

EECS 16B CSM

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EECS 16B
CSM

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Principal
Component
Analysis

Signals

Principal Component Analysis

Motivation

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- used for statistical analysis
- clustering
- correlation

How to PCA

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

- 1 find $\overline{n_i}$ to center \mathbf{A} around mean
- 2 find covariance matrix $\mathbf{C} = \frac{1}{m} [\tilde{\mathbf{A}}]^\top \tilde{\mathbf{A}}$
- 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

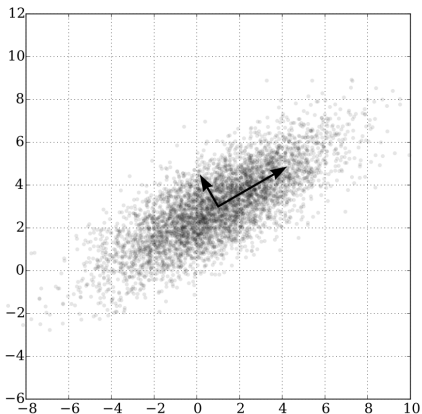
Visualization

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Sampling

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

Interpolation

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- 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

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

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

Interpolation

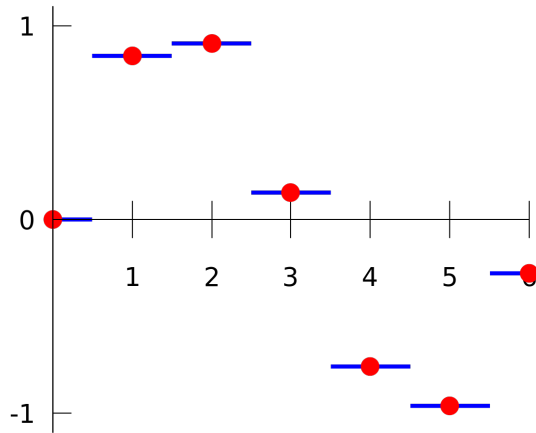
Zero-Hold

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Interpolation

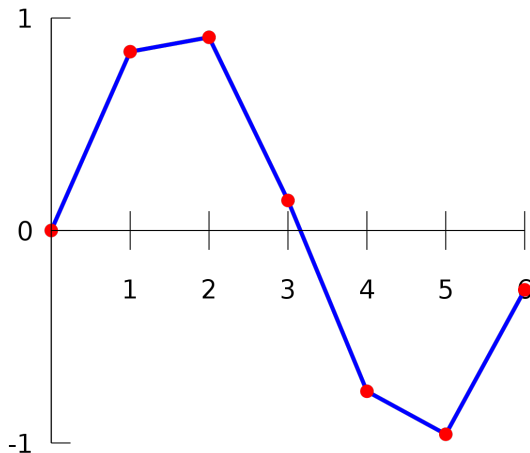
Linear

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Interpolation

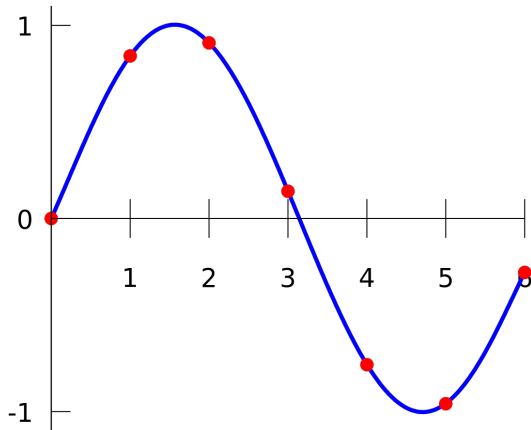
Polynomial

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Interpolation

Sinc

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