

# Persistent Homology and Spectral Analysis

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# Persistent Homology

- A visual and computational tool for examining large data sets (Edelsbrunner and Hare, 2010)
- A way of investigating the evolution of topological features under a changing filtration parameter.

# Topological Filtration

- A **filtered topological space**  $X$  is a topological space such that  $X = X_m$  together with a sequence of subspaces

$$\emptyset = X_1 \subseteq X_2 \subseteq X_3 \subseteq \cdots \subseteq X_m = X$$

# Persistent homology

- Associated with the topological filtration is a sequence of inclusions maps  $\iota: P_i \rightarrow P_j$  for  $i < j$  such that

$$0 \rightarrow X_1 \rightarrow X_2 \rightarrow \cdots \rightarrow X_m = X.$$

# Persistent homology

- As usual, we have a sequence of induced homomorphisms

$$0 \rightarrow H_n(X_1) \rightarrow H_n(X_2) \rightarrow \cdots \rightarrow H_n(X_m) = H_n(X)$$

induced from the sequence of inclusions maps.

# Persistent homology

- The sequence is connected by the homomorphisms  $f_n^{i,j}: H_n(X_i) \rightarrow H_n(X_j)$
- The images of the homomorphisms are the  $n$ -th persistent homology groups denoted by  $H_n^{i,j} = \text{Im} f_n^{i,j}$

# Birth and Deaths of Classes

- A homology class  $\gamma$  is said to be born at  $X_i$  if  $\gamma \notin H_n^{i-1,j}$ . A homology class  $\gamma$  born at  $X_i$  is said to die entering  $X_j$  if it merges with an older class while proceeding from  $X_{j-1}$  to  $X_j$ .
- This process is called the Elder Rule.

# Birth and Deaths of Classes

Purple = Image of Maps

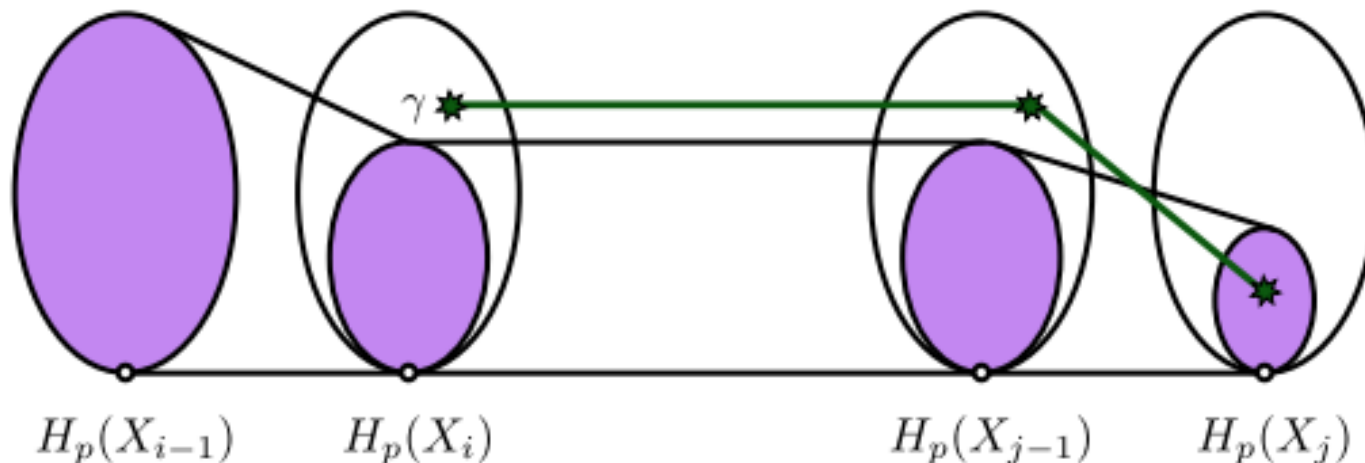


FIGURE 2.1: The class  $\gamma$  is born at  $X_i$  because it is not in the image of the map from  $H_p(X_{i-1})$ . It dies entering  $X_j$  because it was still not in the image of  $H_p(X_{i-1})$  at  $H_p(X_{j-1})$ , but has merged with an older class upon entering  $H_p(X_j)$ .



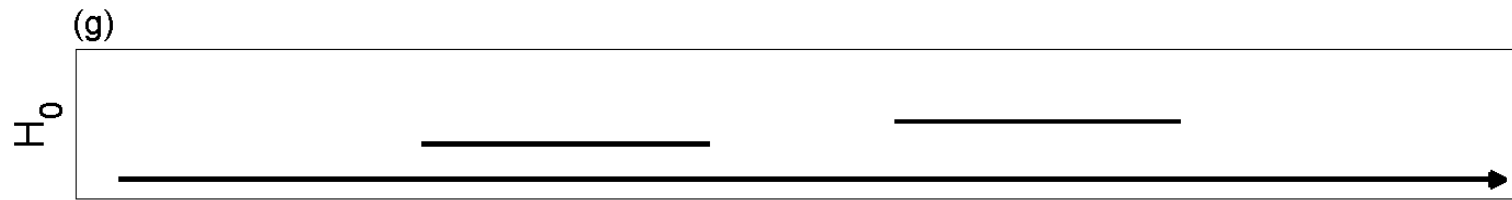
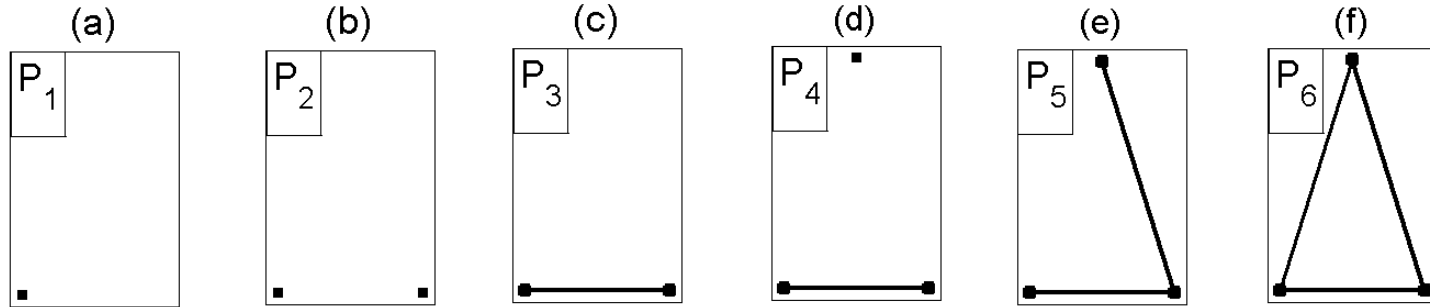
# Persistent indices

- For a homology class that is born at  $X_i$  and that dies entering  $X_j$ , there is a persistence index, which is defined as  $j - i$  and is called the index of persistence of the class (Edelsbrunner and Harer, 2010).

# Barcodes

- An arbitrary horizontal collection of lines representing the birth and deaths of homology classes
- A visual tool

# Example

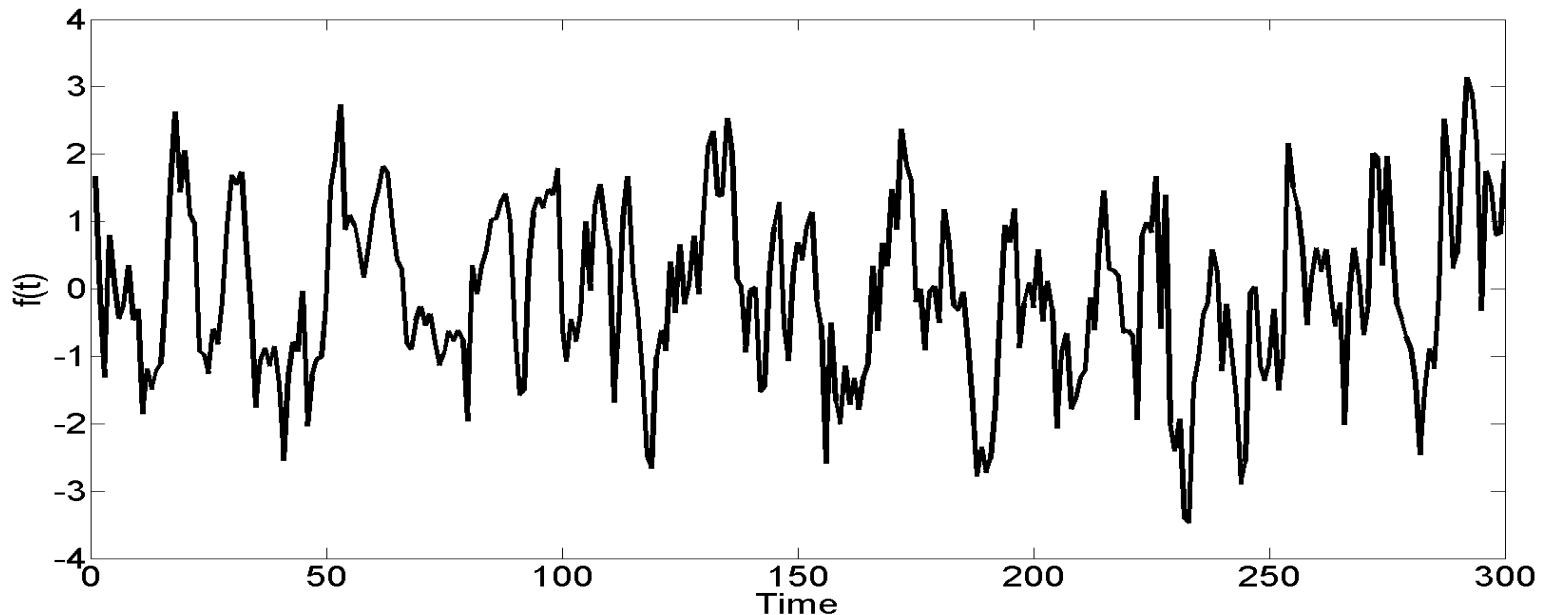


$$H_p(P_1) \longrightarrow H_p(P_2) \longrightarrow H_p(P_3) \longrightarrow H_p(P_4) \longrightarrow H_p(P_5) \longrightarrow H_p(P_6)$$

# An application of persistent homology

# Time series analysis

- Suppose we are given a time series  $f(t)$ . Are there any interesting features in the time series.
- Does the time series contain physically meaningful information or is the time series a random function of time?



# Fourier Transform

- One way to extract information from a time series is to use a Fourier transform

$$\widehat{f}(\omega) = \int_{-\infty}^{\infty} f(t) e^{-2\pi i t \omega} dt$$

to decompose the variance of the time series as a function of frequency

# Wavelet Transform

- Another transform is the wavelet transform, which can be used to decompose the variance of a time series as a function of time and frequency.

$$X(b, s) = \frac{1}{\sqrt{s}} \int_{-\infty}^{\infty} \psi \left( \frac{t-b}{s} \right) \overline{f(t)} dt$$

- Wavelet power is defined as  $|X(b, s)|^2$

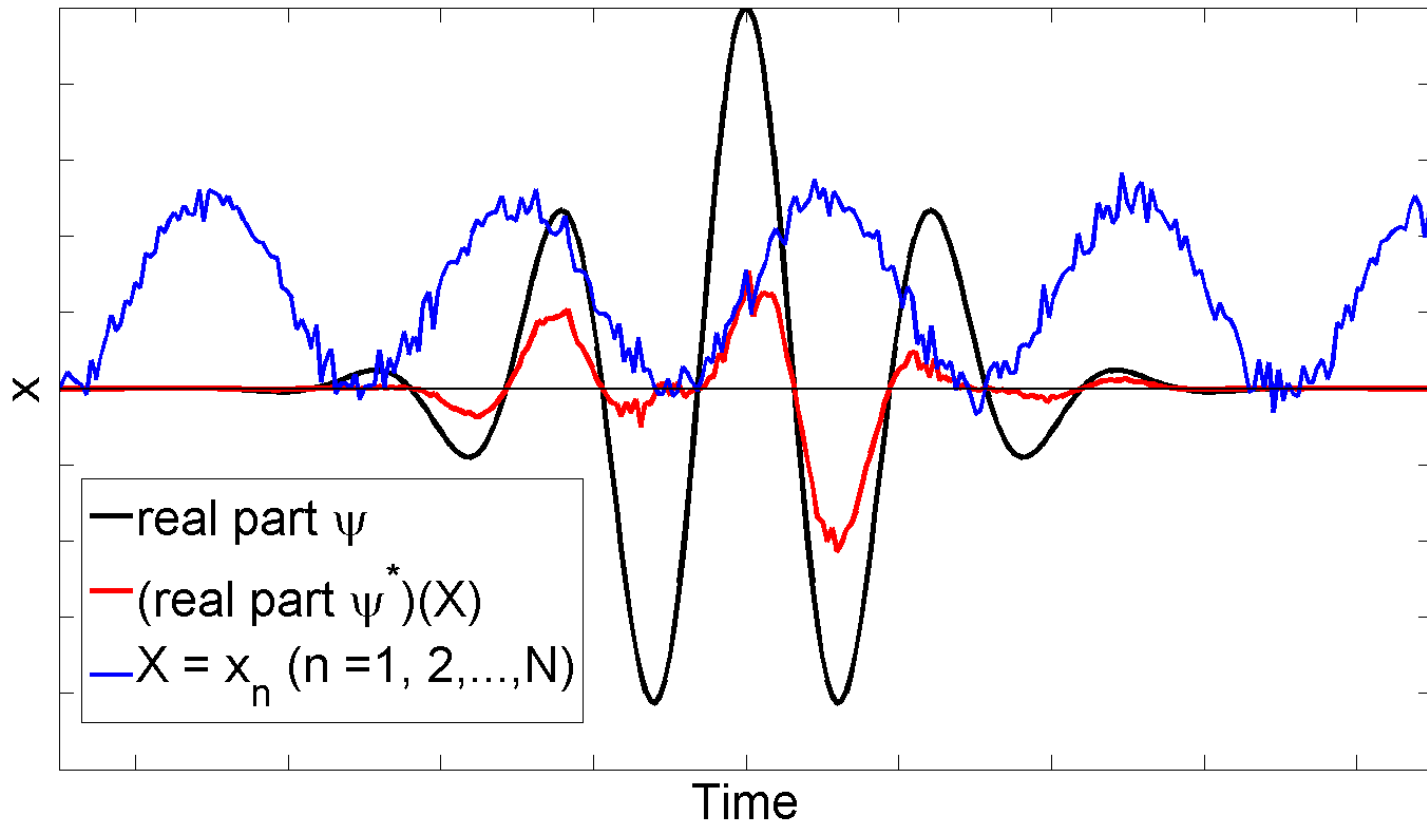
# Morlet Wavelet

- $\psi_0(\eta) = \pi^{-1/4} e^{i\omega_0\eta} e^{-\frac{1}{2}\eta^2}$
- $\omega_0$  is the dimensionless frequency,
- $\eta = s \cdot t$ ,
- $s$  is the wavelet scale
- $t$  is time



# The Wavelet Transform

Application of Wavelet Transform



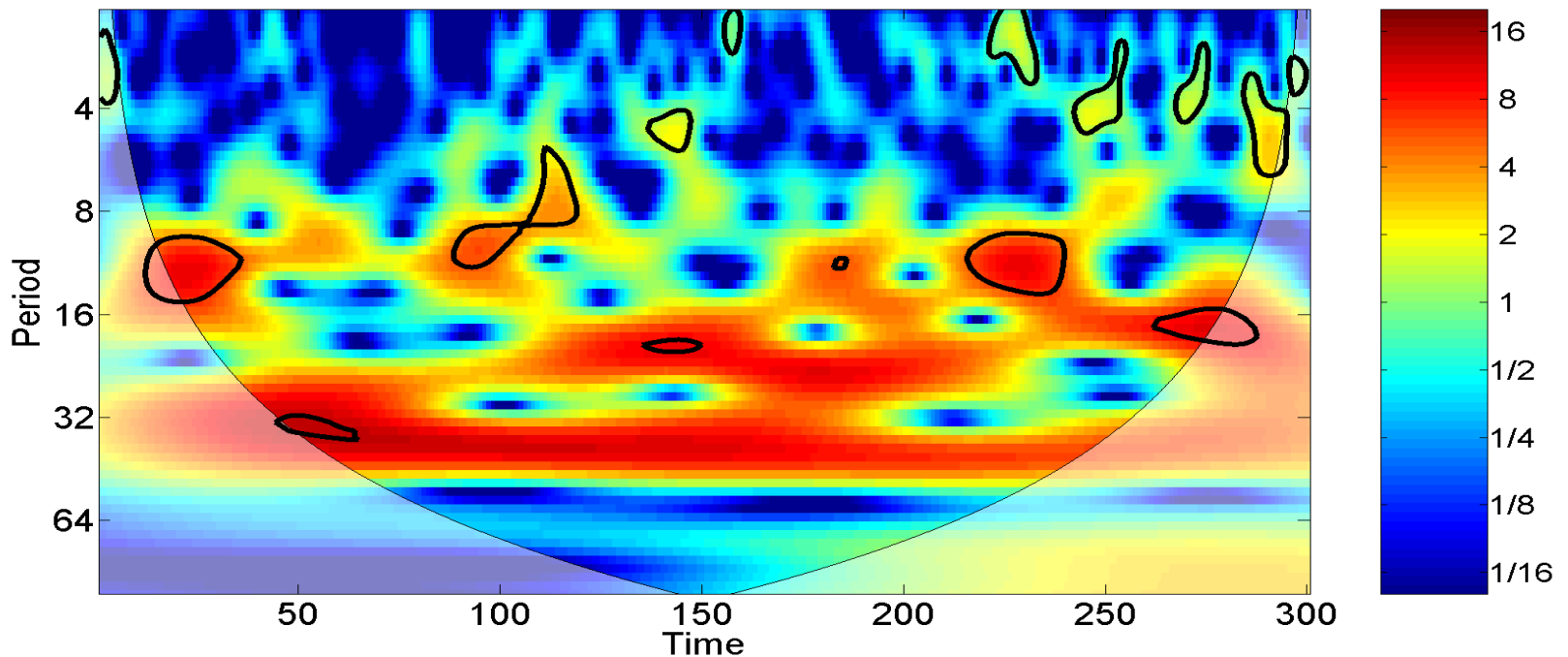
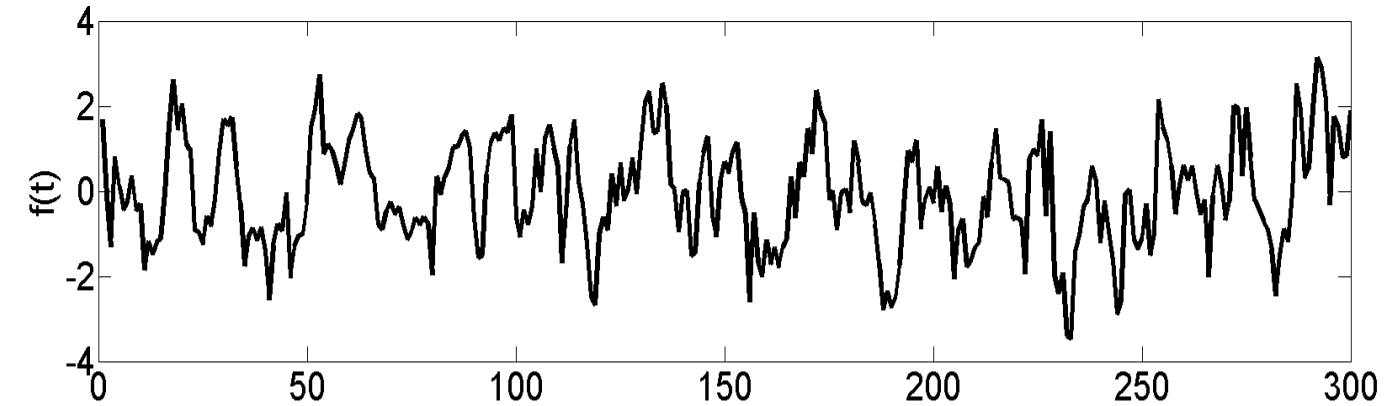
# Significance Testing

- Random fluctuations can produce large wavelet power.
- How can we distinguish random fluctuations from potentially physically meaningful structures?

# Significance Testing

- One way to address the problem is to assign to each wavelet power coefficient a probability  $p$  that the wavelet power did not arise from a random (stochastic) fluctuation when a null hypothesis is true (Torrence and Compo, 1998).

# The Wavelet Power Spectrum



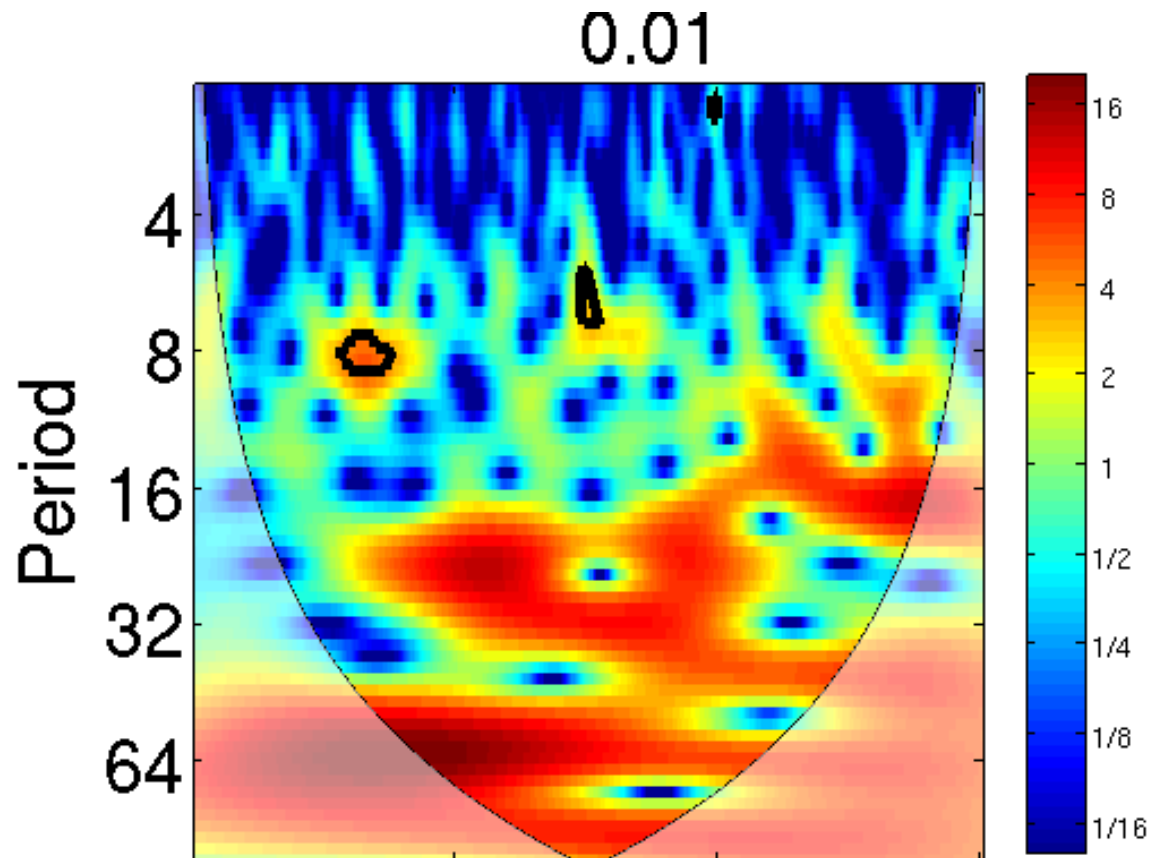
# Significance Patches

- The sets  $P_i = \{(b, s) : p \leq p_i, \}$ , where  $p_i < p_j$  for  $i < j$  are subspaces of  $\mathbb{H} \subset \mathbb{R}^2$  and thus we have

$$0 \rightarrow H_n(P_1) \rightarrow H_n(P_2) \rightarrow \cdots \rightarrow H_n(P_m) = H_n(\mathbb{H})$$

- We can now calculate persistent homology in the present setting

# Persistent Homology of Noise

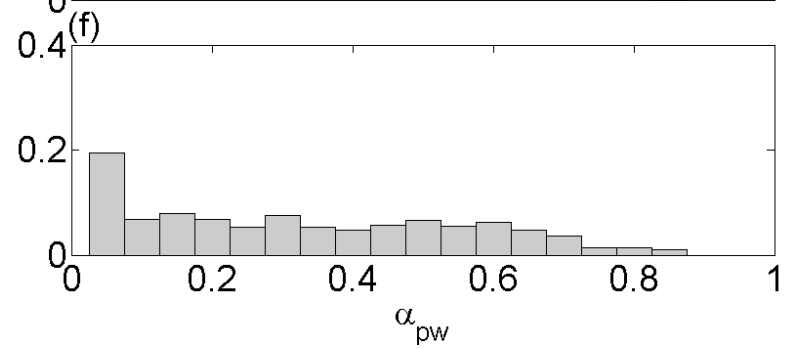
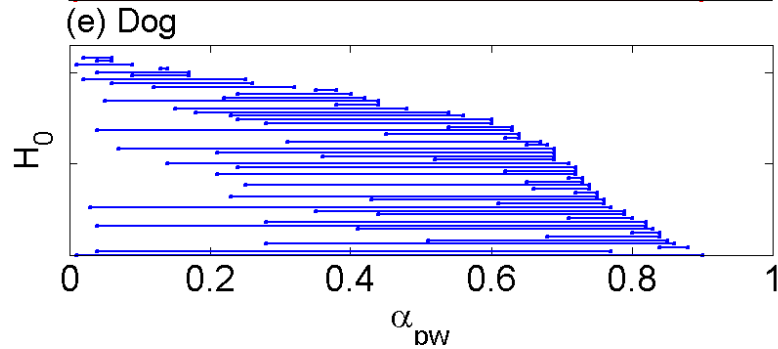
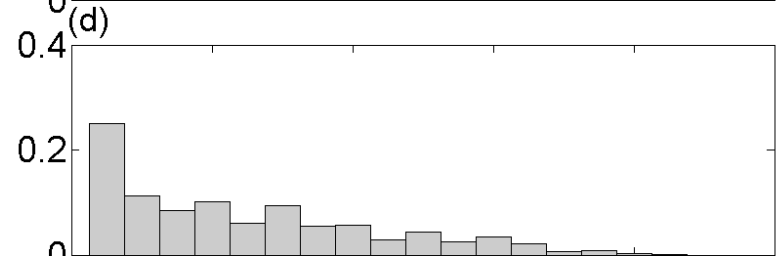
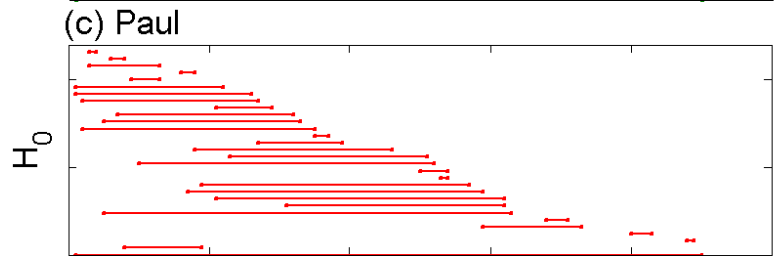
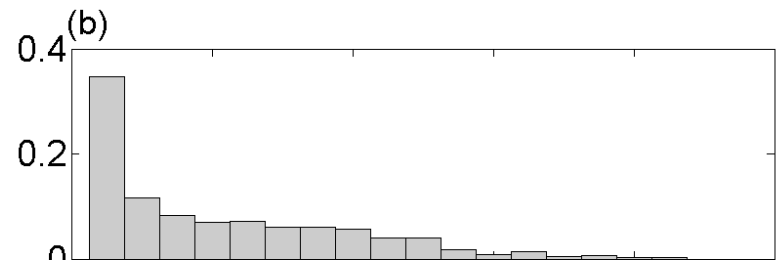
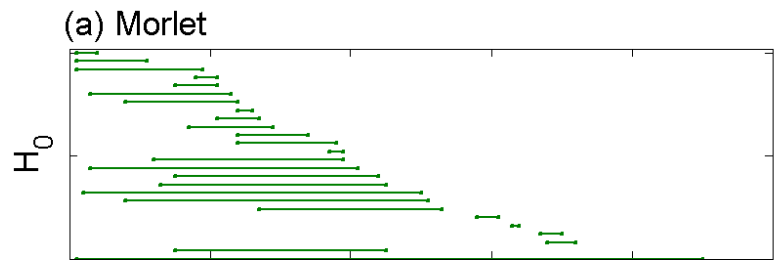


# Persistent Homology of noise

- Lets generate a large ensemble of random time series and corresponding wavelet power spectra to see if there are topological patterns

# Barcodes for noise

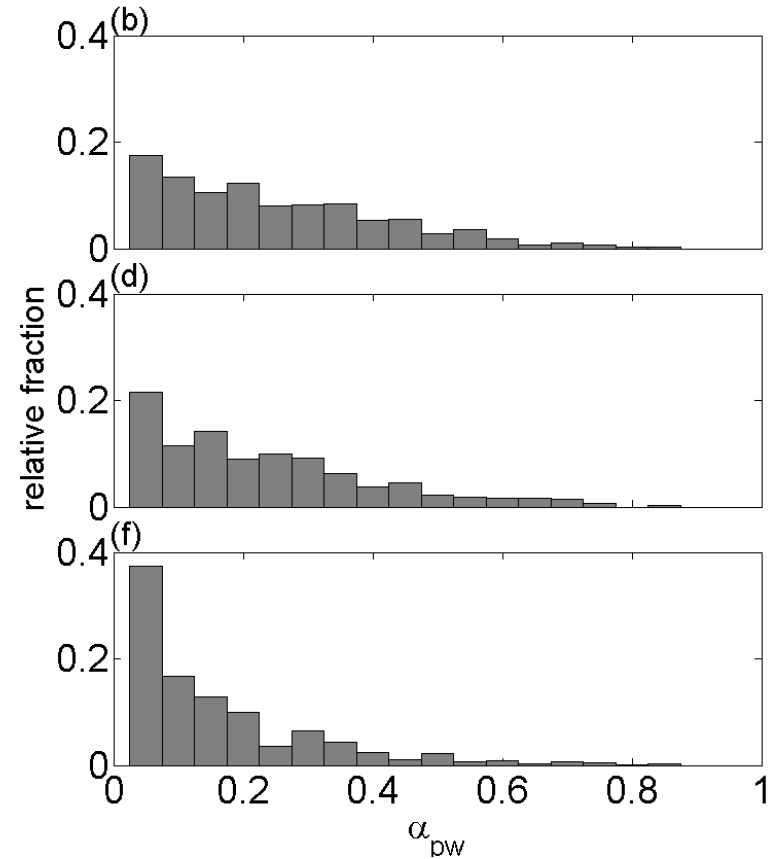
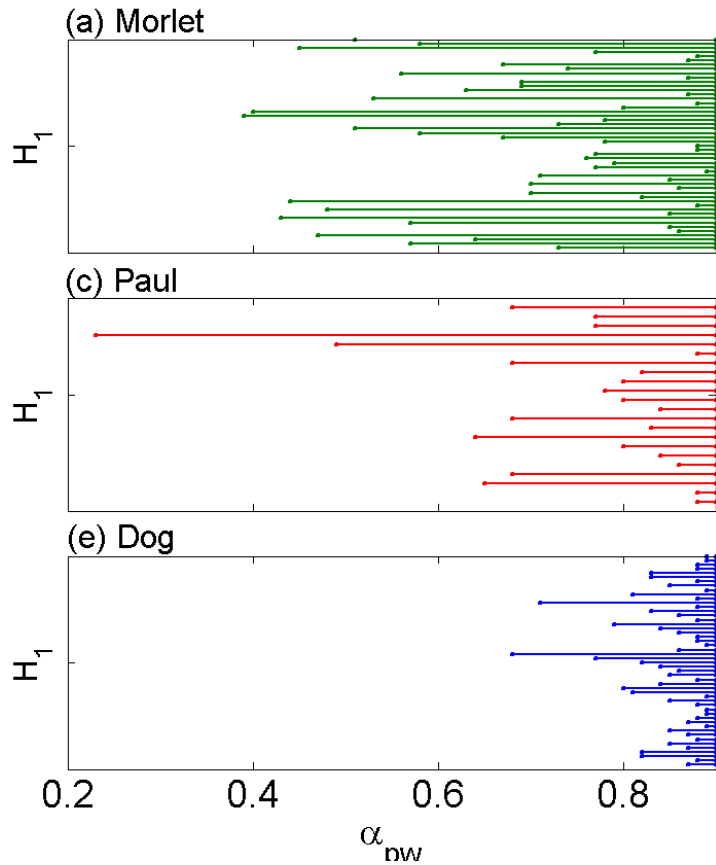
Barcodes and Persistent Indices for Patches





# Barcodes for noise

Barcodes and Persistent Indices for Holes



# Conclusions

- Persistent homology can help understand properties of random time series.
- Noise has topological signatures in wavelet power spectra.