EECS 16B CSM

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Principal Component Analysis

Signals

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Motivation

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- used for statistical analysis
- clustering
- correlation

How to PCA

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Given $A \in \mathbb{R}^{n \times m}$, n measurements with m samples,

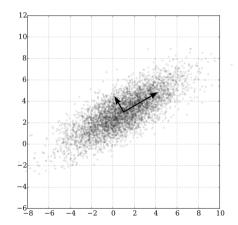
- II find $\overline{n_i}$ to center A around mean
- $oldsymbol{2}$ find covariance matrix $oldsymbol{C} = rac{1}{m} \left[oldsymbol{\widetilde{A}}
 ight]^{\! op} \! oldsymbol{\widetilde{A}}$
- 3 plot any two eigenvectors/principal components v_1, v_2 against centered points
- 4 data is scaled by σ_1, σ_2
- 5 more stretched along vector \implies larger correlation

Visualization

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Sampling

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- continuous → discrete
- \blacksquare measuring an analog signal at a frequency ω
- band limiting
 - lacktriangledown if $\omega>2\omega_{max}$, signal perfectly recovered (Nyquist frequency)

Signals

 \blacksquare discrete \rightarrow continuous

- we want to pass through every sampling point, not approximate it
- composed of a weighted sum of basis functions

Given basis function

$$\Phi_i(x) = \begin{cases} 1 & x = i \\ 0 & \text{elsewhere} \end{cases} \tag{1}$$

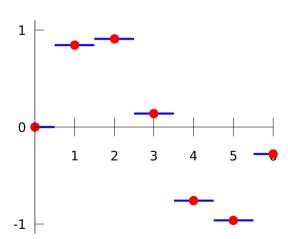
$$y(x) = \sum_{i=1}^{n} y_i \Phi_i(x) \tag{2}$$

Interpolation Zero-Hold

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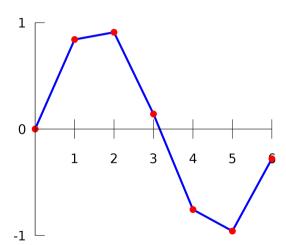
Interpolation

Linear

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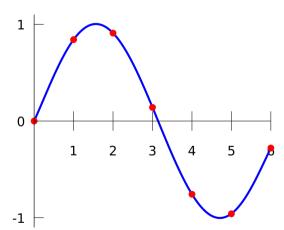
Interpolation

Polynomial

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Interpolation Sinc

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