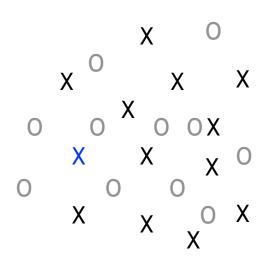
Data Visualization

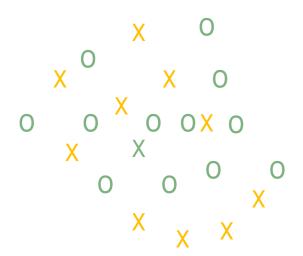
The

Foundations

The Modes of Perception

Find the outlier





Fast Slow

The Modes of Perception

Pre-attentive

- fast
- parallel processing
- effortless

Pattern recognition

- semi-fast
- governed by laws of Gestalt

Attentive

- slow
- sequential
- high effort (attention is a very limited resource)

Main Properties of Graphics

Category	Example
Position	
Shape	
Size	
Color	
Orientation (Line)	
Length (Line)	
Type and Size (Line)	/ / : /
Brightness	

Main Properties of Graphics Humans

Category	Amount of pre-attentive information
Position	very high
Shape	
Size	approx. 4
Color	approx. 8
Orientation (Line)	approx. 4
Length (Line)	
Type and Size (Line)	
Brightness	approx. 8

Pre-attentive Perception

- Position
 - fast
 - effective
 - high number of different positions
- Color
 - use with care
- Shape
- Orientation

Pre-attentive perception is effortless. Exploit this as much as you can.

Pattern Detection

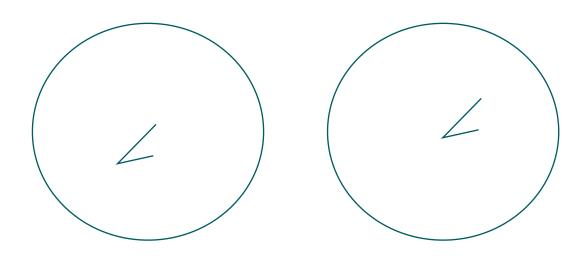
"It is interesting to note that our brain [...] subconsciously always prefers meaningful situations and objects."

- Emergence
- Reiification
- Multi-stability
- Invariance

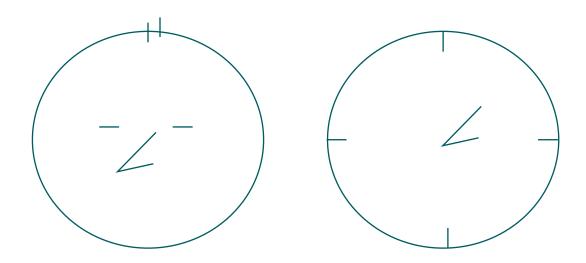
Pattern detection can be trained. Exploit this for frequent visualizations.

What is this?

What is this?

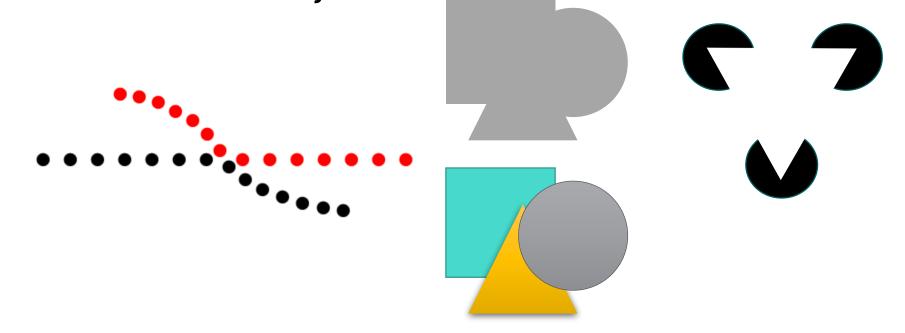


What is this?



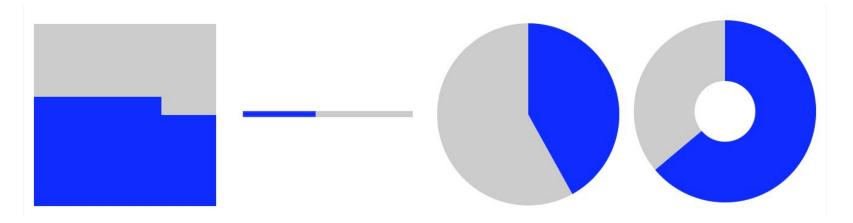
Laws of Gestalt

"It is interesting to note that our brain, in accordance with the laws of Gestalt, subconsciously always prefers meaningful situations and objects."



Accuracy of Graphics

Square Pie vs Stacked Bar vs Pie vs Donut



What do you think?

Why do we visualize data?

Explore

- use different techniques
- avoid "construction" bias
- be careful with "aesthetics"
- challenge findings -> use attentive mode

Explain

- focus on message or "story"
- use pre-attentive mode

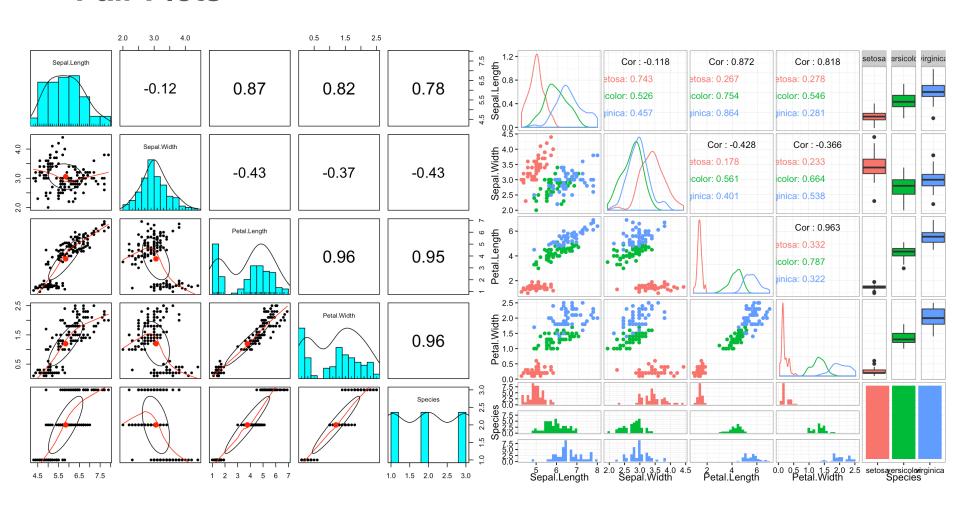
Don't trust your perception ;-)

Data Visualization

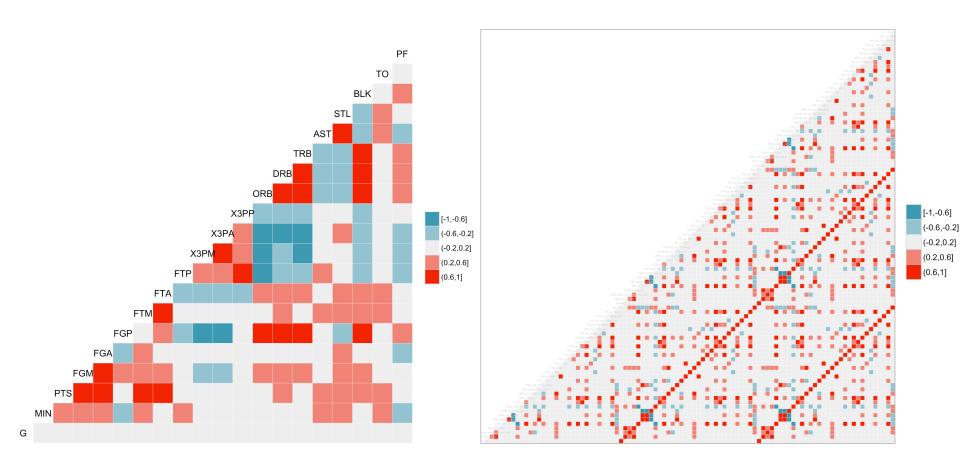
ln

Higher Dimensions

Pair Plots



Correlation Plots



Fundamental Problems

- No accurate method in higher dimensions
 - Approximation methods
 - "Simulated" dimensions (color, size, shape)
 - Animations?
- No notion of quality or accuracy for visualizations
 - Information Theory?
 - "Stability"?

All visualizations are wrong, but some are useful.

Approximation Methods

Pair Plots

- Axis-aligned projections
- Interpretable in terms of original variables

Singular Value Decomposition

- Optimal with respect to 2-norm (Euclidean norm) and supremum norm
- Comes with an error estimate

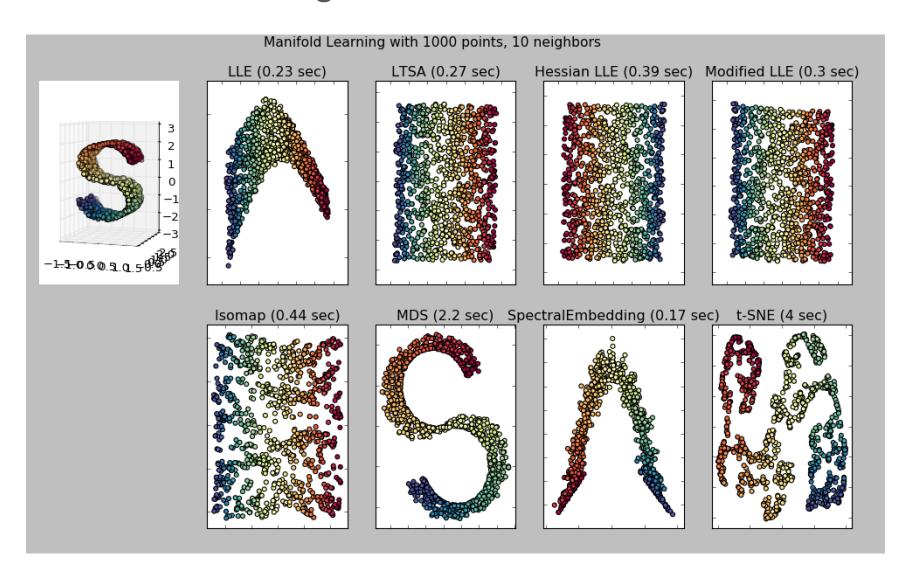
Other methods

- Stochastic Neighbor Embedding ((t-)SNE)
- "Manifold Learning"

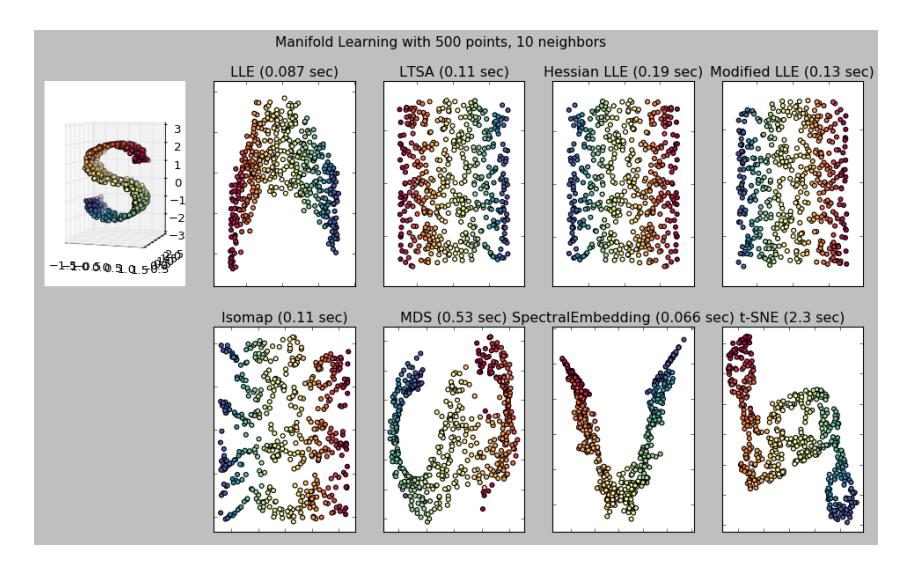
Manifold Learning Methods

- Locally Linear Embedding
 - Neighborhood-preserving embedding
- Isomap
 - quasi-isometric
- Multi-Dimensional Scaling
 - quasi-isometric
- Spectral Embedding
 - Spectral clustering based on similarity
- Stochastic Neighbor Embedding (SNE, t-SNE)
 - preserves conditional probabilities for similarity
- Local Tangent Space Alignment (LTSA)

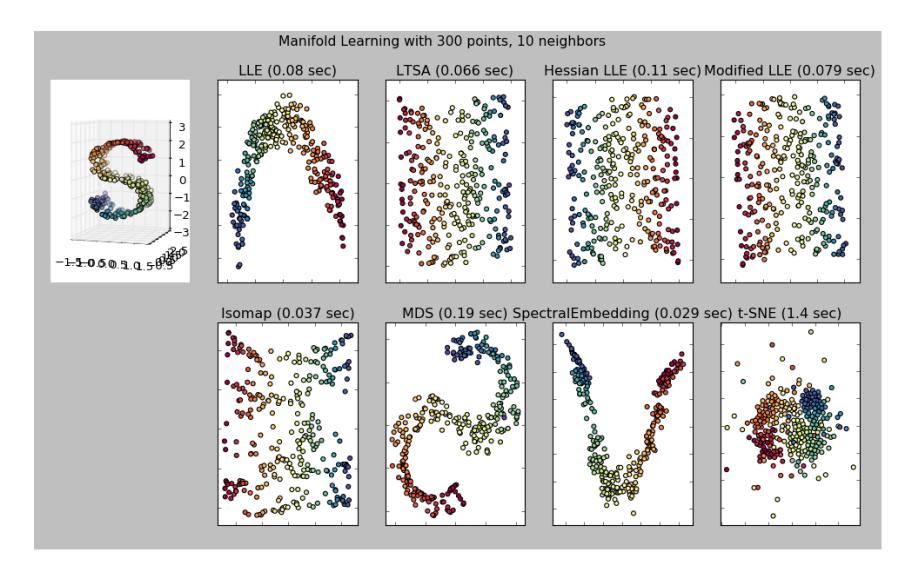
Manifold Learning



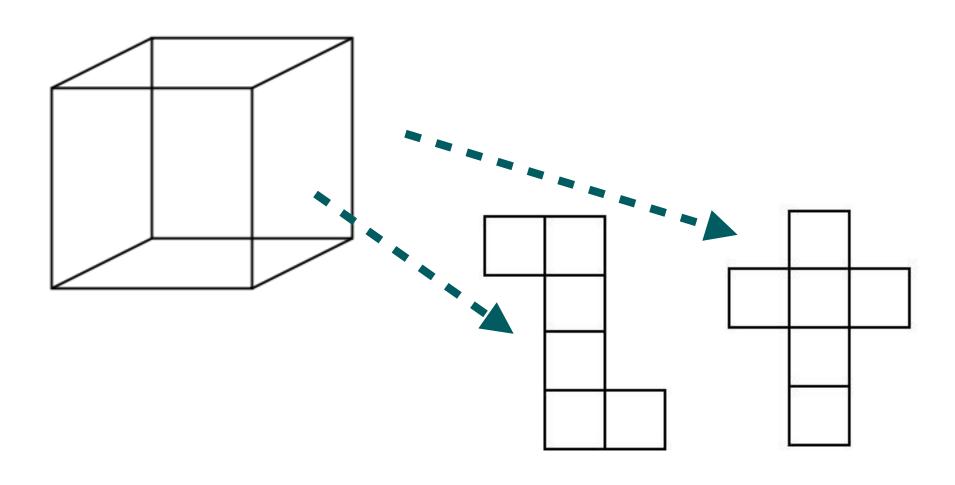
Manifold Learning



Manifold Learning



Local Tangent Space Alignment



Principal Components and Curves

Principal Component Analysis

- orthogonal decomposition based on SVD
- linear in all variables
- tries to preserve variance

Principal Curves

- minimize the Sum of Squared Errors with respect to all variables (as PCA, preserve variance)
- nonlinear
- smooth

Principal Components and Curves

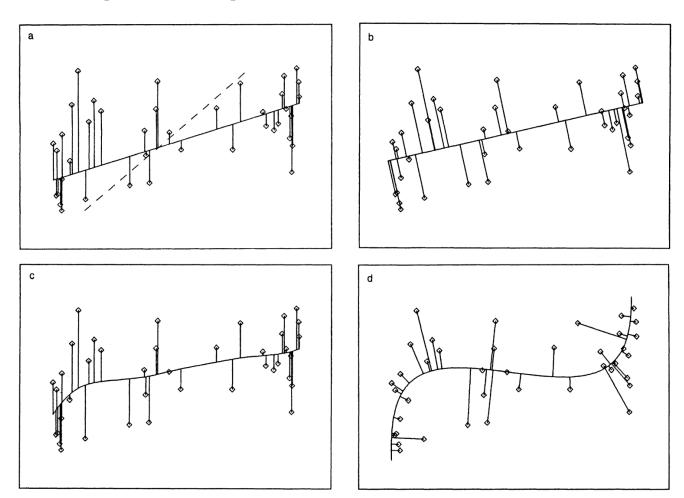
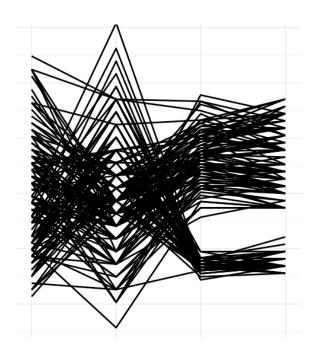


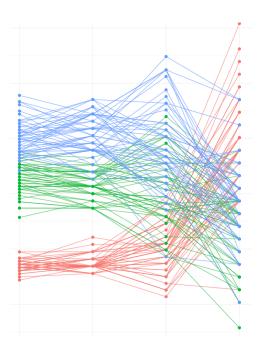
Figure 1. (a) The linear regression line minimizes the sum of squared deviations in the response variable. (b) The principal-component line minimizes the sum of squared deviations in all of the variables. (c) The smooth regression curve minimizes the sum of squared deviations in the response variable, subject to smoothness constraints. (d) The principal curve minimizes the sum of squared deviations in all of the variables, subject to smoothness constraints.

Parallel Coordinates

Parallel Coordinates

- especially useful for high-dimensional data
- depends on ordering and scaling





The Grand Tour

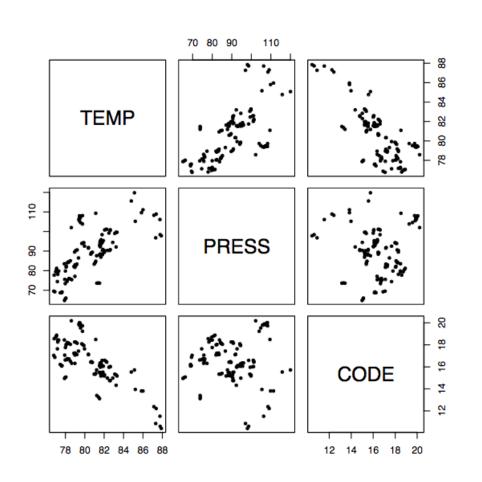
Animated sequence of 2-D projections

- https://en.wikipedia.org/wiki/
 Grand_Tour_(data_visualisation)
- Asimov (1985): The grand tour: a tool for viewing multidimensional data.

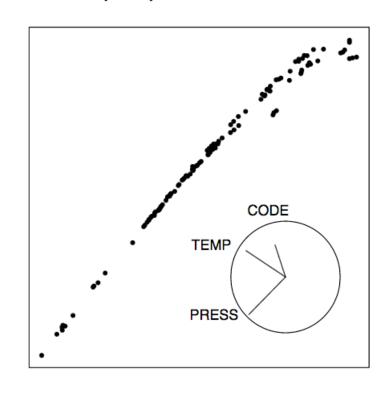
Underlying idea

- Randomly generate 2-D projections (random walk)
- Over time generate a dense subset of all possible
 2-D projections
- Optional: Follow a given path / guided tour

The Grand Tour



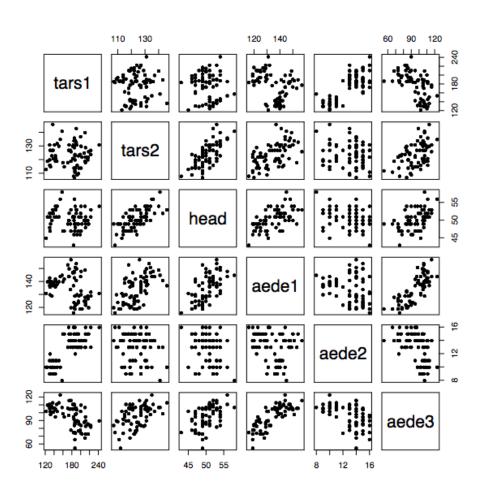
(Non-)linear association



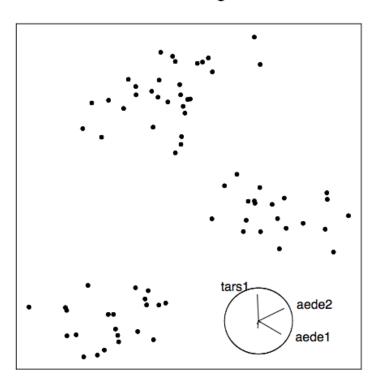
Projection 2

Projection 1

The Grand Tour



Clustering



Projection 2

Projection 1