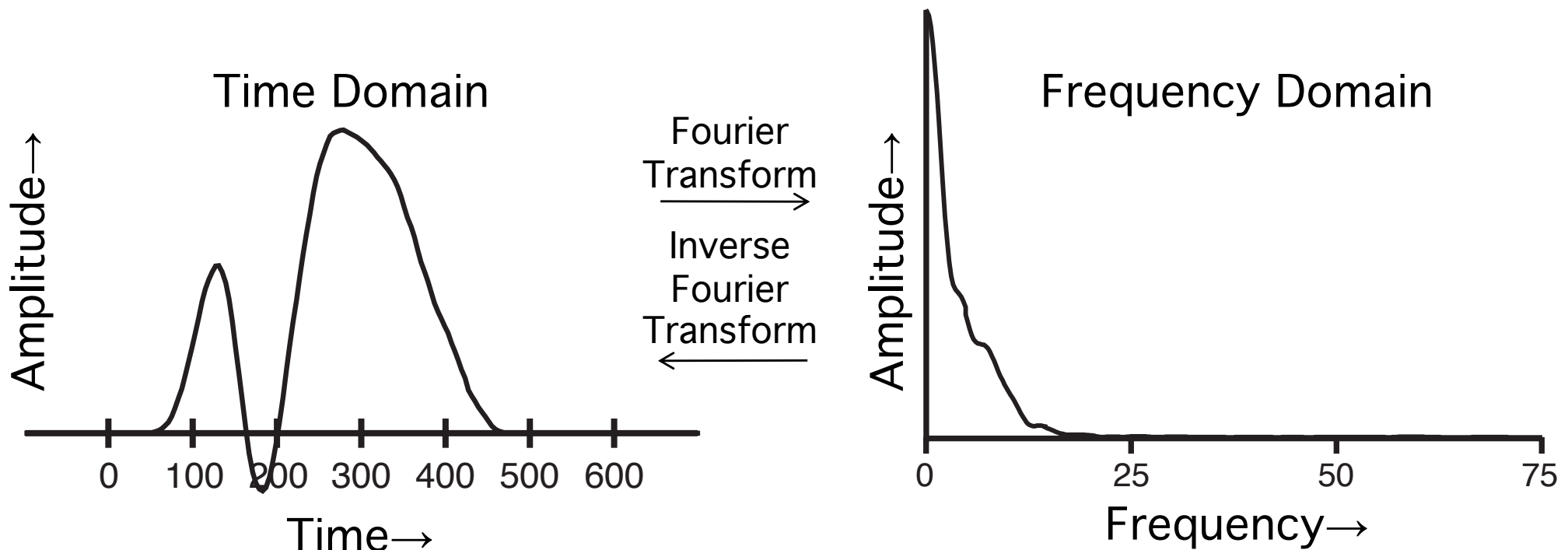
Average of Single-Trial EEG Epochs



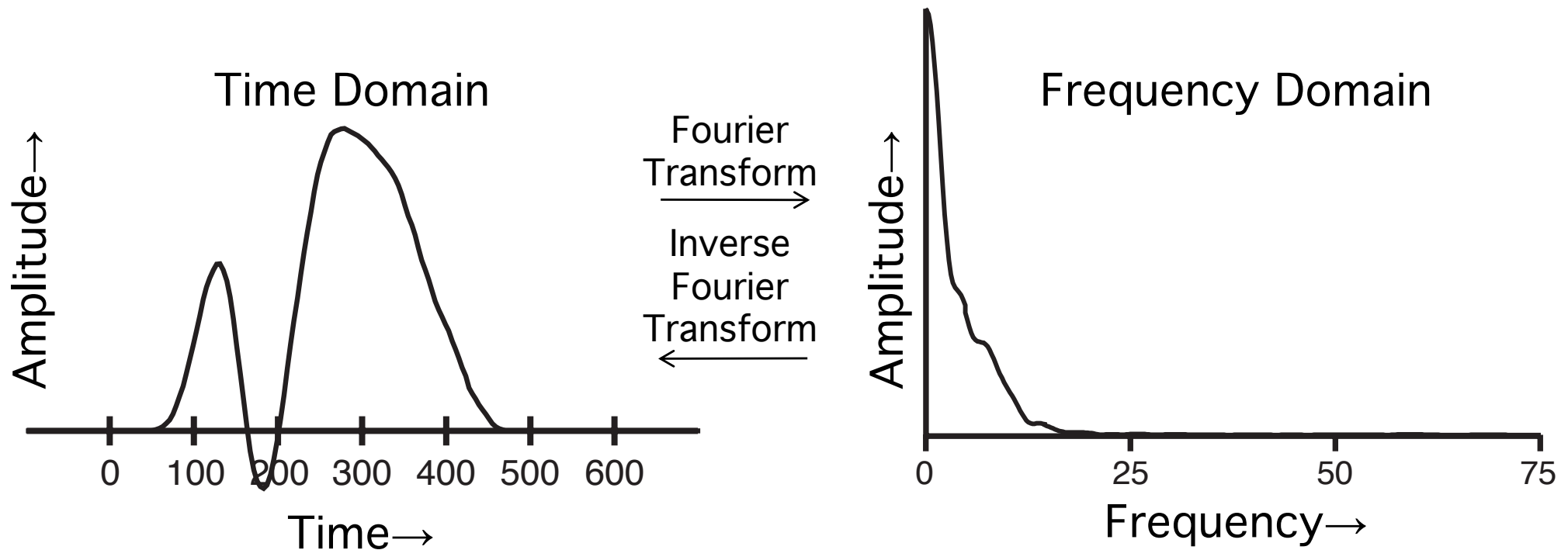
Time-frequency analysis makes phase-random oscillations visible by estimating the amplitude independent of the phase.

Fourier analysis tells us the amplitude at each frequency, independently of the phase, but it gets rid of time.

Time-frequency analysis gives us a blend of time and frequency information.



In time-frequency analysis, we give up some precision in time and some precision in frequency so that we can have a little of each.

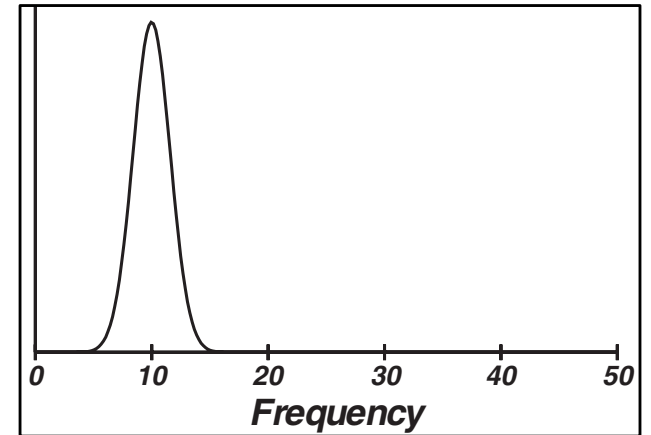


Fundamental Principle #2: Precision in the frequency domain is inversely related to precision in the time domain

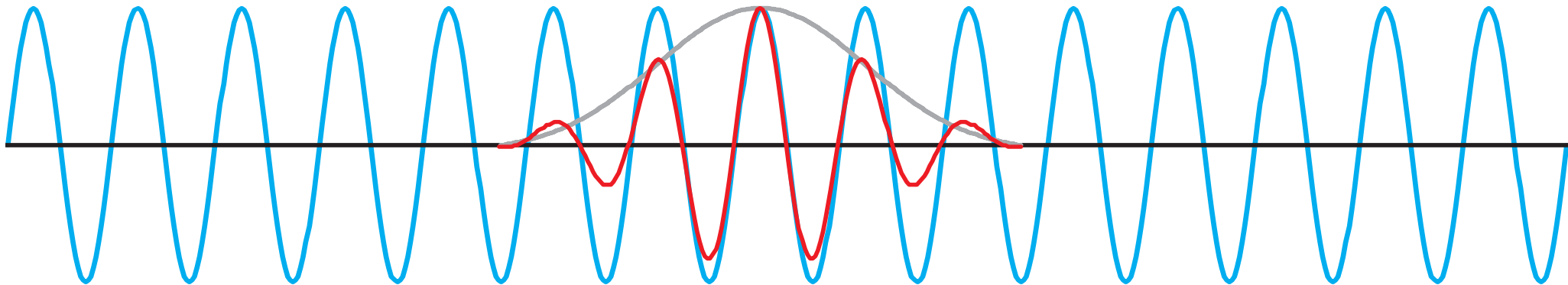
Time-Frequency Analysis

Instead of using infinite-duration sine waves, we reconstruct a time-domain waveform by summing together a set of wavelets.

Each wavelet is created by taking the sine wave and windowing it, often with a Gaussian windowing function.

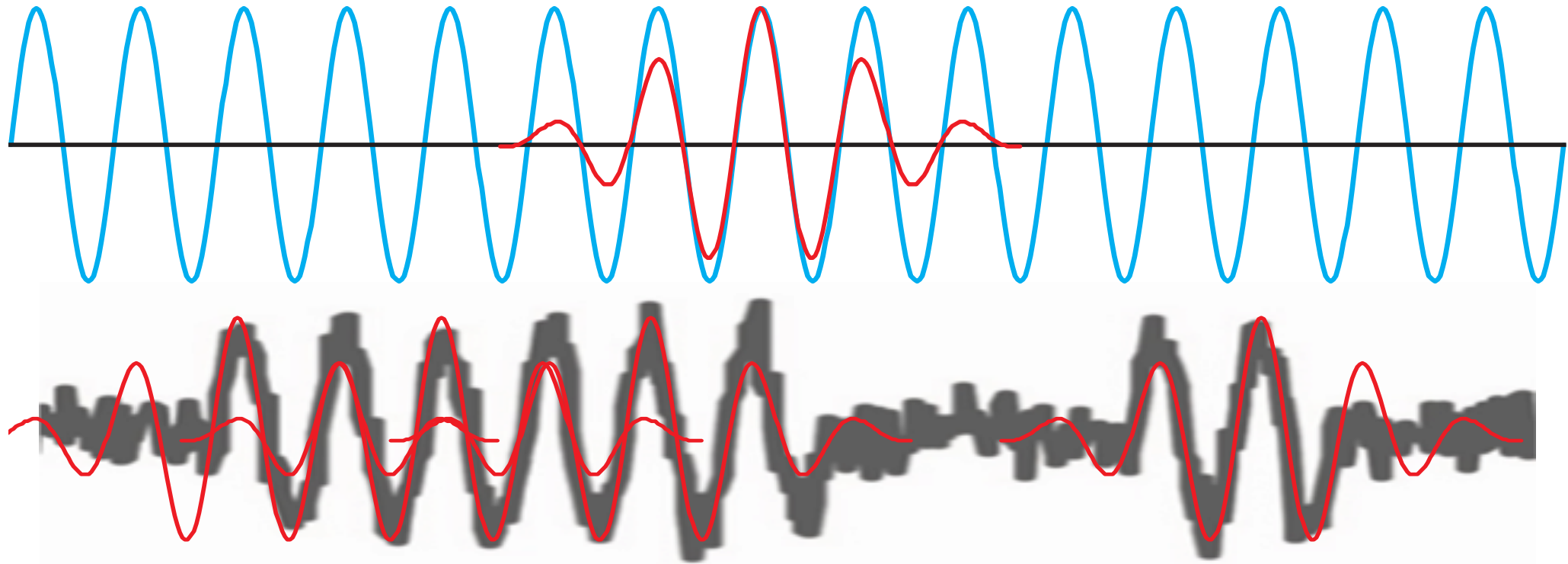


We've lost some frequency resolution. In the frequency domain, the wavelet contains a somewhat broad range of frequencies around 10 Hz.

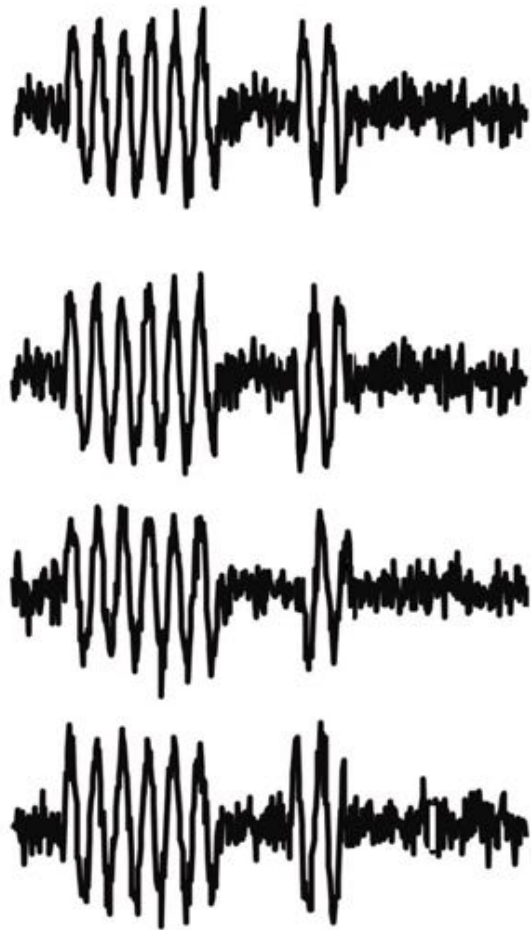


Time-Frequency Analysis

You can see how a single-trial of our simulated EEG data could be fit by combining a several 10 Hz wavelets.

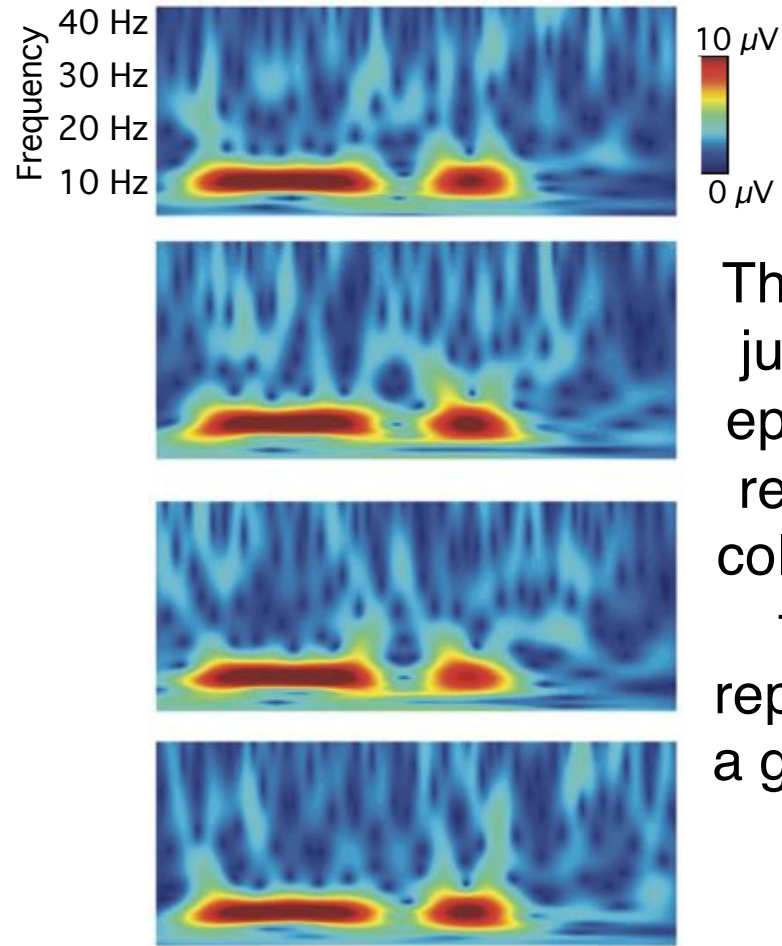


Single-Trial EEG Epochs



0 Time 1000 ms

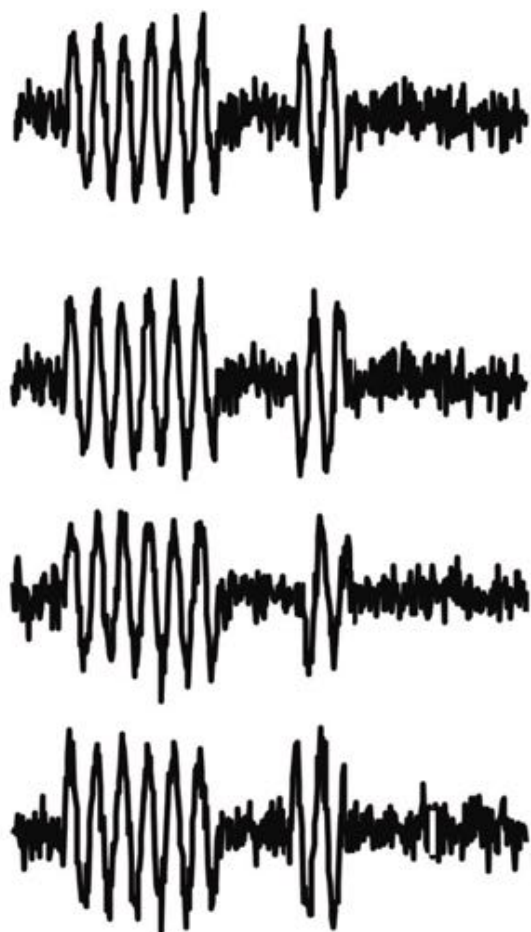
Time-Frequency Transforms



0 Time 1000 ms

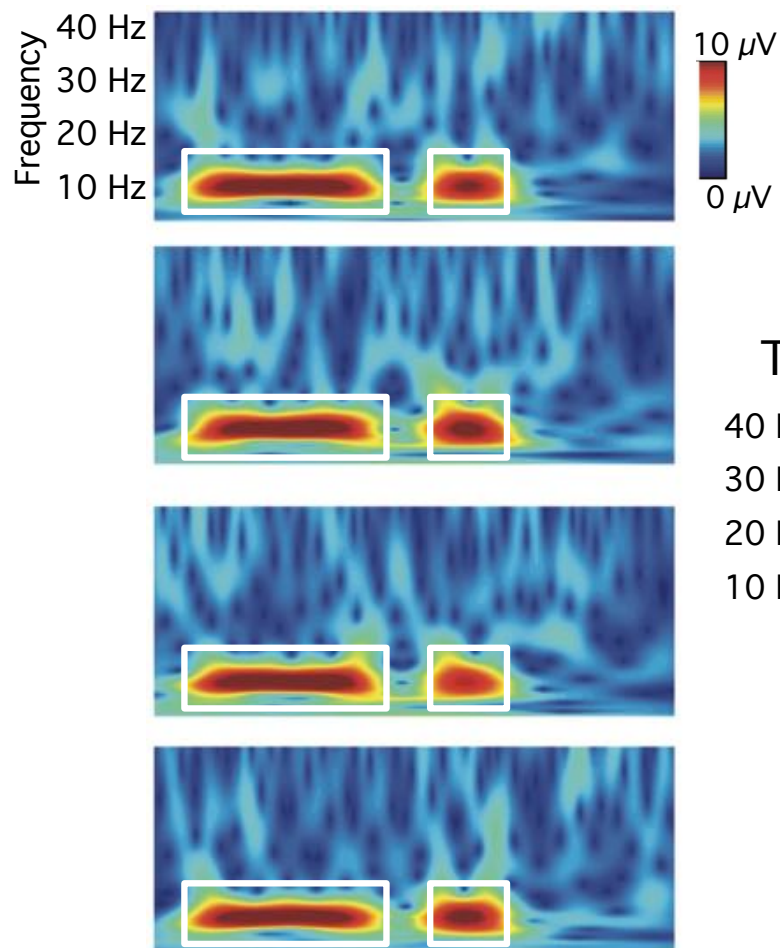
The X axis represents time, just as in the original EEG epochs. But now the Y axis represents frequency. The color at each location in this two-dimensional space represents the magnitude of a given frequency at a given time.

Single-Trial EEG Epochs



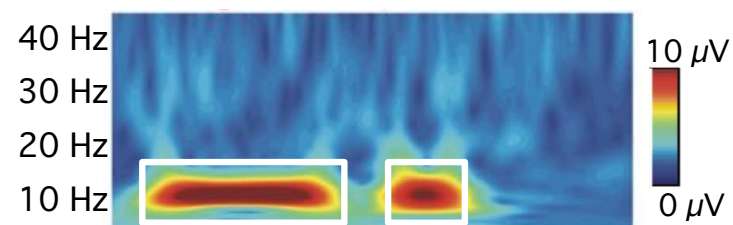
0 Time 1000 ms

Time-Frequency Transforms

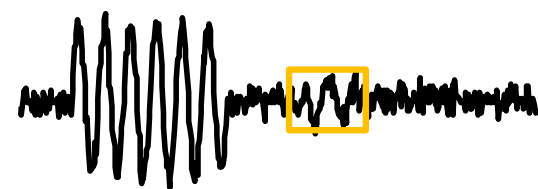


0 Time 1000 ms

Average of Time-Frequency Transforms



Average of Single-Trial EEG Epochs



0 Time 1000 ms

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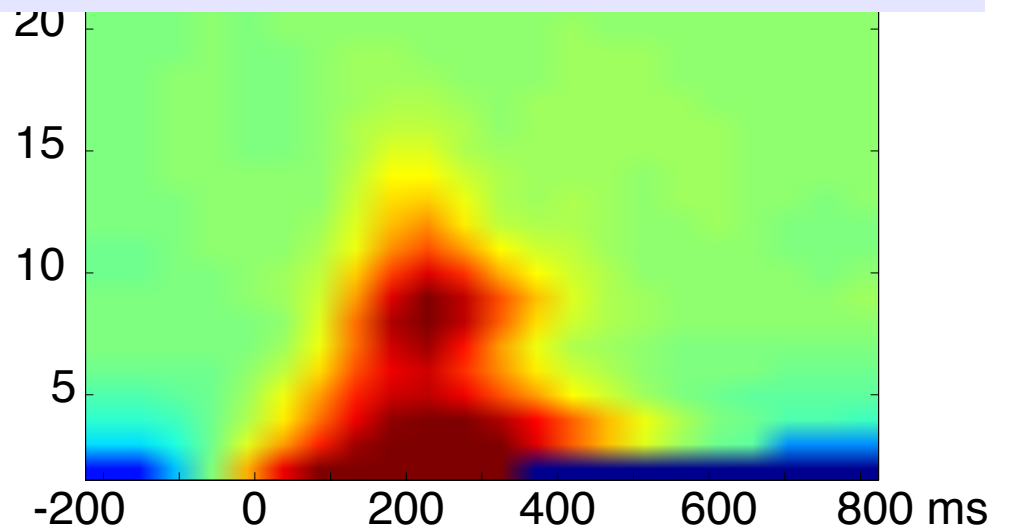
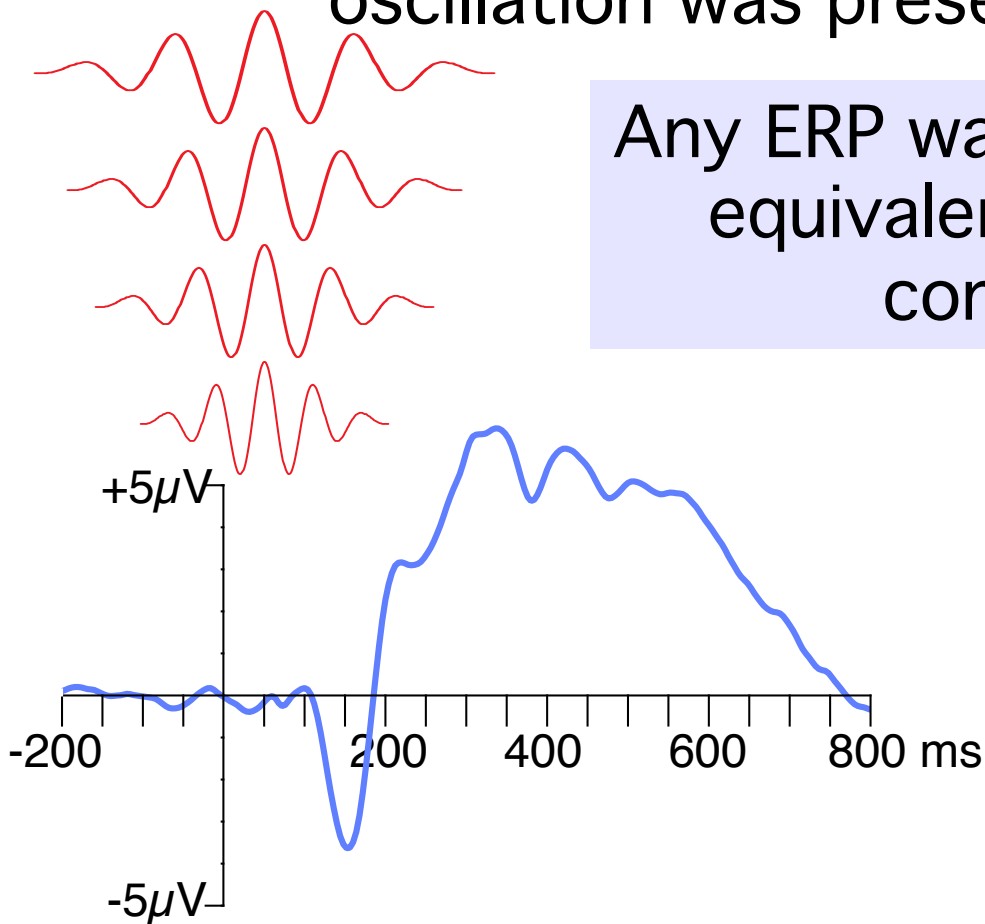
Key Background Issues

Fundamental Principle #1 Revisited

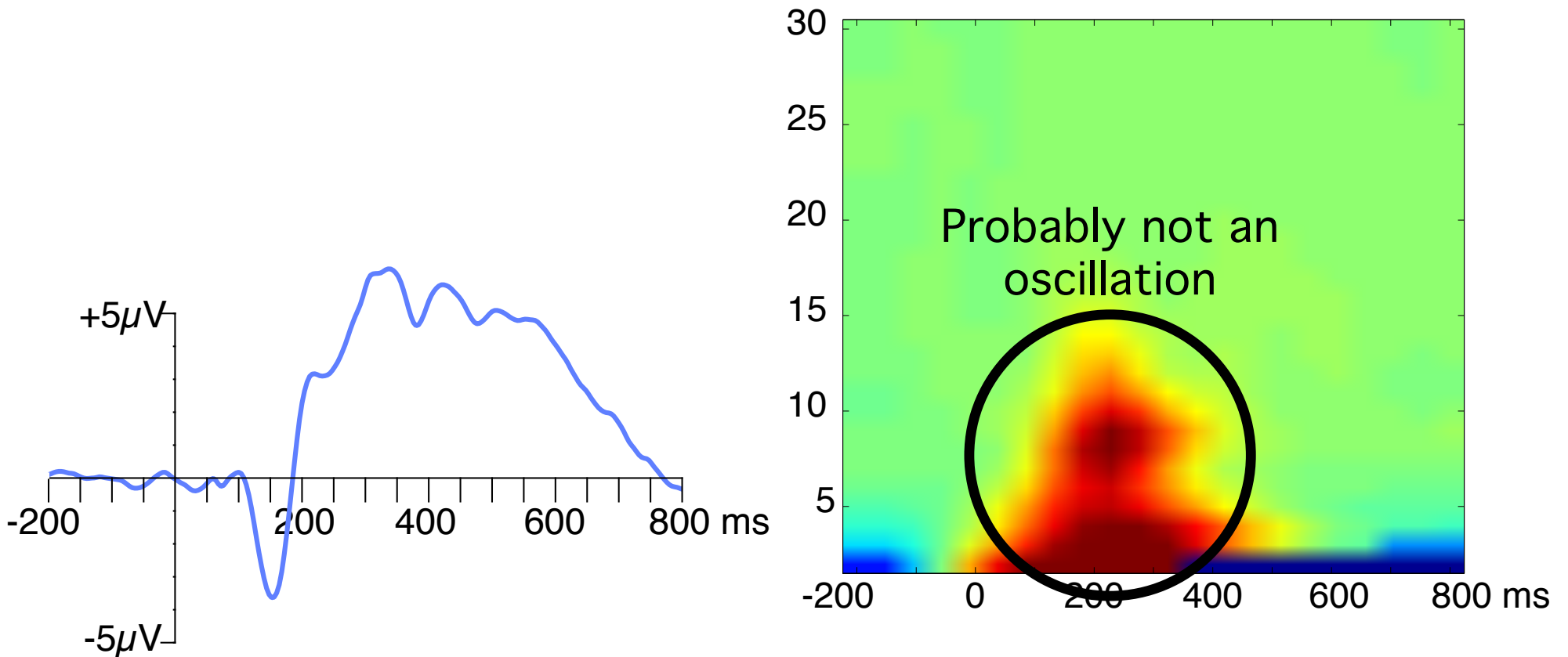


Fundamental Principle #1: Power at a frequency in a time-frequency transform does not mean that an oscillation was present at that frequency

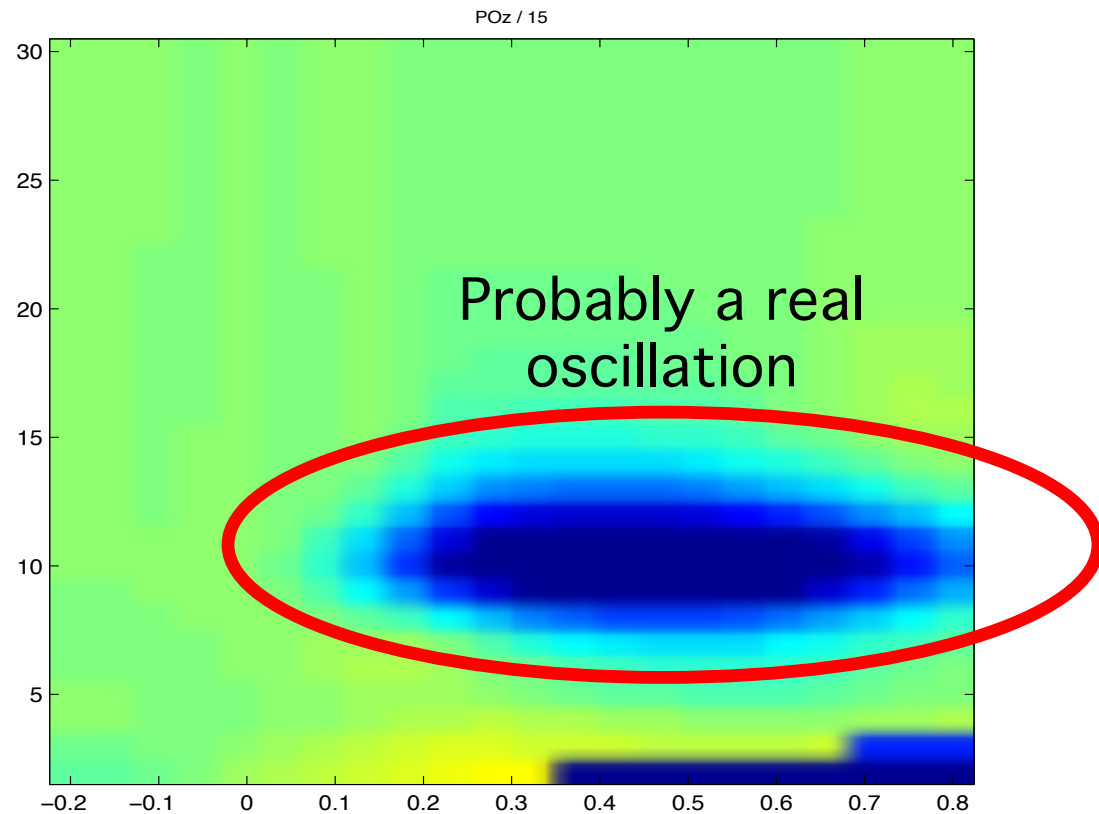
Any ERP waveform has a time-frequency equivalent, whether or not the ERP contains any oscillations



Rule of Thumb: In most cases, a broad band of power is not a true oscillation, but a narrow band of power does reflect a true oscillation



Rule of Thumb: In most cases, a broad band of power is not a true oscillation, but a narrow band of power does reflect a true oscillation

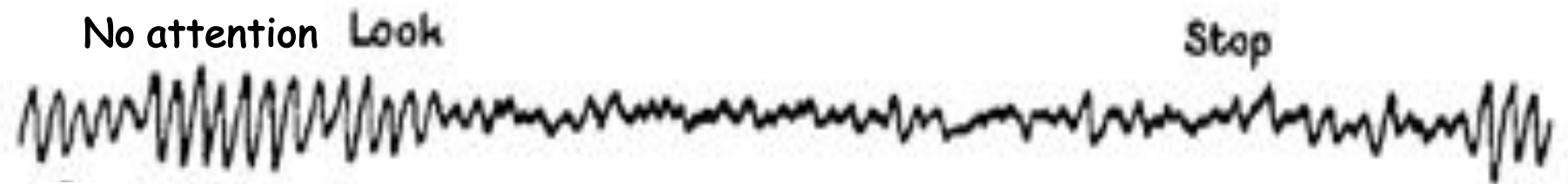
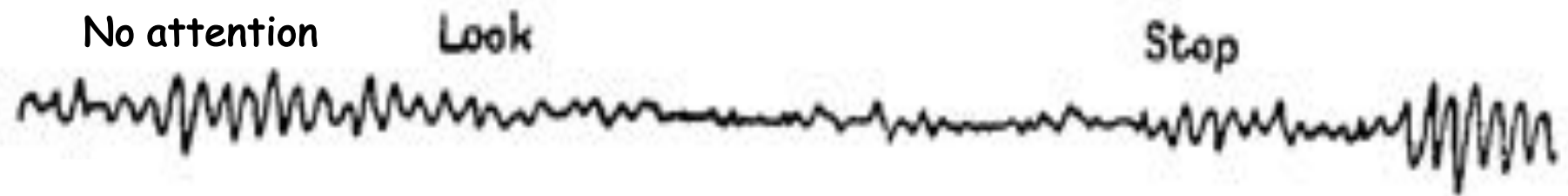


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Key Background Issues

Time-Frequency Example





Alpha is also briefly suppressed following a task-relevant stimulus



Lateralized Suppression of Alpha-Band EEG Activity As a Mechanism of Target Processing

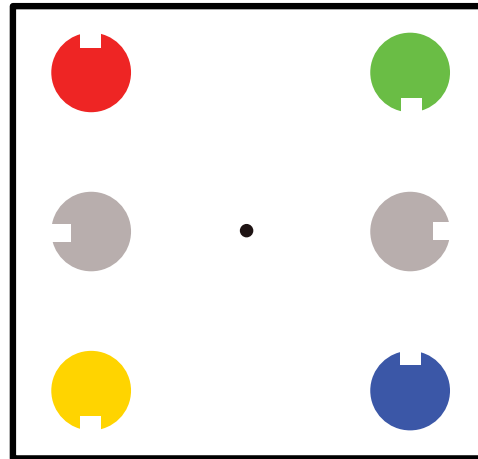
Felix Bacigalupo^{1,2,3,4} and Steven J. Luck¹

¹Center for Mind and Brain, University of California, Davis, California 95616, ²Escuela de Psicología, Facultad de Ciencias Sociales, Pontificia Universidad Católica de Chile, Santiago, Chile, ³Departamento de Psiquiatría, Facultad de Medicina, Pontificia Universidad Católica de Chile, Santiago, Chile, and ⁴Centro Interdisciplinario de Neurociencia, Pontificia Universidad Católica de Chile, Santiago, Chile.

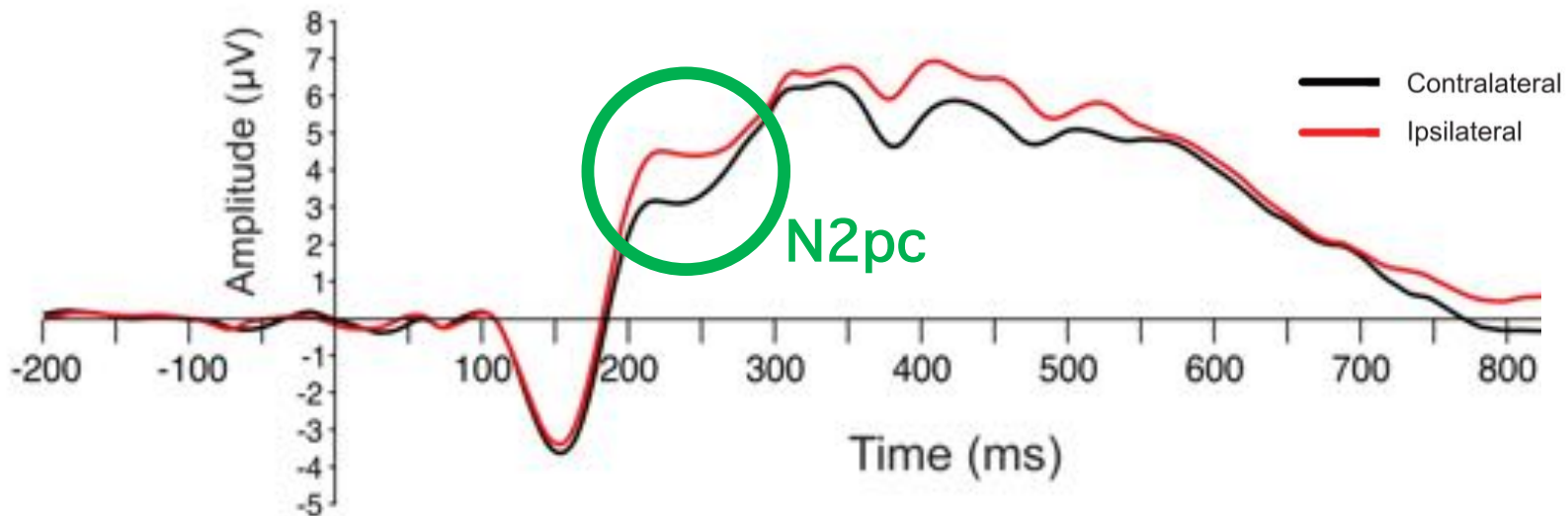
Alpha-band (8–12 Hz) EEG activity has been linked to visual attention since the earliest EEG studies. More recent studies using spatial cuing paradigms have shown that alpha is suppressed over the hemisphere contralateral to a to-be-attended location, suggesting that alpha serves as a mechanism of preparatory attention. Here, we demonstrate that alpha also plays a role in active target processing. EEG activity was recorded from a group of healthy male and female human subjects in two visual search experiments. In addition to alpha activity, we also assessed the N2pc event-related potential component, a lateralized transient EEG response that has been tightly linked with the focusing of attention on visual targets. We found that the visual search targets triggered both an N2pc component and a suppression of alpha-band activity that was greatest over the hemisphere contralateral to the target (which we call “target-elicited lateralized alpha suppression” or TELAS). In Experiment 1, both N2pc and TELAS were observed for targets presented in the lower visual field but were absent for upper-field targets. However, these two lateralized effects had different time courses and they responded differently to manipulations of crowding in Experiment 2. These results indicate that lateralized alpha-band activity is involved in active target processing and is not solely a preparatory mechanism and also that TELAS and N2pc reflect a related but separable neural mechanism of visuospatial attention.

Bacigalupo, F., & Luck, S. J. (2019). Lateralized suppression of alpha-band EEG activity as a mechanism of target processing. *The Journal of Neuroscience*, *39*, 900–917.

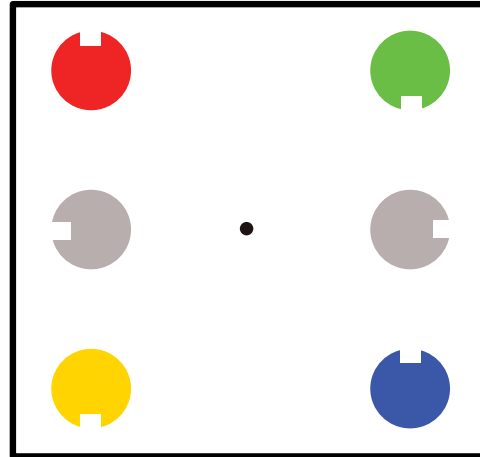
Subjects maintained fixation centrally and used covert attention to perceive the target



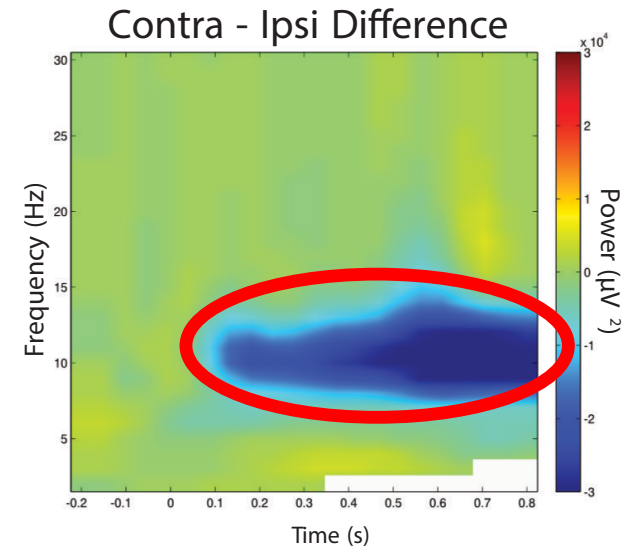
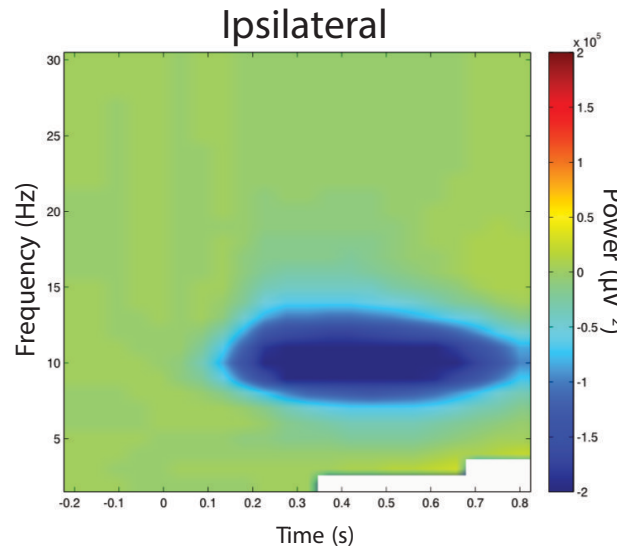
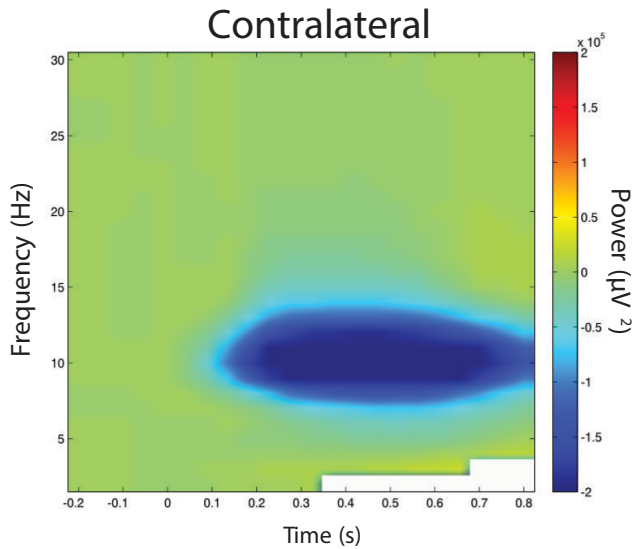
Task: Find item of attended color and report whether it has a gap on the top or the bottom



Subjects maintained fixation centrally and used covert attention to perceive the target



Task: Find item of attended color and report whether it has a gap on the top or the bottom



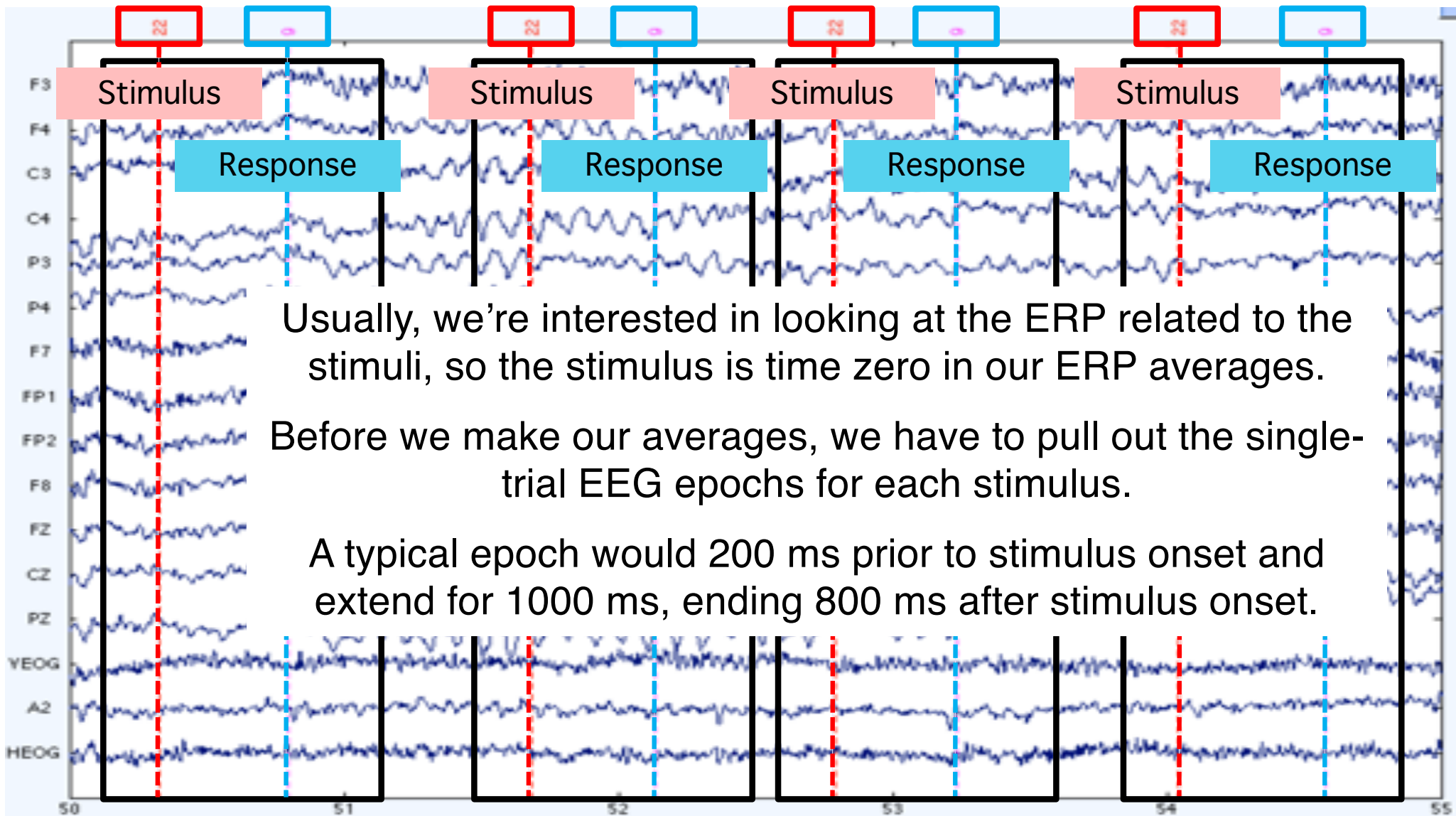
Bacigalupo & Luck (2019)

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Key Background Issues

Epoching & Baseline Correction

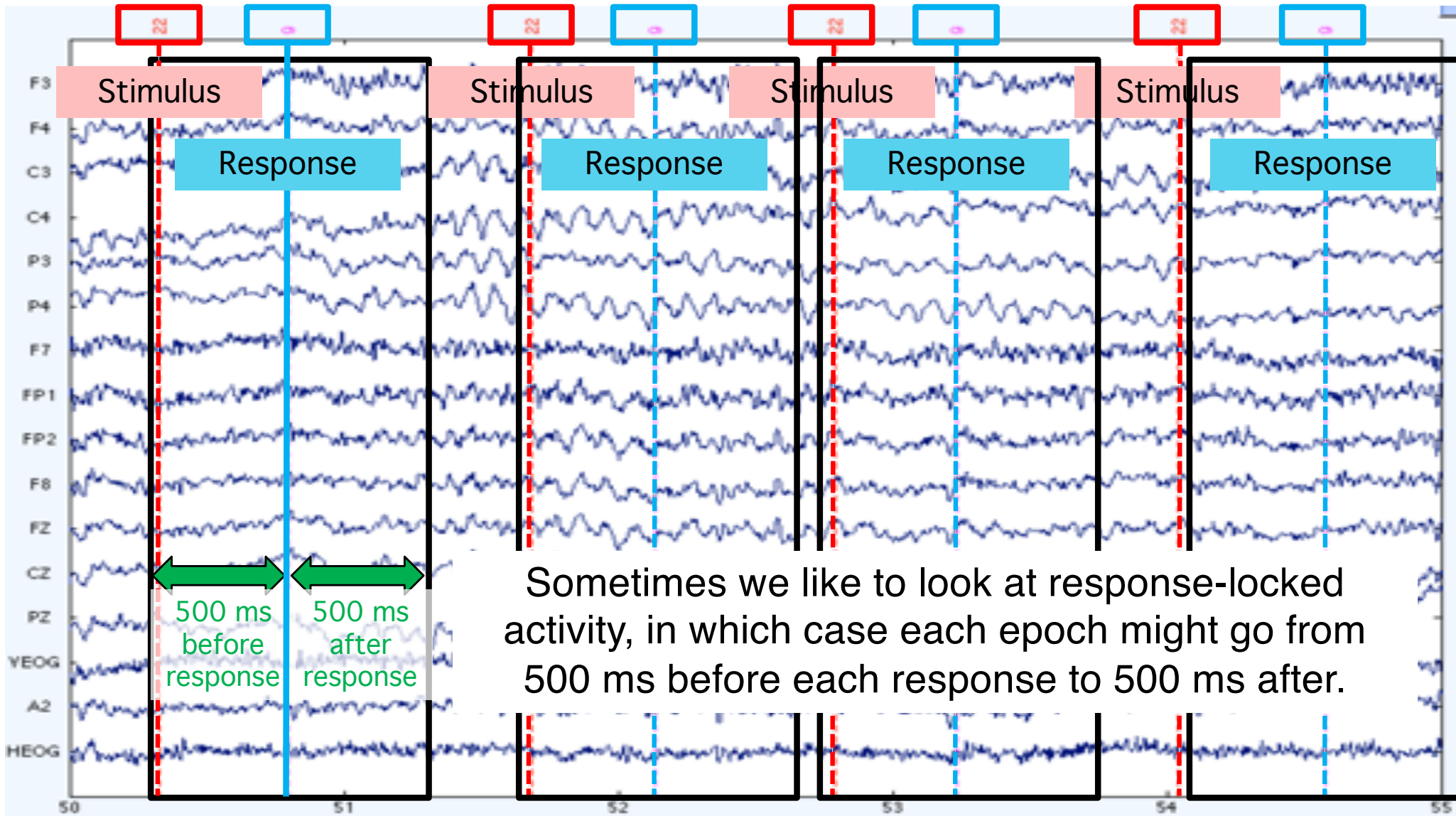




Usually, we're interested in looking at the ERP related to the stimuli, so the stimulus is time zero in our ERP averages.

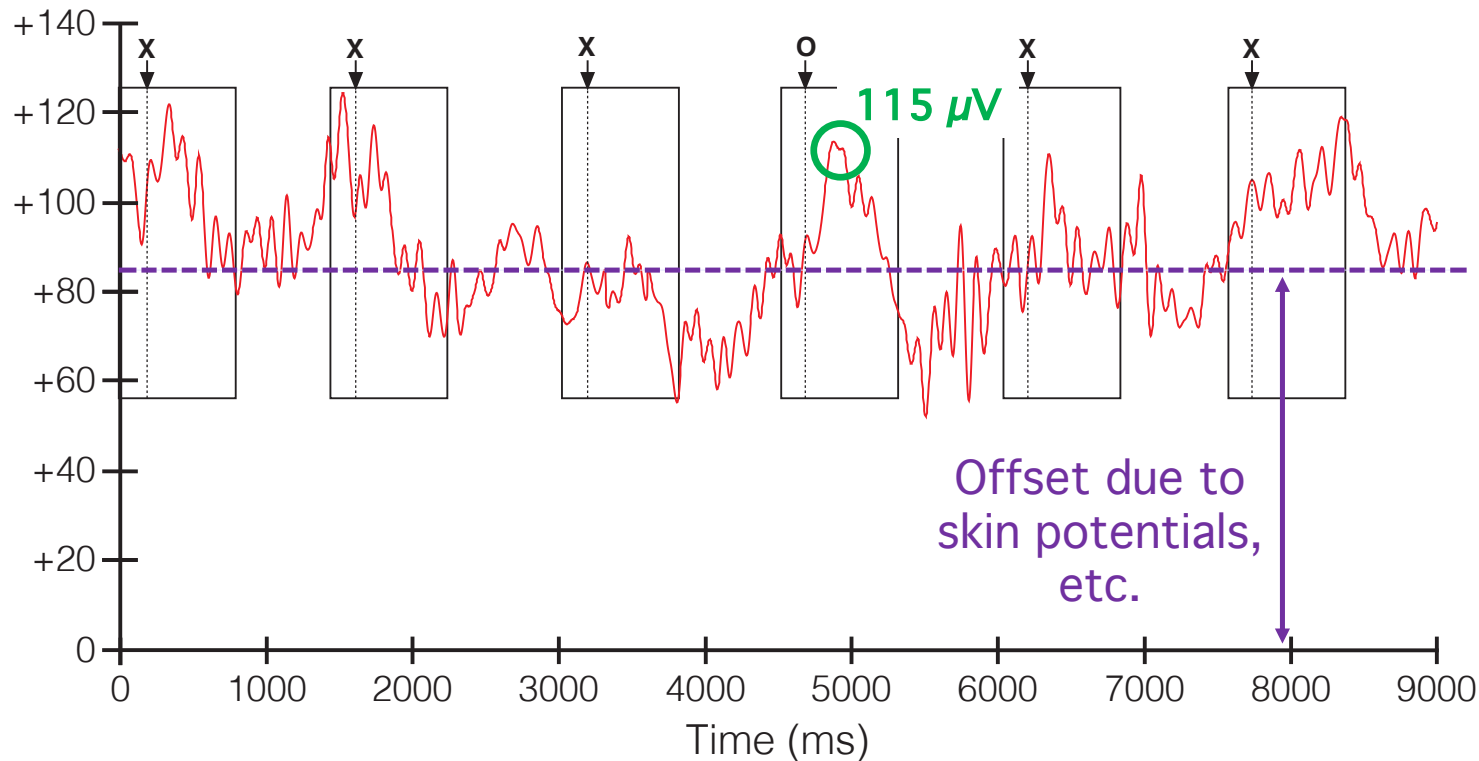
Before we make our averages, we have to pull out the single-trial EEG epochs for each stimulus.

A typical epoch would 200 ms prior to stimulus onset and extend for 1000 ms, ending 800 ms after stimulus onset.



The EEG is riding on top of non-neural slow potentials. This voltage offset changes slowly over time, and it can be huge.

If we didn't somehow subtract out the offset, our measures of ERP amplitudes would be incredibly distorted. If we didn't subtract out this offset, we'd have enormous unexplained variance, and nothing would ever be statistically significant.

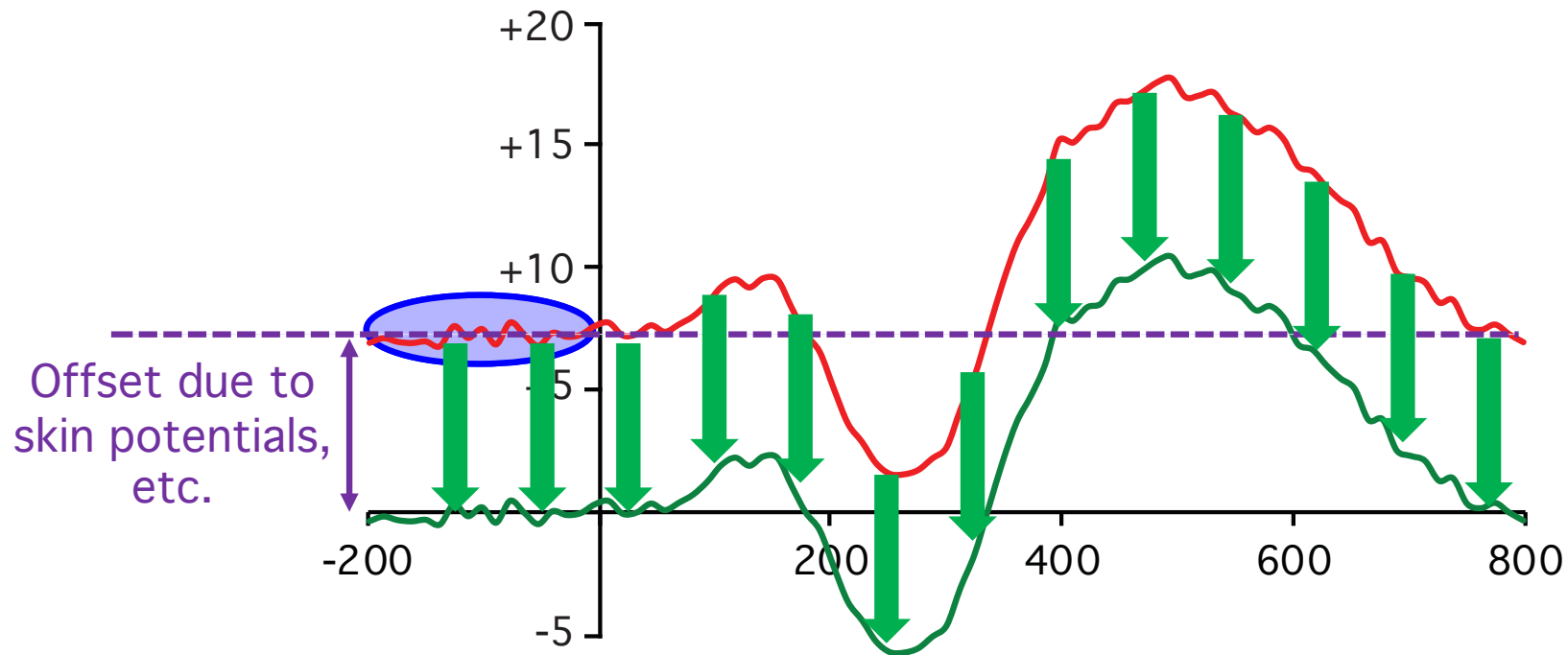


Baseline Correction Procedure

Goal: Subtract estimate of offset voltage from the waveform

Mean prestimulus voltage is usually a reasonable estimate

Subtract this value from each point in the waveform

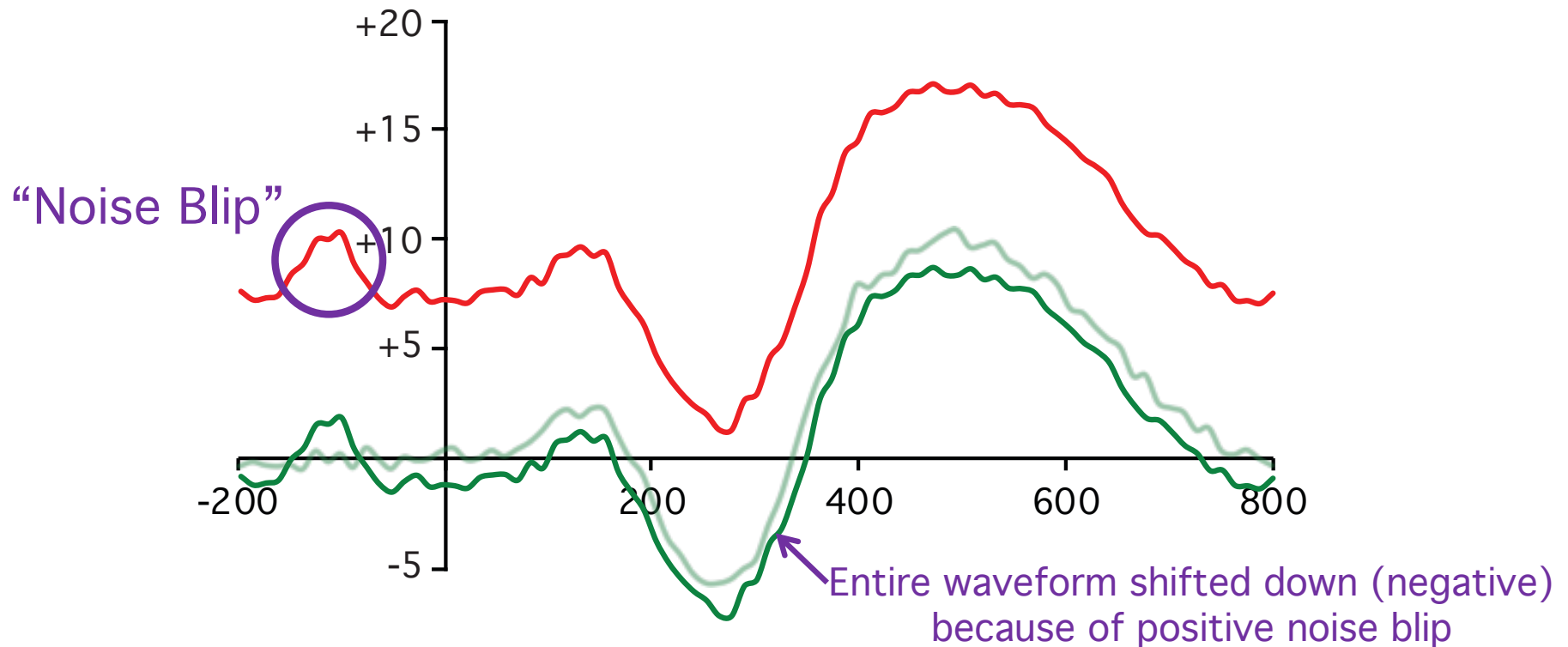


Baseline Correction Procedure

Goal: Subtract estimate of offset voltage from the waveform

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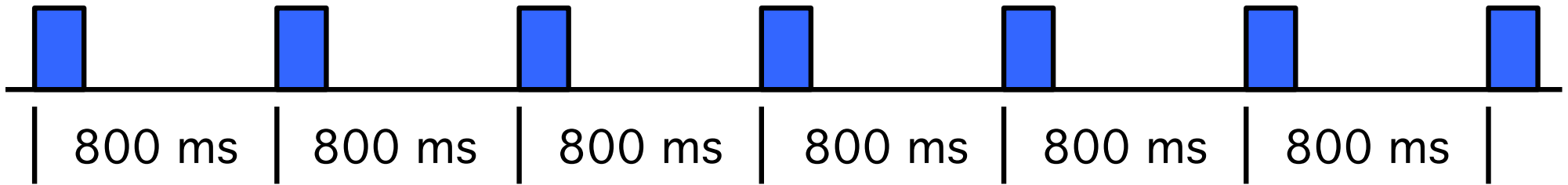
Noise or overlap in the baseline period will be propagated to the entire waveform

This video was made possible by NIH grant R25MH080794 and is shared under the terms of a Creative Commons license ([CC BY-SA 4.0](https://creativecommons.org/licenses/by-sa/4.0/))

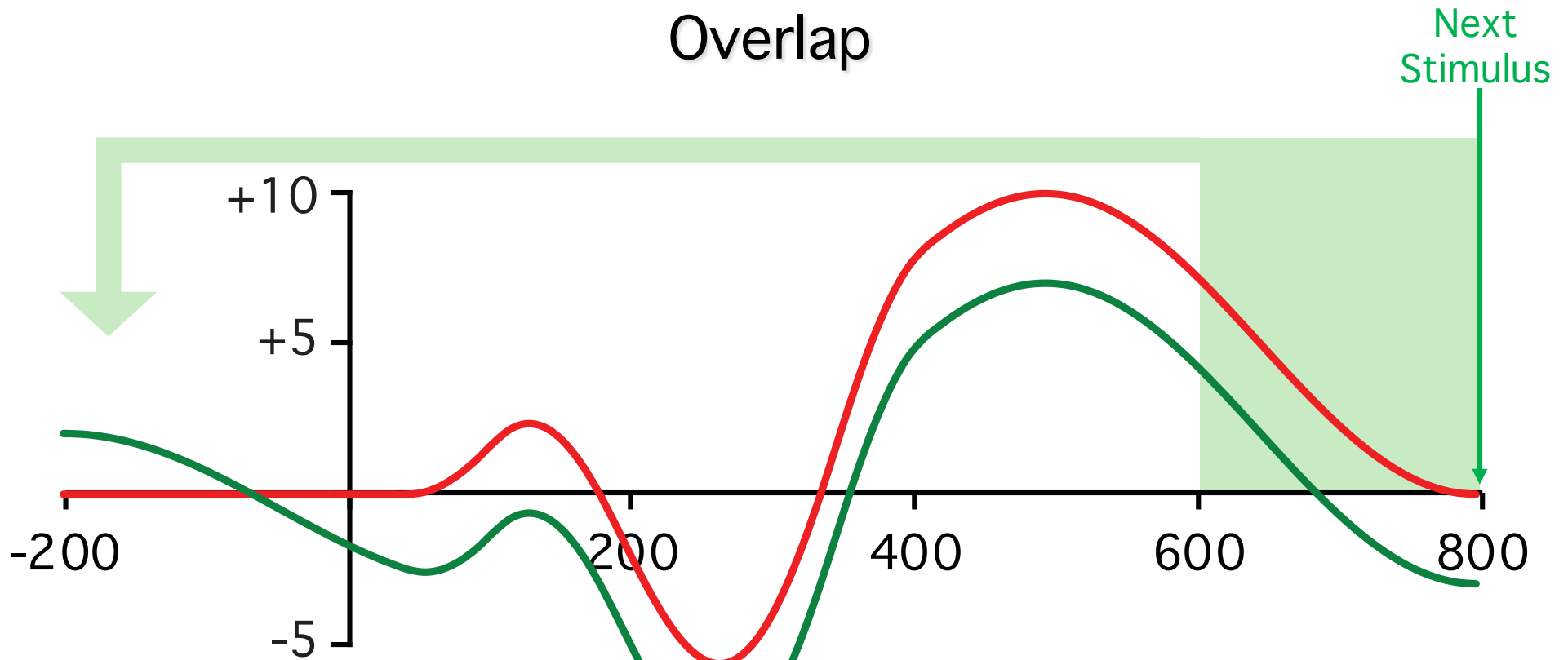
Key Background Issues Overlap



Overlap



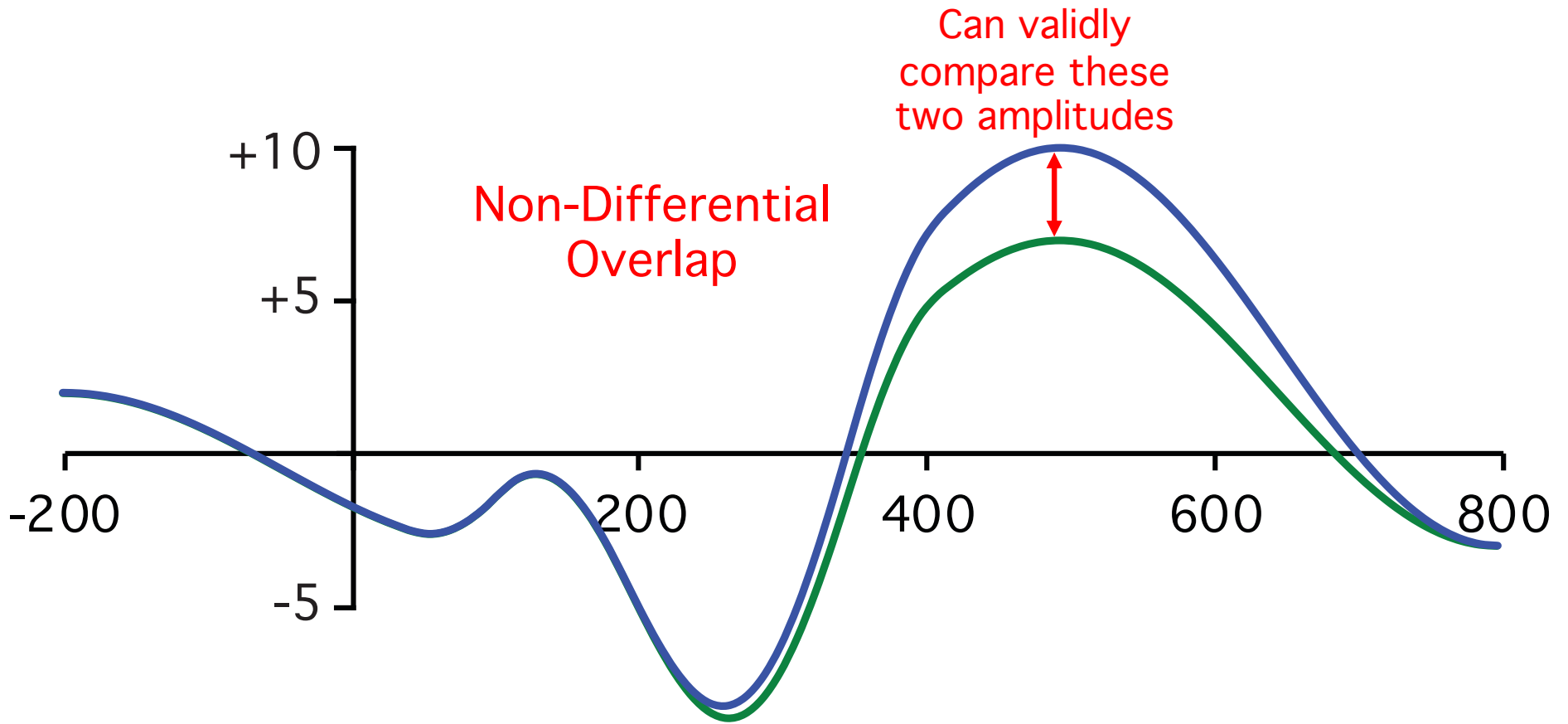
Overlap



The last part of the waveform from the current stimulus will be present during the prestimulus baseline period of the next stimulus.

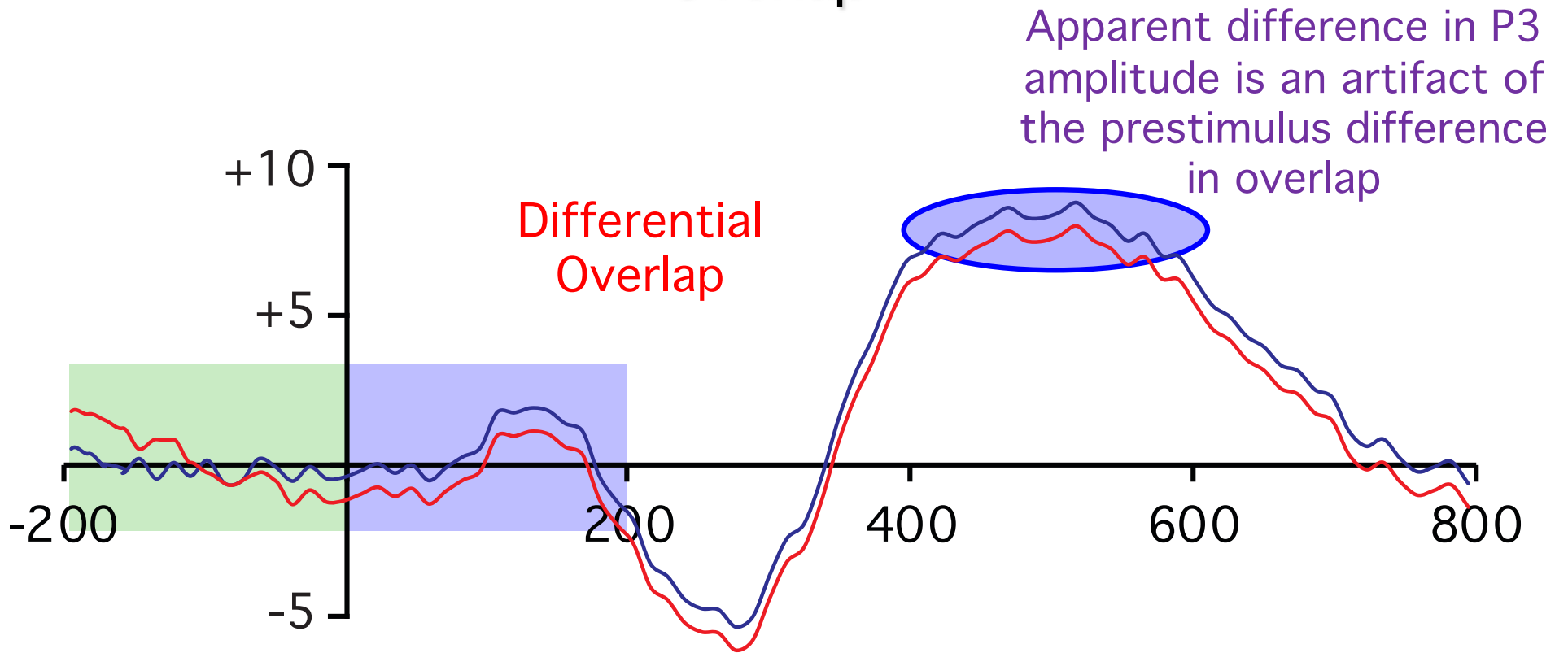
When we do our baseline correction, the overlap distorts our estimate of the offset, and we end up massively overcorrecting. The whole waveform gets shifted downward.

Overlap

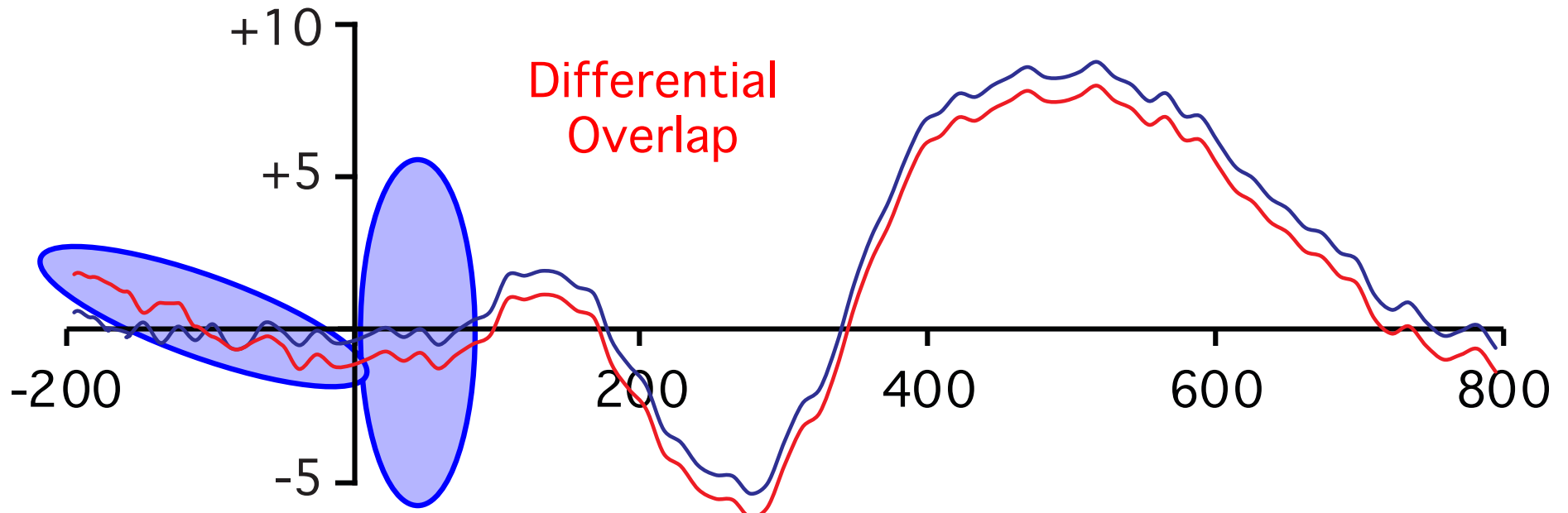


Overlap is not usually a problem unless it differs between conditions

Overlap



Overlap



If you see a steeper tilt during the baseline period in one condition than in another, you should be concerned.

And if you see effects that begin right around time zero and last for hundreds of milliseconds, you should be concerned.