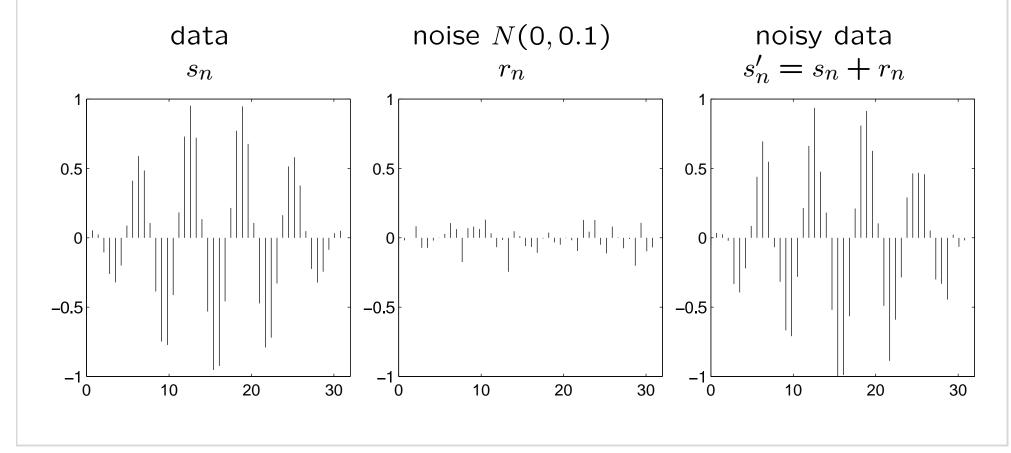
Chapter 3: Data Preprocessing

- 1. Error Types and Handling
- 2. Filtering
- 3. Standardization and Transformation
- 4. Data Merging

Random Errors

- measurement and transmission errors
- modeling as additive noise

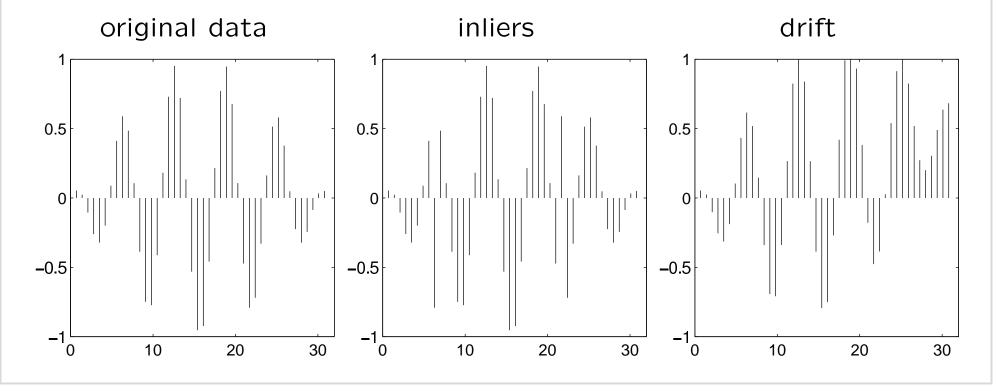


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Inliers, Outliers, and Drift

- single incorrect data: inliers/outliers
- processing errors: permuted or wrong data (e.g. 1.000/1,000)
- measurement errors: offset, scaling, drift



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Outlier Detection

• comparison with range limits

$$\left(x_k^{(i)} < x_{\min}^{(i)}\right) \vee \left(x_k^{(i)} > x_{\max}^{(i)}\right)$$

- range limits $x_{\min}^{(i)}$, $x_{\max}^{(i)}$ e.g. given by:
 - 1. sign (price, temperature, time)
 - 2. sensor range, considered time interval
 - 3. defined or physically plausible values
- 2-sigma rule

$$\left| \frac{x_k^{(i)} - \bar{x}^{(i)}}{s_x^{(i)}} \right| > 2$$

 problem: unusual but valuable data can not be distinguished from incorrect data (real outliers)

Error Handling

- invalidity list
- invalidity value

$$x_k^{(i)} = \text{NaN (not a number)}$$

implementation in 64 bit IEEE floating point format

- ullet replace by mean, median, minimum, or maximum of the valid feature data x^i
- replace by nearest neighbor $x_k^{(i)} = x_j^{(i)}$

$$||x_j - x_k||_{\neg i} = \min_{l \in \{1, \dots, n\}} ||x_l - x_k||_{\neg i}$$

where $\|.\|_{\neg i}$ ignores feature i and invalid or missing data

Error Handling

• linear interpolation for equidistant time series

$$x_k^{(i)} = \frac{x_{k-1}^{(i)} + x_{k+1}^{(i)}}{2}$$

• linear interpolation for non-equidistant time series

$$x_k^{(i)} = \frac{x_{k-1}^{(i)} \cdot (t_{k+1} - t_k) + x_{k+1}^{(i)} \cdot (t_k - t_{k-1})}{t_{k+1} - t_{k-1}}$$

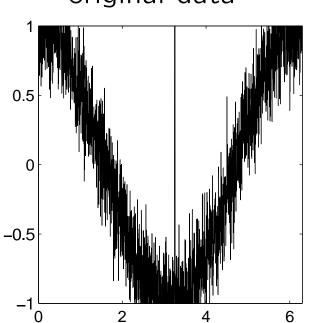
- nonlinear interpolation, e.g. splines
- model-based estimation by regression
- filtering
- ullet outlier removal: the complete vector x_k is removed
- ullet feature removal: the complete feature $x^{(i)}$ is removed

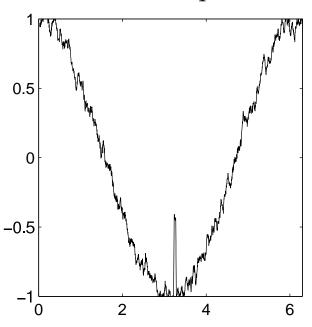
Moving Average

• moving average of (even) order $q \in \{2, 4, 6, \ldots\}$

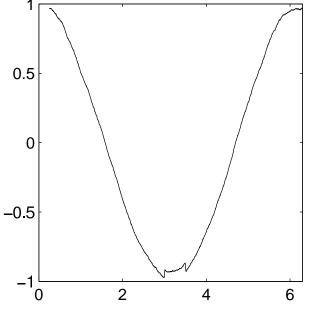
$$y_k = \frac{1}{q+1} \sum_{i=k-\frac{q}{2}}^{k+\frac{q}{2}} x_i$$
 $y_k = \frac{1}{q+1} \sum_{i=k-q}^{k} x_i$

$$y_k = \frac{1}{q+1} \sum_{i=k-q}^{k} x_i$$





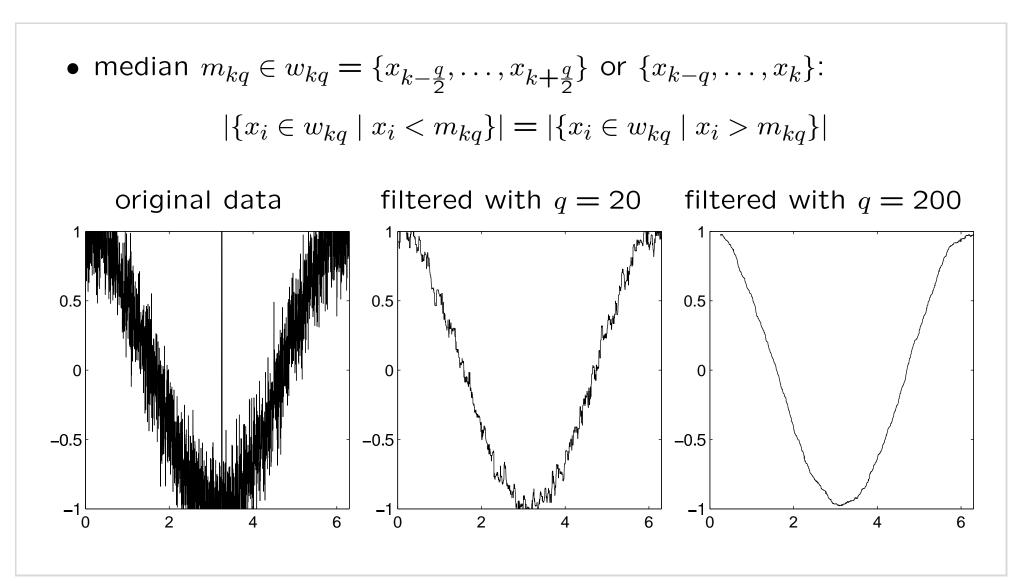
original data filtered with q = 20 filtered with q = 200



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Moving Median



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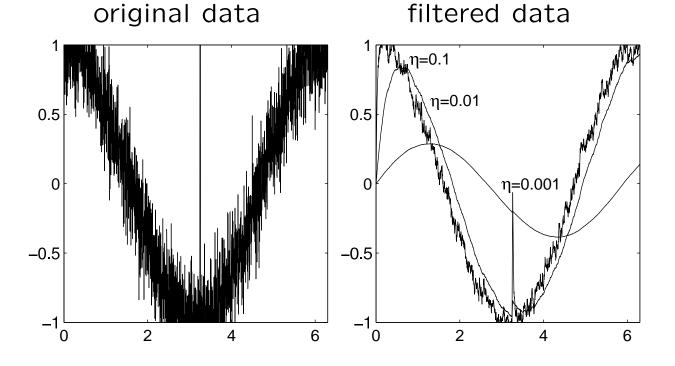
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Exponential Filter

• simple filter that forgets exponentially

$$y_k = y_{k-1} + \eta \cdot (x_k - y_{k-1}), \quad k = 2, \dots, n \quad \eta \in [0, 1]$$

• initialization (standardized data) $y_0 = (0, ..., 0)$



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Discrete Linear Filter

difference equation for linear filters of order q

$$y_k = \sum_{i=0}^{q} \frac{b_i}{a_0} \cdot x_{k-i} - \sum_{i=1}^{q} \frac{a_i}{a_0} \cdot y_{k-i}$$

filter properties specified by coefficient vectors

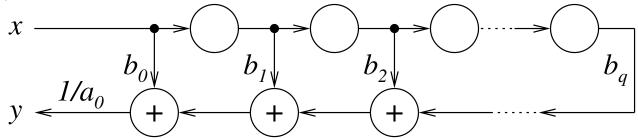
$$a = (a_0, \dots, a_q), \quad b = (b_0, \dots, b_q)$$

- finite impulse response (FIR): $a_1 = ... = a_q = 0$, otherwise infinite impulse response (IIR)
- exponential filter: $a = (1, \eta 1), b = (\eta, 0)$
- first order FIR low pass
 - = second order moving average
 - = first order Butterworth low pass with limit frequency 0.5:

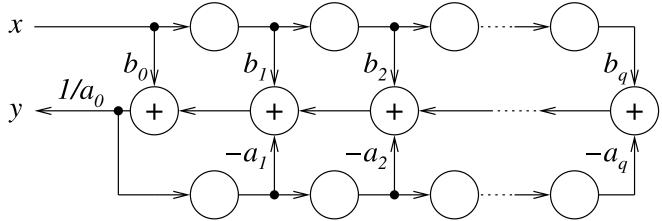
$$a = (1), b = (0.5, 0.5)$$

Discrete Linear Filter

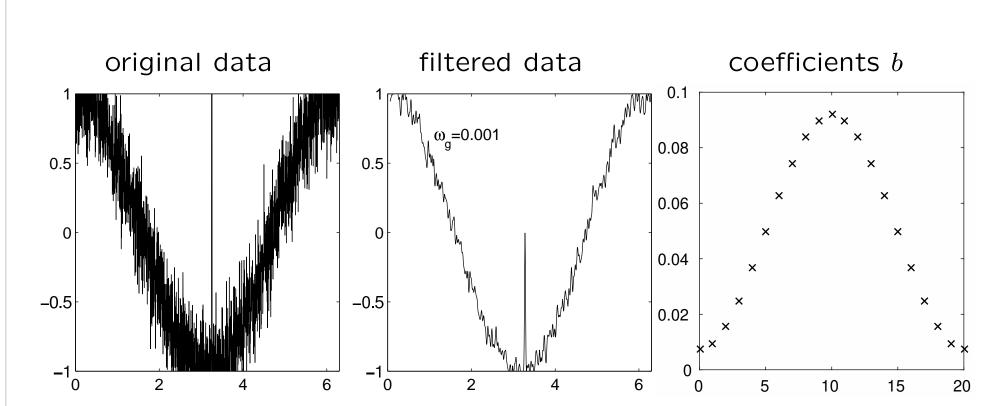
• FIR filter



• IIR filter

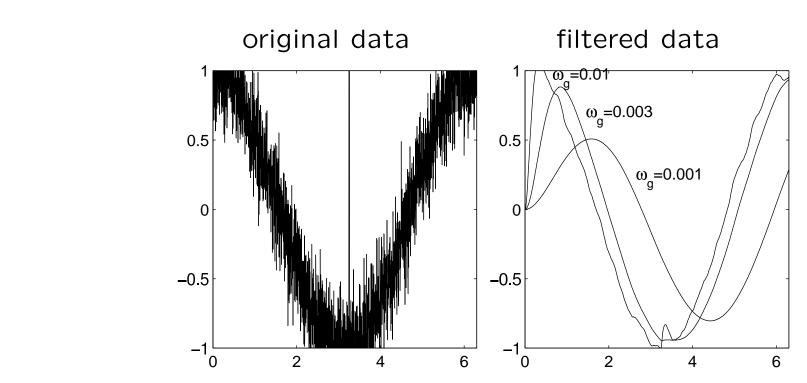


FIR low pass of order 20



- coefficient a = (1)
- coefficients b symmetric, $\sum_{i=0}^{q} b_i = 1$, $b_i > 0 \ \forall i = 0, \dots, q$

Second Order Butterworth Low Pass



ω_g	a_0	a_1	a_2	b_0	b_1	b_2
0.01	1	-1.96	0.957	$2.41 \cdot 10^{-4}$	$4.83 \cdot 10^{-4}$	$2.41 \cdot 10^{-4}$
0.003	1	-1.99	0.987	$2.21 \cdot 10^{-5}$	$4.41 \cdot 10^{-5}$	$2.21 \cdot 10^{-5}$
0.001	1	-2	0.996	$2.46 \cdot 10^{-6}$	$4.92 \cdot 10^{-6}$	$2.46 \cdot 10^{-6}$

Standardization

- problem: multi-dimensional data with considerably different component ranges
- observed hypercube

$$[x_{\min}^{(1)}, x_{\max}^{(1)}] \times \ldots \times [x_{\min}^{(p)}, x_{\max}^{(p)}]$$

limits are arbitrary

$$x_{\min}^{(i)} \neq \min_{k=1,\dots,n} x_k^{(i)}, \quad x_{\max}^{(i)} \neq \max_{k=1,\dots,n} x_k^{(i)}$$

hypercube standardization

$$y_k^{(i)} = \frac{x_k^{(i)} - x_{\min}^{(i)}}{x_{\max}^{(i)} - x_{\min}^{(i)}}$$

μ – σ Standardization

mean

$$\bar{x}^{(i)} = \frac{1}{n} \sum_{k=1}^{n} x_k^{(i)}$$

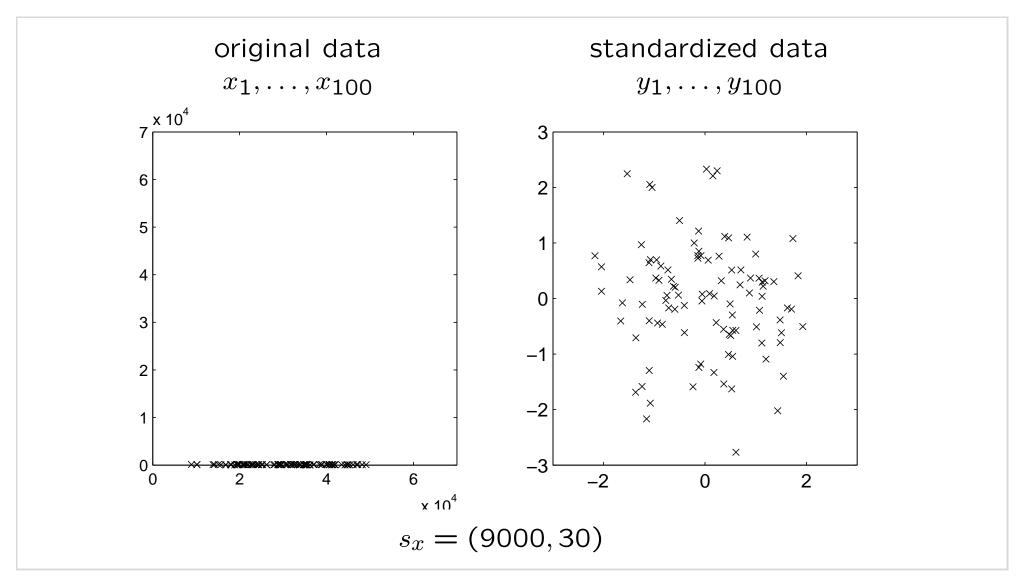
standard deviation

$$s_x^{(i)} = \sqrt{\frac{1}{n-1} \sum_{k=1}^n (x_k^{(i)} - \bar{x}^{(i)})^2} = \sqrt{\frac{1}{n-1} \left(\sum_{k=1}^n \left(x_k^{(i)}\right)^2 - n\left(\bar{x}^{(i)}\right)^2\right)}$$

• μ - σ standardization

$$y_k^{(i)} = \frac{x_k^{(i)} - \bar{x}^{(i)}}{s_x^{(i)}}$$

Example Standardization



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Data Transformations

• inverse transformation $f: R \setminus \{0\} \to R \setminus \{0\}$

$$f(x) = f^{-1}(x) = \frac{1}{x}$$

• root transformation $f:(c,\infty)\to R^+$

$$f(x) = \sqrt[b]{x - c}, \quad f^{-1}(x) = x^b + c, \quad c \in R, \ b > 0$$

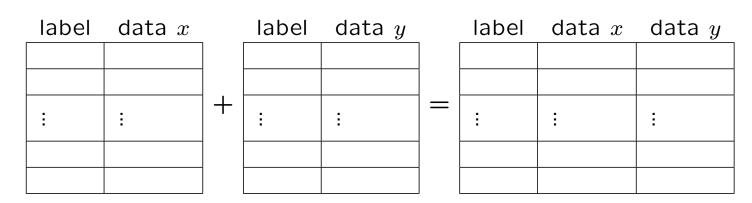
• logarithmic transformation $f:(c,\infty)\to R$

$$f(x) = \log_b(x - c), \quad f^{-1}(x) = b^x + c, \quad c \in R, b > 0$$

• Fisher-Z transformation $f:(-1,1)\to R$

$$f(x) = \operatorname{artanh} x = \frac{1}{2} \cdot \ln \frac{1+x}{1-x}, \quad f^{-1}(x) = \tanh x = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

Data Merging



- labels:
 - code, e.g. person, item
 - (relative) time, e.g. in sequential processes
 - (relative) location, e.g. position on an item
- problems:
 - similar labels considered equivalent
 - labels that do not match all data
 - labels that match multiple data

Chapter 4: Visualization

- 1. Diagrams
- 2. Principal Component Analysis
- 3. Multi Dimensional Scaling
- 4. Sammon Mapping
- 5. Auto-Encoder
- 6. Histograms
- 7. Spectral Analysis