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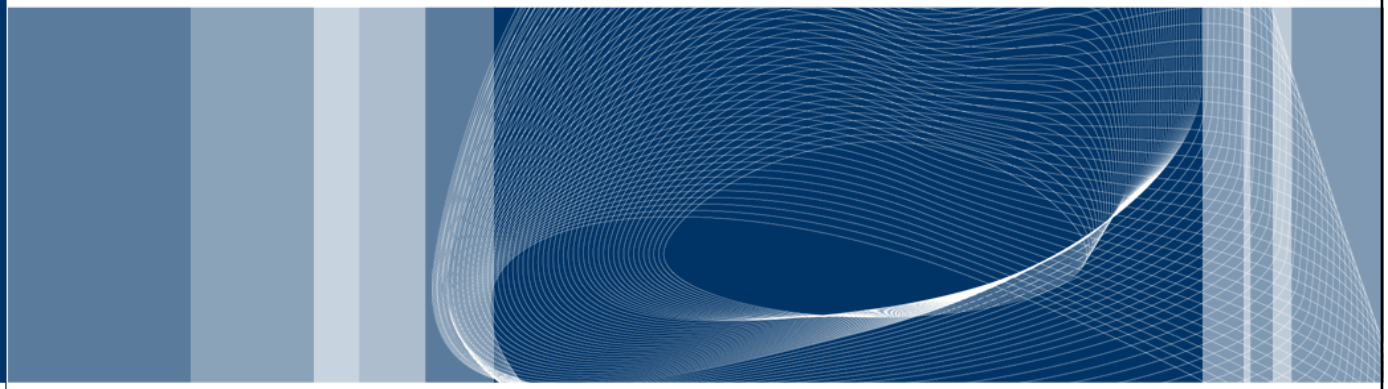


Data Exploration and Visualization

Data Mining and Text Mining

Prof. Pierluca Lanzi

Before trying anything,
you should know your data!

What is Data Exploration?

- Preliminary exploration of the data aimed at identifying their most relevant characteristics
- What the key motivations?
  - Help to select the right tool for preprocessing and data mining
  - Exploit humans' abilities to recognize patterns not captured by automatic tools
- Related to Exploratory Data Analysis (EDA)
  - Invented/advocated by statistician John Tukey

Exploratory Data Analysis

- "An approach of analyzing data to summarize their main characteristics without using a statistical model or having formulated a prior hypothesis."

- "Exploratory data analysis was promoted by John Tukey to encourage statisticians to explore the data, and possibly formulate hypotheses that could lead to new data collection and experiments."

- Resources
  - Seminal book: "Exploratory Data Analysis" by Tukey
    https://books.google.it/books/about/Exploratory_Data_Analysis.html?id=UT9dAAAAIAAJ
  - Online introduction in Chapter 1 of NIST Engineering Statistics Handbook
    http://www.itl.nist.gov/div898/handbook/index.htm
  - Wikipedia article
    http://en.wikipedia.org/wiki/Exploratory_data_analysis

What Data Exploration Techniques?

- Exploratory Data Analysis (as originally defined by Tukey), was mainly focused on
  - Visualization
  - Clustering and anomaly detection (viewed as exploratory techniques)
  - In data mining, clustering and anomaly detection are major areas of interest, and not thought of as just exploratory
- In this section, we focus on data exploration using
  - Summary statistics
  - Visualization
- We will return to data exploration when discussing clustering

Summary Statistics

Summary Statistics

- What are they?
  - Numbers that summarize properties of the data
- Summarized properties include
  - Location, mean, spread, skewness, standard deviation, mode, percentiles, etc.
- Most summary statistics can be calculated in a single pass

Frequency and Mode

- The frequency of an attribute value
  - The percentage of time the value occurs in the data set
  - For example, given the attribute 'gender' and a representative population of people, the gender 'female' occurs about 50% of the time.
- The mode of an attribute is the most frequent attribute value
- The notions of frequency and mode are typically used with categorical data

Measures of Location: Mean and Median

- The mean is the most common measure of the location of a set of points
- However, the mean is very sensitive to outliers
- Thus, the median or a trimmed mean is also commonly used

$$\text{mean}(x) = \overline{x} = \frac{1}{m}\sum_{i=1}^{m} x_i$$

$$\text{median}(x) = \begin{cases} x_{(r+1)} & \text{if } m \text{ is odd, i.e., } m = 2r+1 \\ \frac{1}{2}(x_{(r)} + x_{(r+1)}) & \text{if } m \text{ is even, i.e., } m = 2r \end{cases}$$

Percentiles

- For continuous data, the notion of a percentile is very useful
- p-th percentile
  - Given an ordinal or continuous attribute x and a number p
  - p-th percentile is a value x_p of x such that p% of the observed values of x are less than x_p
- For instance, the 50th percentile is the value $x_{50\%}$ such that 50% of all values of x are less than $x_{50\%}$

Trimean & Truncated Mean

- **Trimean**
  - It is the weighted mean of the first, second and third quartile

$$TM = \frac{x_{25} + 2x_{50} + x_{75}}{4}$$

- **Truncated Mean**
  - Discards data above and below a certain percentile
  - For example, below the 5th percentile and above the 95th percentile

- **Interquartile Mean**
  - Truncate data at 25th and 75th percentile
  - If the data $(x_1, \ldots, x_n)$ is sorted by value we have:

$$X_{IQM} = \frac{2}{n} \sum_{i=0.25n+1}^{0.75n} x_i$$

Measures of Spread: Range and Variance

- Range is the difference between the max and min
- The variance or standard deviation is the most common measure of the spread of a set of points

$$\text{variance}(x) = s_x^2 = \frac{1}{m-1}\sum_{i=1}^{m}(x_i - \overline{x})^2$$

- However, this is also sensitive to outliers, so that other measures are often used

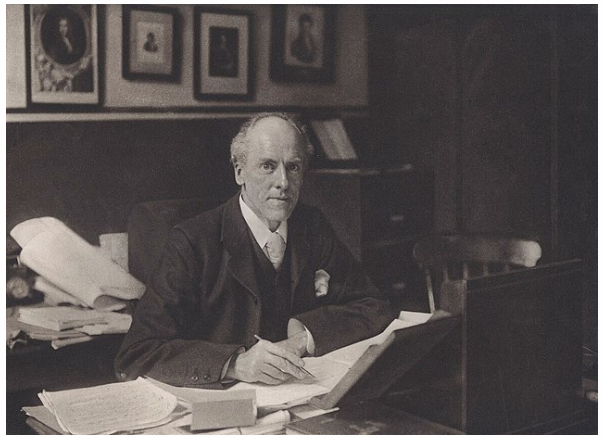
$$\text{AAD}(x) = \frac{1}{m}\sum_{i=1}^{m}|x_i - \overline{x}|$$

$$\text{MAD}(x) = median\left(\{|x_1 - \overline{x}|, \ldots, |x_m - \overline{x}|\}\right)$$

$$\text{interquartile range}(x) = x_{75\%} - x_{25\%}$$

Correlation Analysis

- Given two attributes, measure how strongly one attribute implies the other, based on the available data
- Use correlation measures to estimate how predictive one attribute is of another



Karl Pearson

- Linear correlation
  - We often look for linear relationship between variables not all variables are linearly related, of course!
  - Linear correlation measures are symmetric
  - They can be positive (high values of one attribute are likely given high values of the other)
  - Or negative (high values are predictive of low values of the other variable)
  - Latter usually referred to as anti-correlation

Correlation Analysis

- Given two attributes it measure how strongly one attribute implies the other, based on the available data

- Numerical Variables
  - For two numerical variables, we can compute the correlation coefficient, Pearson's product moment coefficient
- Ordinal Variables
  - We can compute Spearman rank correlation coefficient
- Categorical Variables
  - For two categorical variables, A and B, we can compute $\chi 2$ (chi-square) statistic test which tests the hypothesis that A and B are independent
- Binary Variables
  - Compute Point-biserial correlation

Correlation vs Causation

- Correlation does not imply causation
  - Just because value of one attribute is highly predictive of value of other doesn't mean that forcing the first variable to take on a particular value will cause the second to change
- Causality has a direction, while correlation typically doesn't
  - Correlation between high income and owning a Ferrari
  - Giving a person a Ferrari doesn't affect their income
  - But increasing their income may make them more likely to buy a Ferrari
- Confounding variables can cause attributes to be correlated:
  - High heart rate and sweating are correlated with each other since they tend to both happen during exercise (confounder)
  - Causing somebody to sweat by putting them in sauna won't necessarily raise their heart rate (it does a little, but not as much as exercise)
  - And giving them beta-blockers to lower their heart rate might not prevent sweating (it might a little, but again not like stopping exercising)

Outliers

- What are outliers?
  - Data objects that do not comply with the general behavior or model of the data, that is, values that appear as anomalous
  - Most data mining methods consider outliers noise or exceptions.
- Outliers may be detected using
  - Manual inspection and knowledge of reasonable values.
  - Statistical tests that assume a distribution or probability model for the data
  - Distance measures where objects that are a substantial distance from any other cluster are considered outliers
  - Deviation-based methods identify outliers by examining differences in the main characteristics of objects in a group

How Do We Manage Outliers?

- Outliers are typically filtered out by eliminating the data points containing them
- Trimming
  - Eliminate the outlier data values
- Winsorizing
  - A 10% Winsorizing, consider the 5th and 95th percentiles
  - Set the values below the 5th percentile to the 5th percentile itself
  - Set the values above the 95th percentile to the 95th percentile itself
- Note that, in some applications, outliers are the focus on the analysis. Fraud detection is a typical example of this.

Normalization

Normalization

- When attributes have vastly different scales (e.g., age vs income), it is necessary to normalize them

- Range normalization
  - Converts all values to the range [0,1]

$$x'_i = \frac{x_i - \min_i x_i}{\max_i x_i - \min_i x_i}$$

- Standard Score Normalization
  - Forces variables to have mean of 0 and standard deviation of 1
  - So if data was normally distributed, most of it (68%) will lie in range [-1,+1]

$$x'_i = \frac{x_i - \mu}{\sigma}$$

Visualization

Why visualize data? Anscombe's Quartet

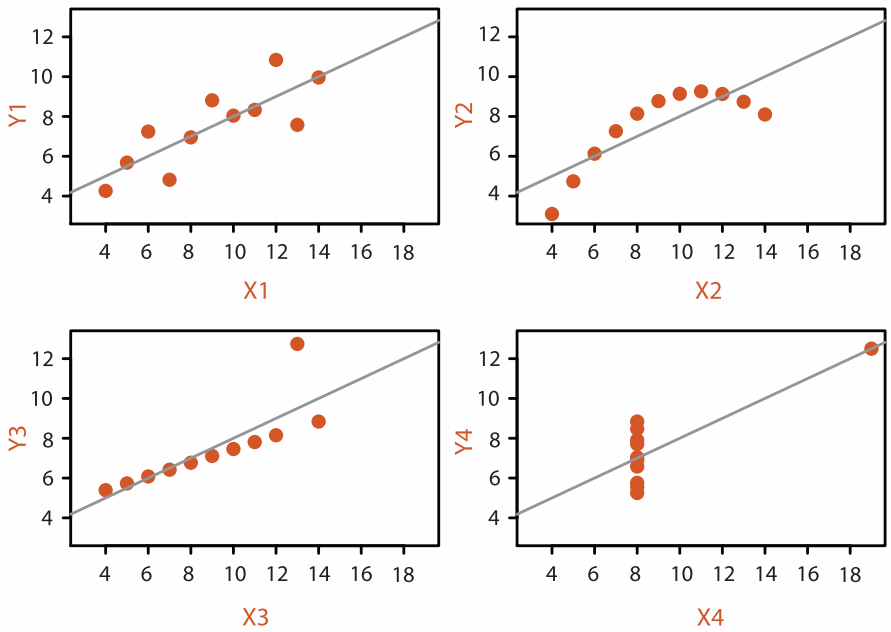
	1		2		3		4	
	X	Y	X	Y	X	Y	X	Y
	10.0	8.04	10.0	9.14	10.0	7.46	8.0	6.58
	8.0	6.95	8.0	8.14	8.0	6.77	8.0	5.76
	13.0	7.58	13.0	8.74	13.0	12.74	8.0	7.71
	9.0	8.81	9.0	8.77	9.0	7.11	8.0	8.84
	11.0	8.33	11.0	9.26	11.0	7.81	8.0	8.47
	14.0	9.96	14.0	8.10	14.0	8.84	8.0	7.04
	6.0	7.24	6.0	6.13	6.0	6.08	8.0	5.25
	4.0	4.26	4.0	3.10	4.0	5.39	19.0	12.50
	12.0	10.84	12.0	9.13	12.0	8.15	8.0	5.56
	7.0	4.82	7.0	7.26	7.0	6.42	8.0	7.91
	5.0	5.68	5.0	4.74	5.0	5.73	8.0	6.89
Mean	9.0	7.5	9.0	7.5	9.0	7.5	9.0	7.5
Variance	10.0	3.75	10.0	3.75	10.0	3.75	10.0	3.75
Correlation	0.816		0.816		0.816		0.816	

https://en.wikipedia.org/wiki/Anscombe%27s_quartet

Why visualize data? Anscombe's Quartet

	1		2		3		4	
	X	Y	X	Y	X	Y	X	Y
	10.0	8.04	10.0	9.14	10.0	7.46	8.0	6.58
	8.0	6.95	8.0	8.14	8.0	6.77	8.0	5.76
	13.0	7.58	13.0	8.74	13.0	12.74	8.0	7.71
	9.0	8.81	9.0	8.77	9.0	7.11	8.0	8.84
	11.0	8.33	11.0	9.26	11.0	7.81	8.0	8.47
	14.0	9.96	14.0	8.10	14.0	8.84	8.0	7.04
	6.0	7.24	6.0	6.13	6.0	6.08	8.0	5.25
	4.0	4.26	4.0	3.10	4.0	5.39	19.0	12.50
	12.0	10.84	12.0	9.13	12.0	8.15	8.0	5.56
	7.0	4.82	7.0	7.26	7.0	6.42	8.0	7.91
	5.0	5.68	5.0	4.74	5.0	5.73	8.0	6.89
Mean	9.0	7.5	9.0	7.5	9.0	7.5	9.0	7.5
Variance	10.0	3.75	10.0	3.75	10.0	3.75	10.0	3.75
Correlation	0.816		0.816		0.816		0.816	

https://en.wikipedia.org/wiki/Anscombe%27s_quartet



Visualization

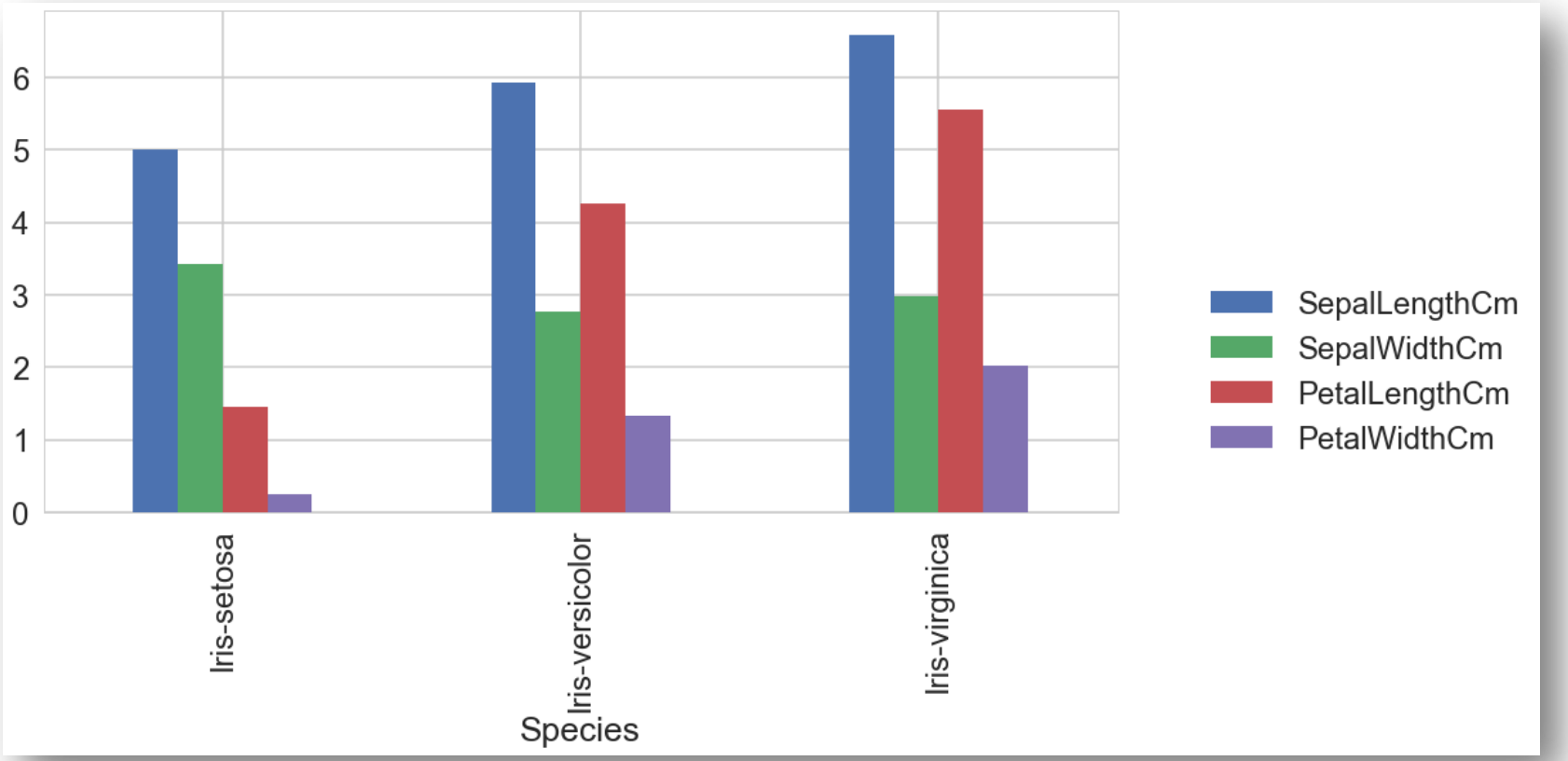
- Visualization is the conversion of data into a visual or tabular format so that the characteristics of the data and the relationships among data items or attributes can be analyzed or reported

- Data visualization is one of the most powerful and appealing techniques for data exploration
  - Humans have a well-developed ability to analyze large amounts of information that is presented visually
  - Can detect general patterns and trends
  - Can detect outliers and unusual patterns

Bar Plots

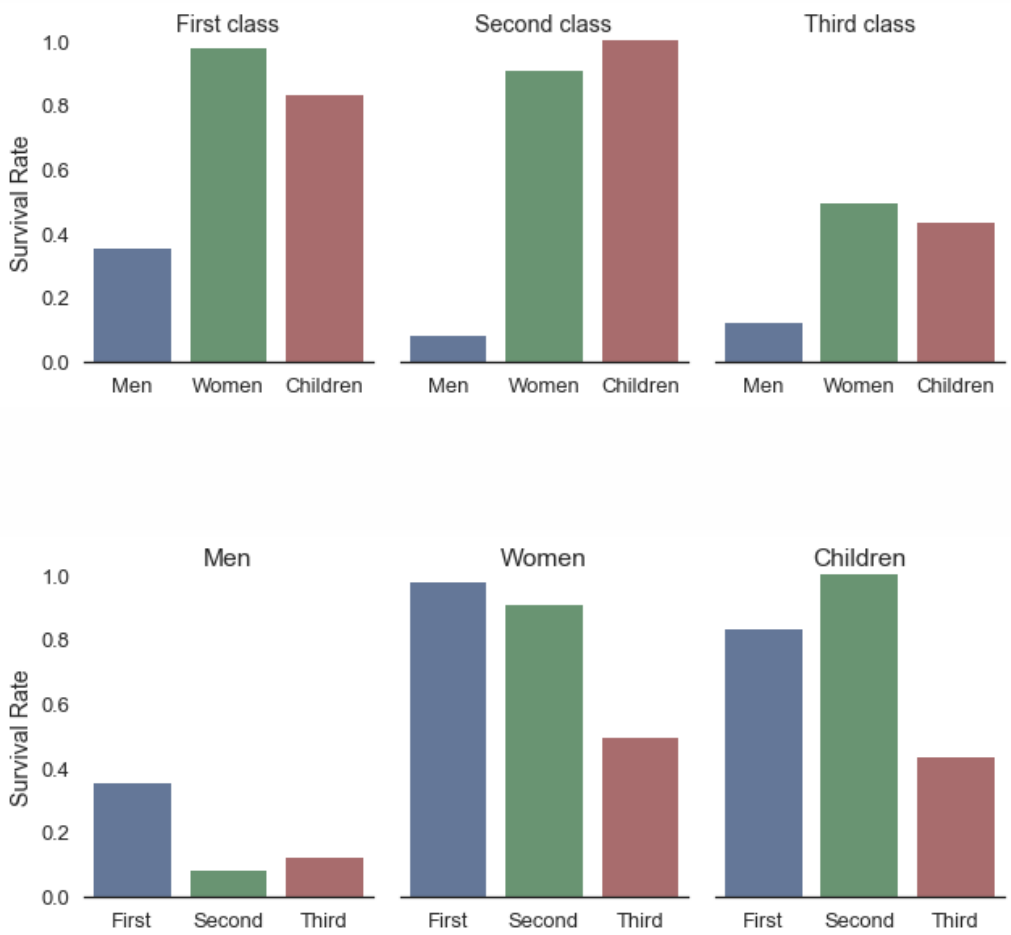
Bar Plots

- They use horizontal or vertical bars to compare categories.
- One axis shows the compared categories, the other axis represents a discrete value
- Some bar graphs present bars clustered in groups of more than one (grouped bar graphs), and others show the bars divided into subparts to show cumulate effect (stacked bar graphs)



Bar plot example

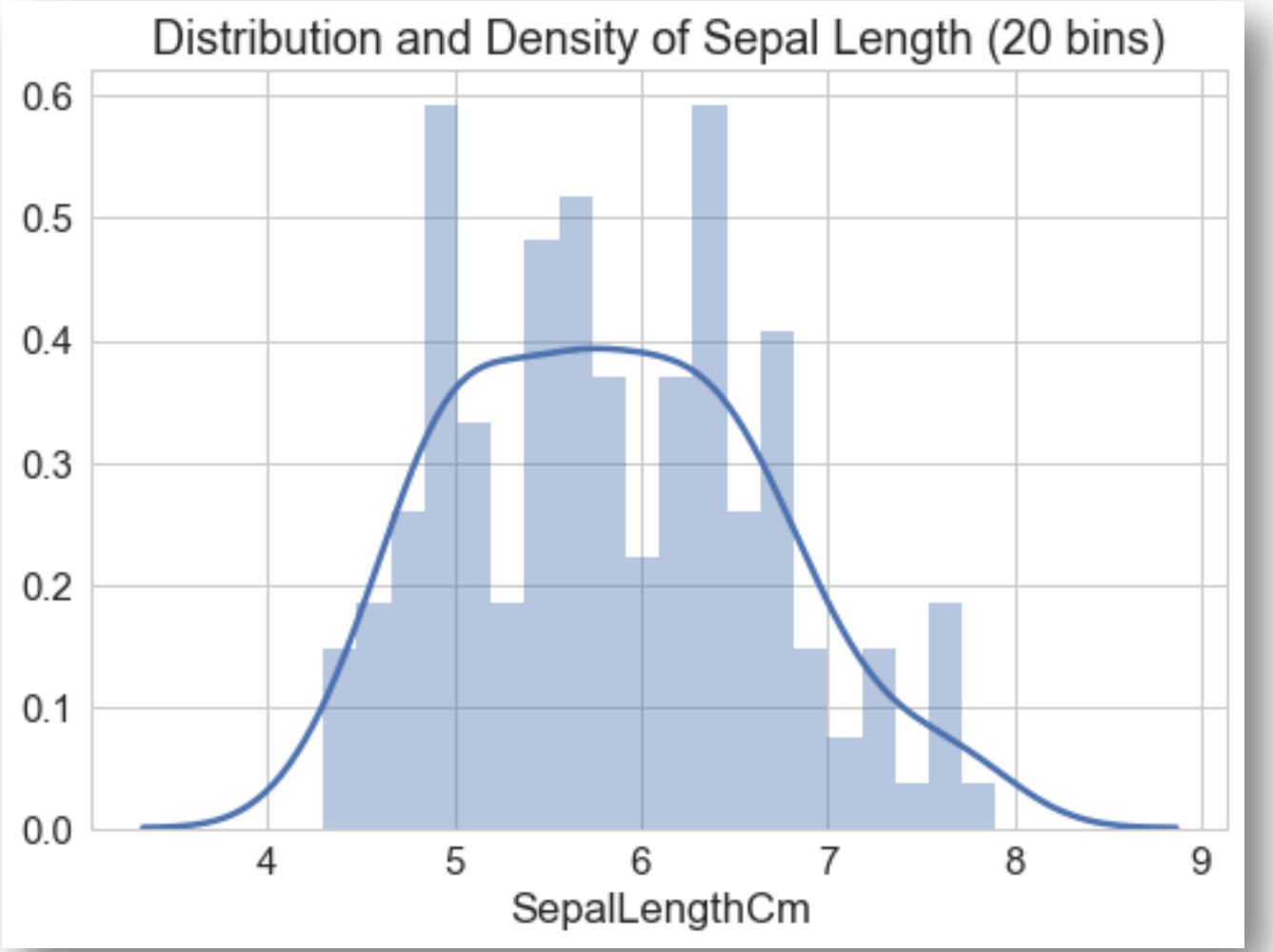
Perspective can change dramatically

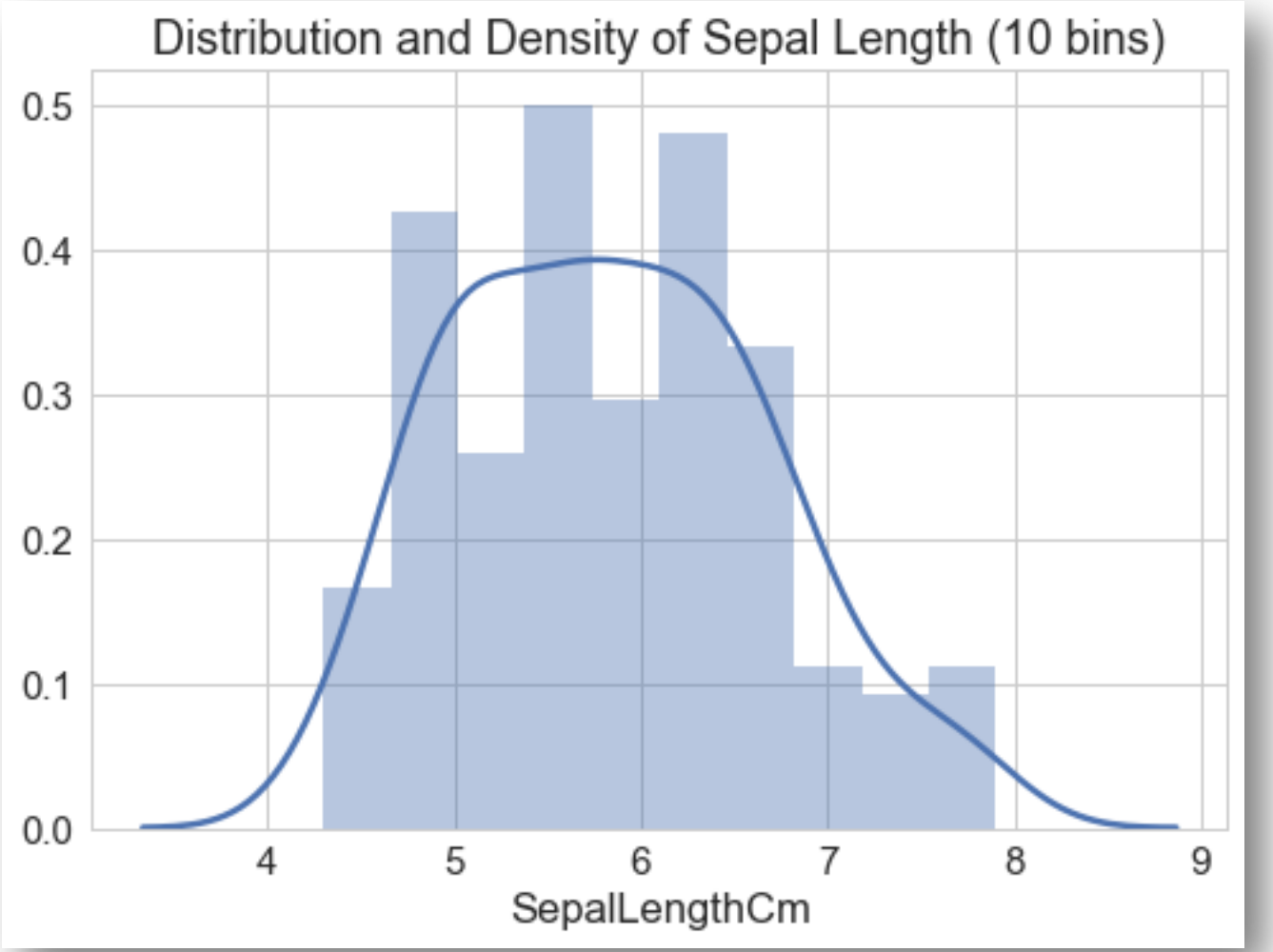


Histograms

Histograms

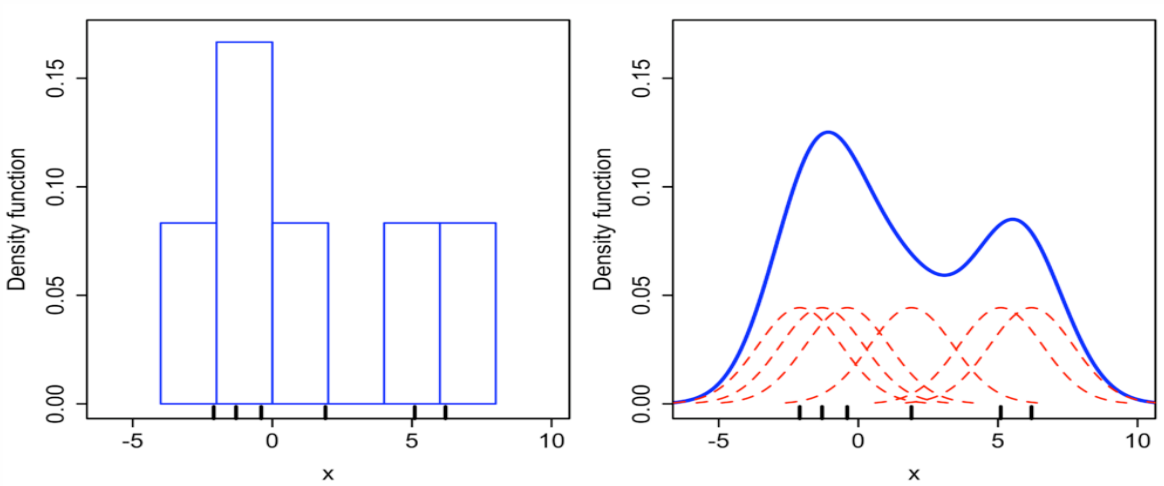
- They are a graphical representation of the distribution of data introduced by Karl Pearson in 1895
- They estimate the probability distribution of a continuous variables
- They are representations of tabulated frequencies depicted as adjacent rectangles, erected over discrete intervals (bins). Their areas are proportional to the frequency of the observations in the interval.
- The height of each bar indicates the number of objects
- Shape of histogram depends on the number of bins


Distribution and Density of Sepal Length (20 bins)
0.6
0.5
0.4
0.3
0.2
0.1
0.0
4
5
6
7
8
9
SepalLengthCm


Distribution and Density of Sepal Length (10 bins)
0.5
0.4
0.3
0.2
0.1
0.0
4
5
6
7
8
9
SepalLengthCm

Kernel Density Estimates

- What were the lines on the previous plots?
- Smoothed line calculated using kernel-density estimation



https://commons.wikimedia.org/wiki/File:Comparison_of_1D_histogram_and_KDE.png

- Place small kernel function (e.g. density function of Gaussian distribution) at each observed datapoint
- Curve is simply the summation over the individual

$$\widehat{f}_h(x) = \frac{1}{n}\sum_{i=1}^{n} K_h(x - x_i) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right) \qquad K(u) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}u^2}$$

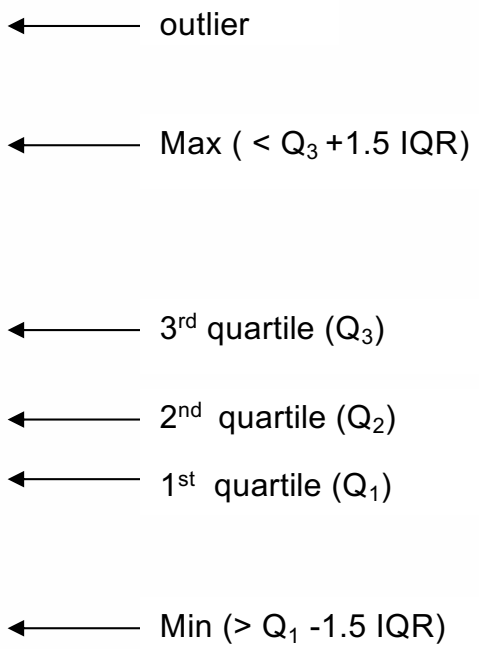
Bandwidth of Kernel Density Estimates

- The bandwidth h of the kernel determines how smooth the estimate is
- Large h generates a smooth function with a possible loss of information
- Small h generates a bumpy function with possible overfitting
- Bandwidth can be determined by cross-validation (hold out some data and estimate the probability)

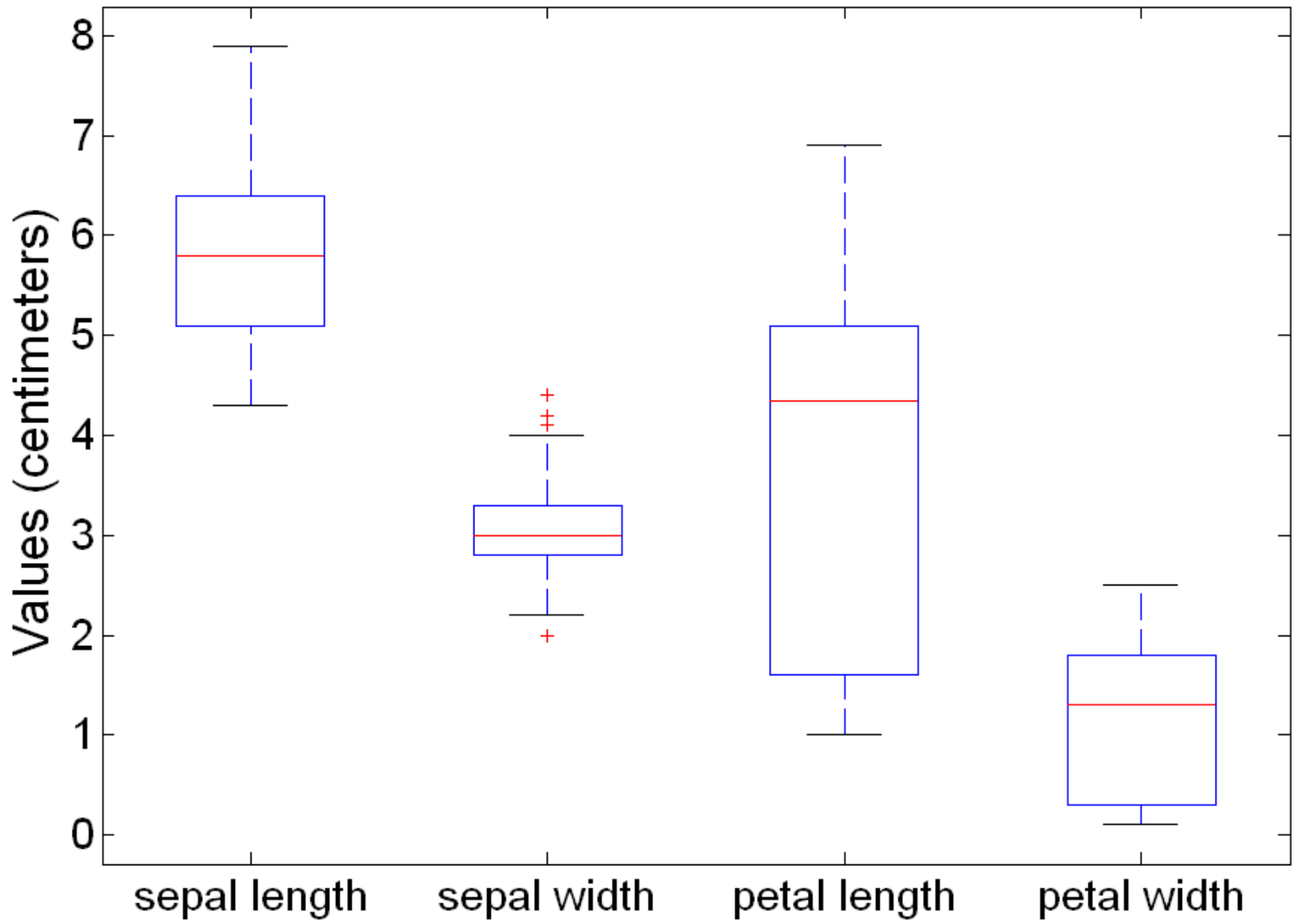
Box Plots

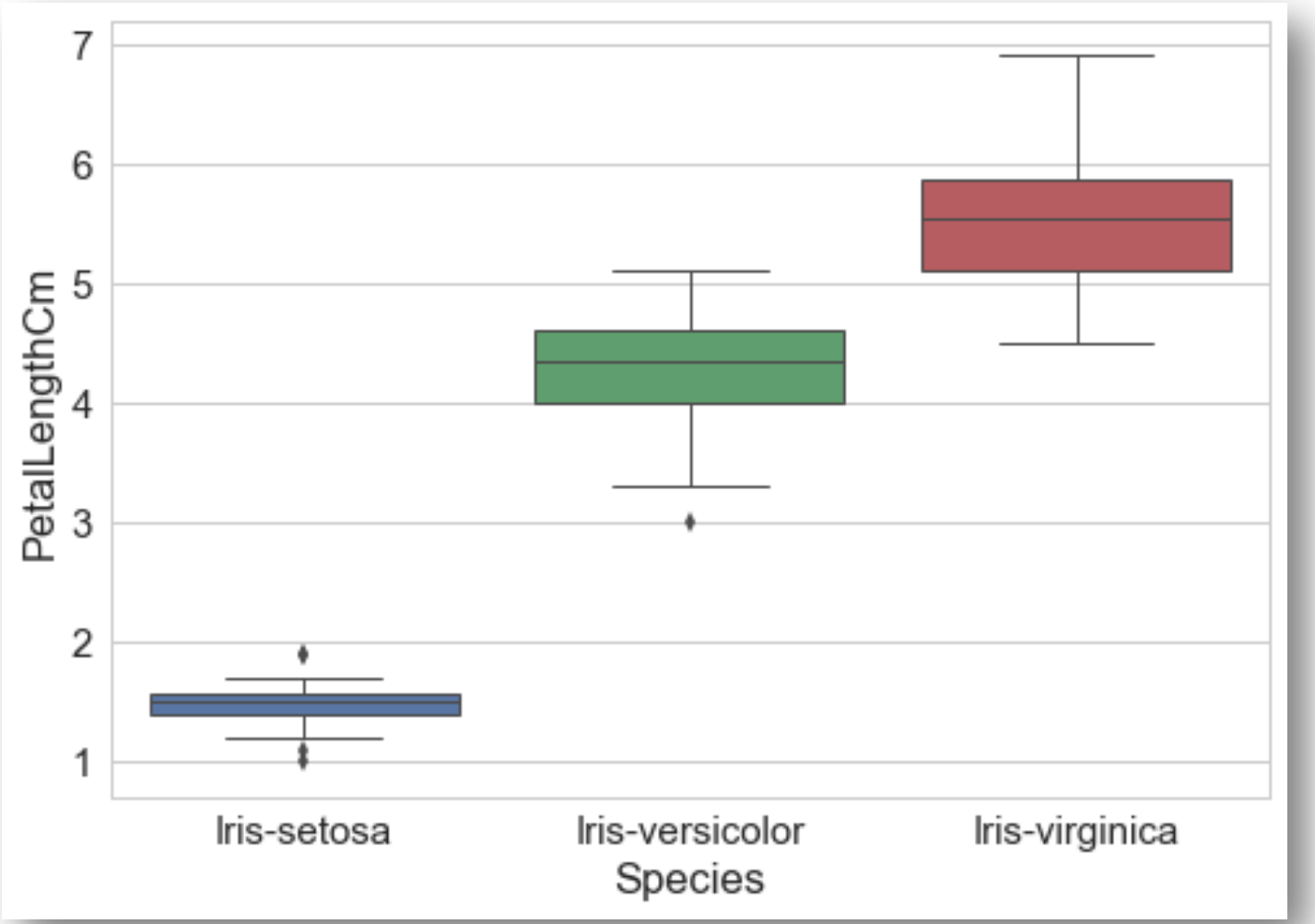
Box Plots

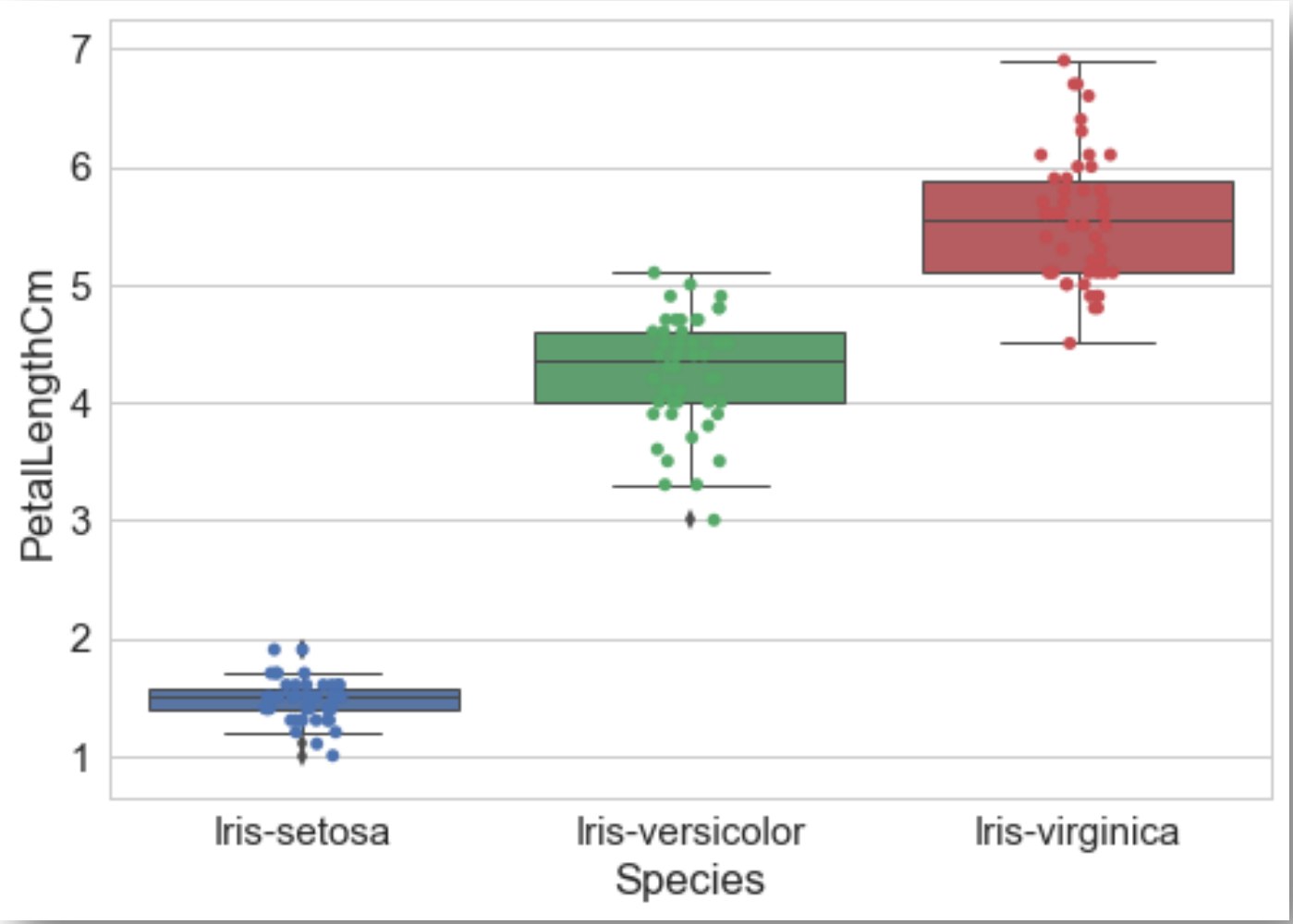
- Box Plots (invented by Tukey)
- Another way of displaying the distribution of data
- Following figure shows the basic part of a box plot
- IQR is the interquartile range or Q3-Q1



Box Plot Example




7
6
5
4
3
2
1
PetalLengthCm
Iris-setosa
Iris-versicolor
Iris-virginica
Species


7
6
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3
2
1
PetalLengthCm
Iris-setosa
Iris-versicolor
Iris-virginica
Species

Violin Plots

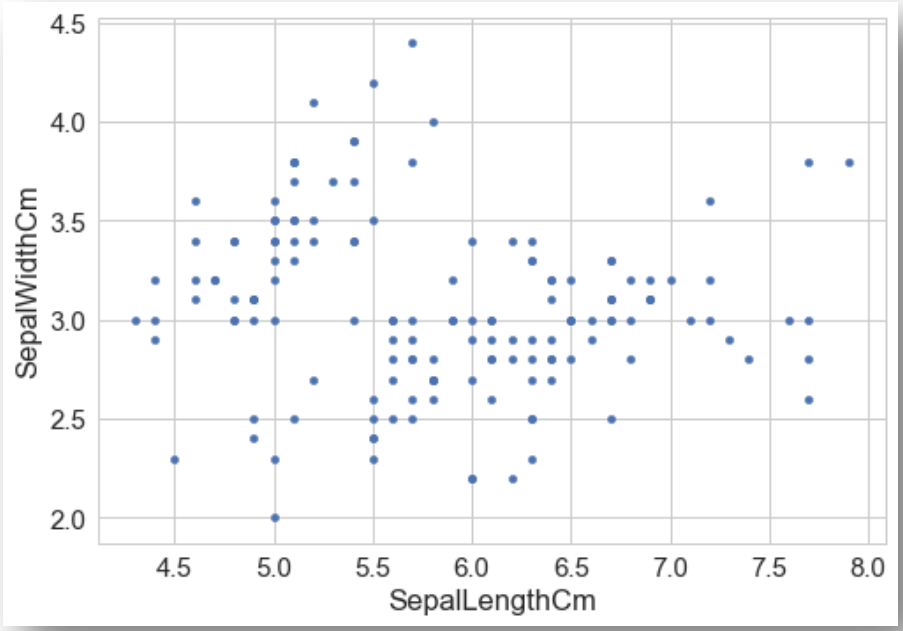
- Uses the kernel density estimate (smoothed histogram) instead of just a box at quartiles

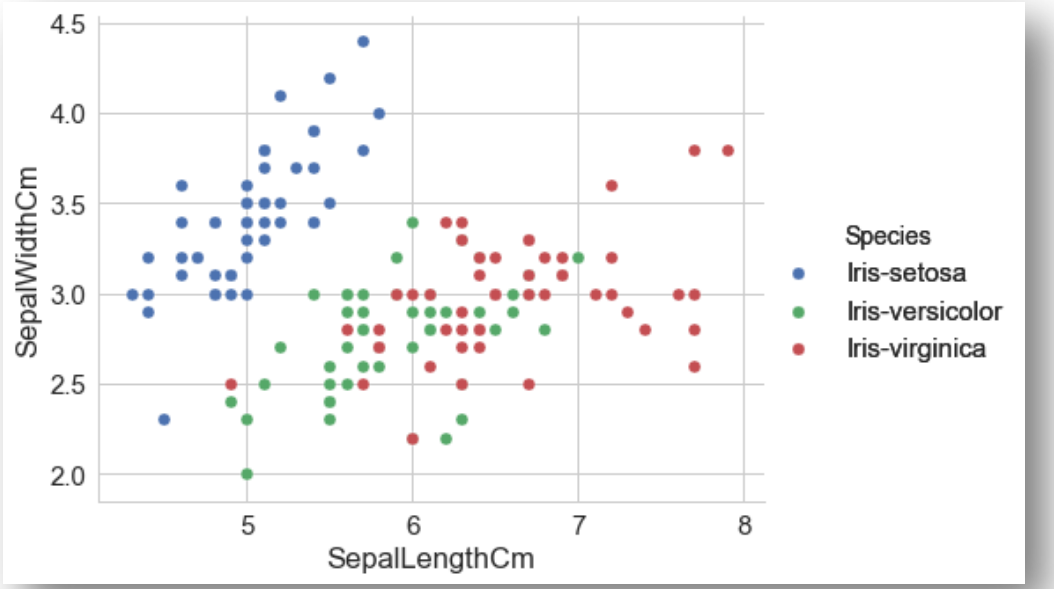
Source: http://www.sthda.com/english/wiki/ggplot2-violin-plot-quick-start-guide-r-software-and-data-visualization

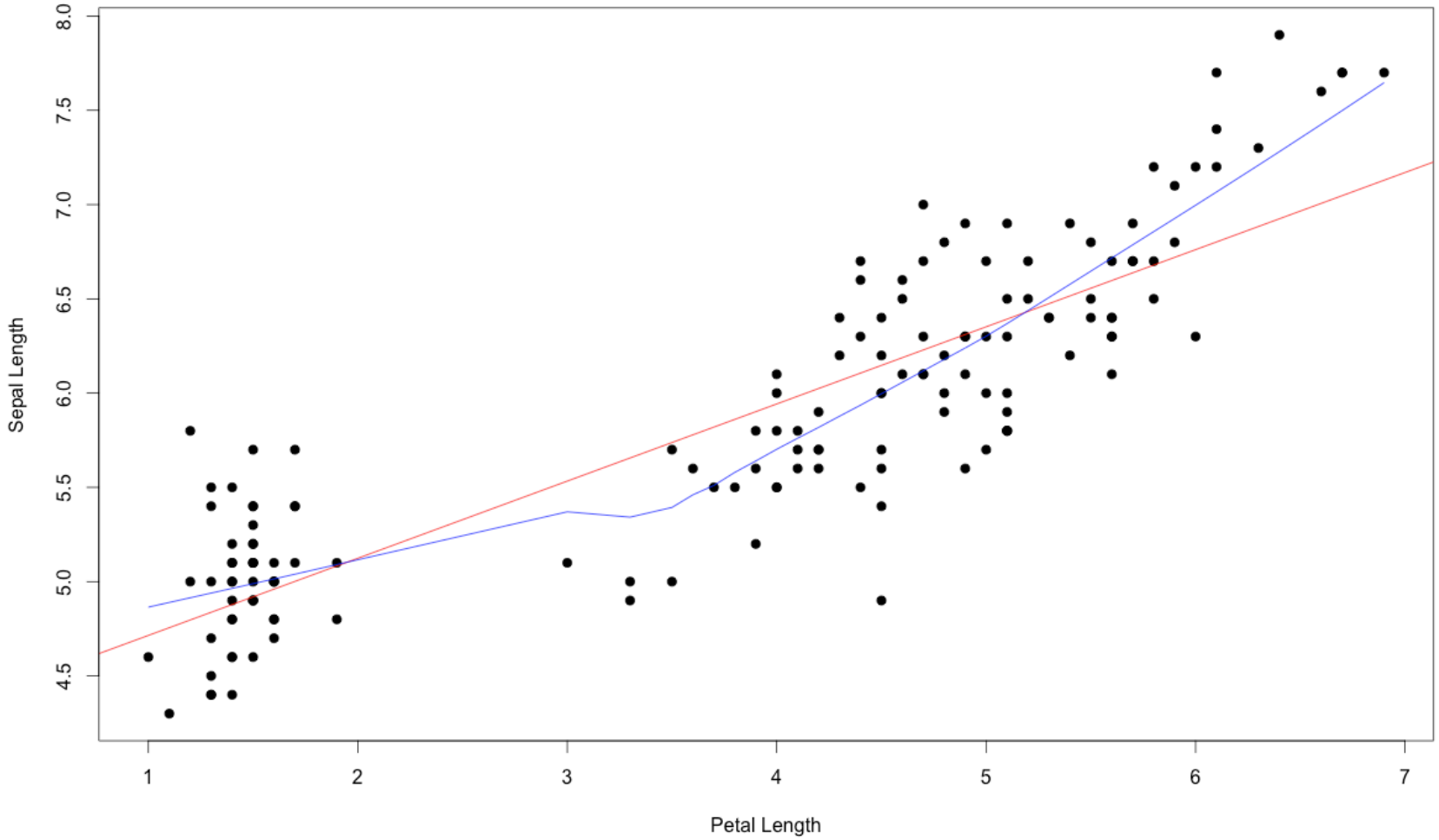
Scatter Plots

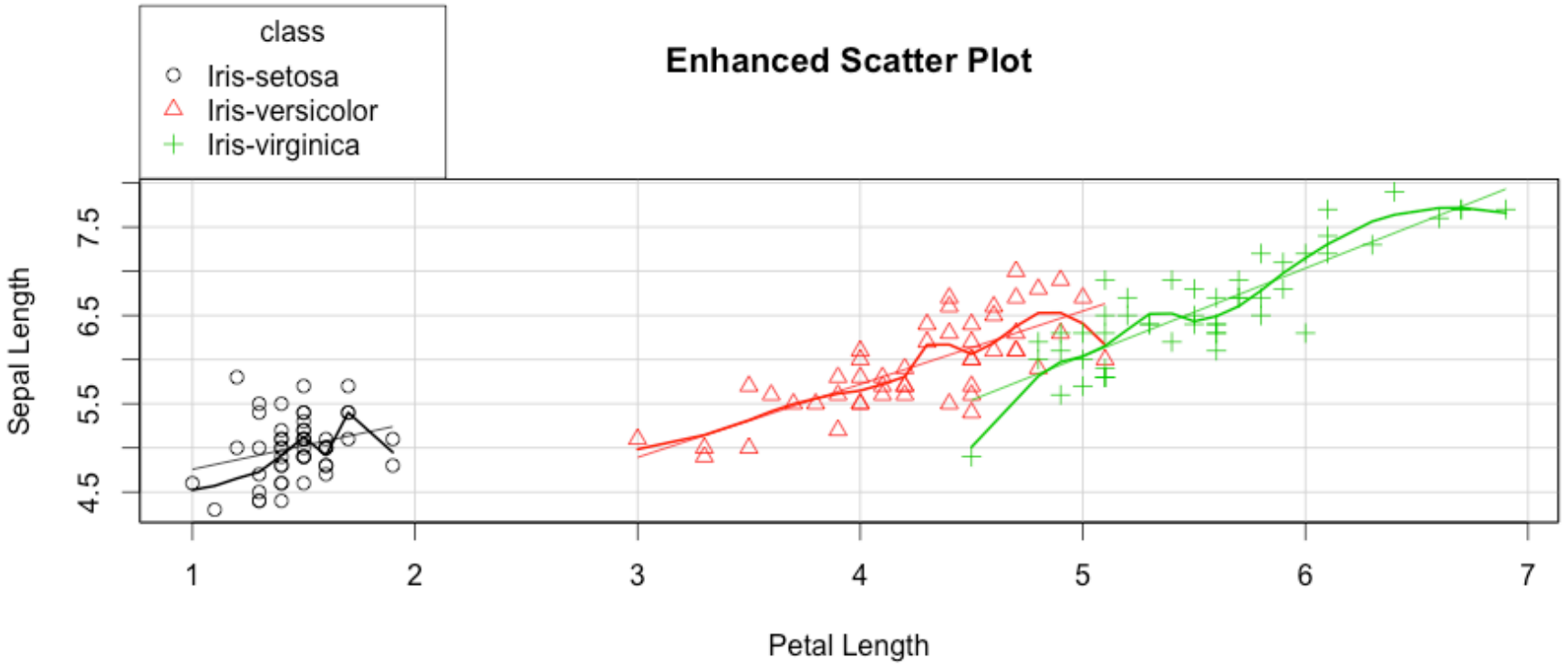
Scatter Plots

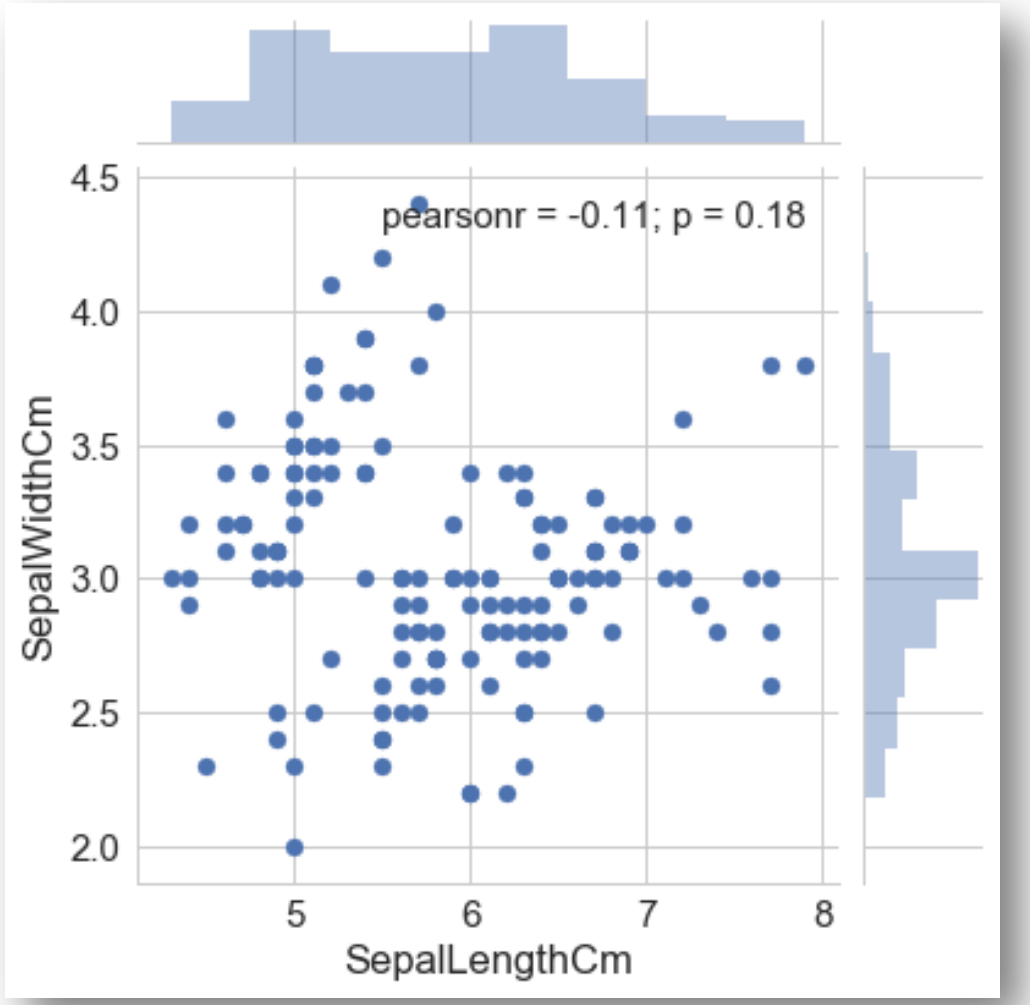
- Used to compare two (or more) attributes
  - Attributes values used to determine the position of the point
  - Two-dimensional scatter plots most common, but three-dimensional plots also used
- Often additional attributes can be displayed by using the size, shape, and color of the markers that represent the objects
- It is useful to have arrays of scatter plots can compactly summarize the relationships of several pairs of attributes
- Examples: http://www.statmethods.net/graphs/scatterplot.html

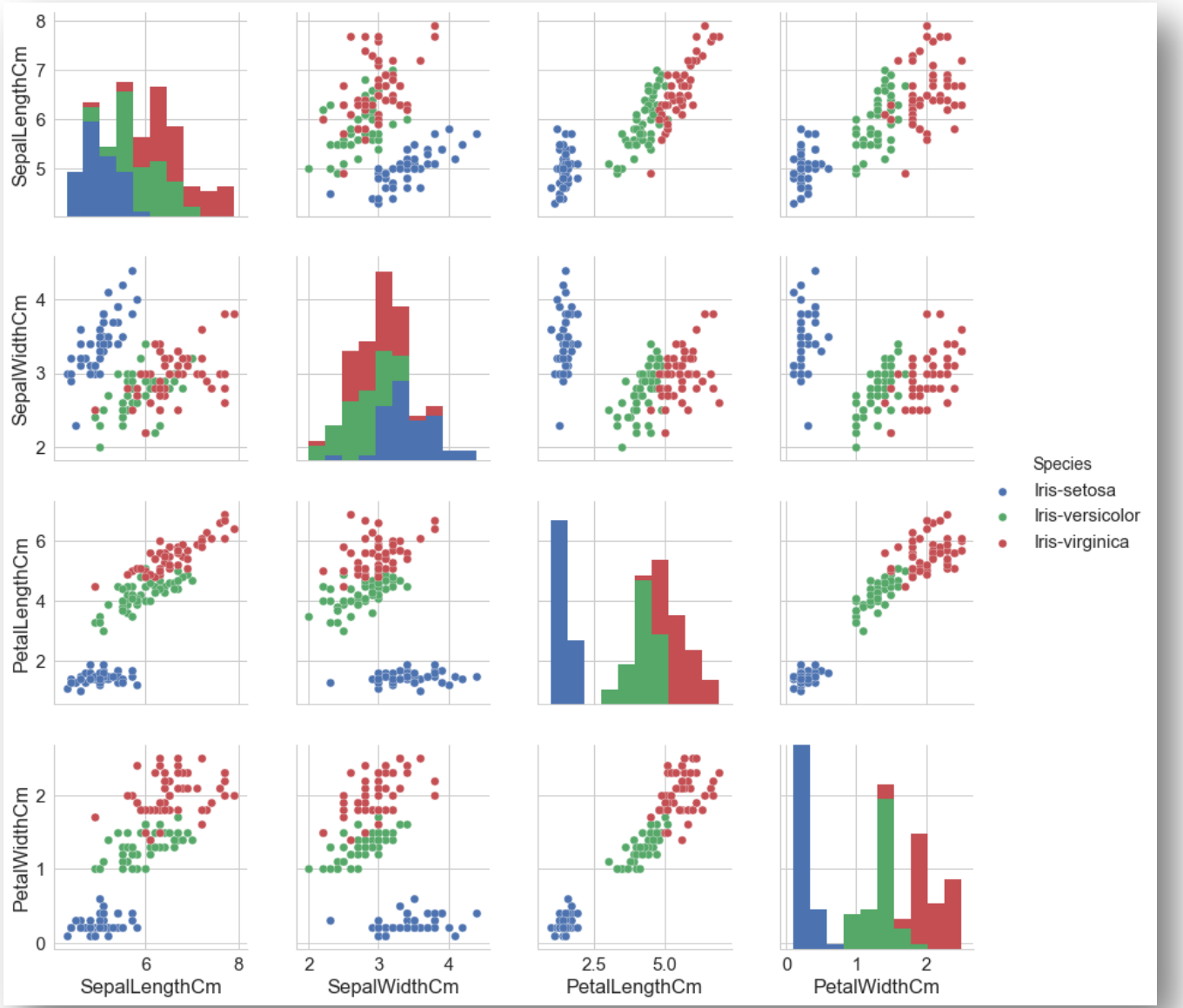

SepalWidthCm
SepalLengthCm
4.5
4.0
3.5
3.0
2.5
2.0
4.5
5.0
5.5
6.0
6.5
7.0
7.5
8.0

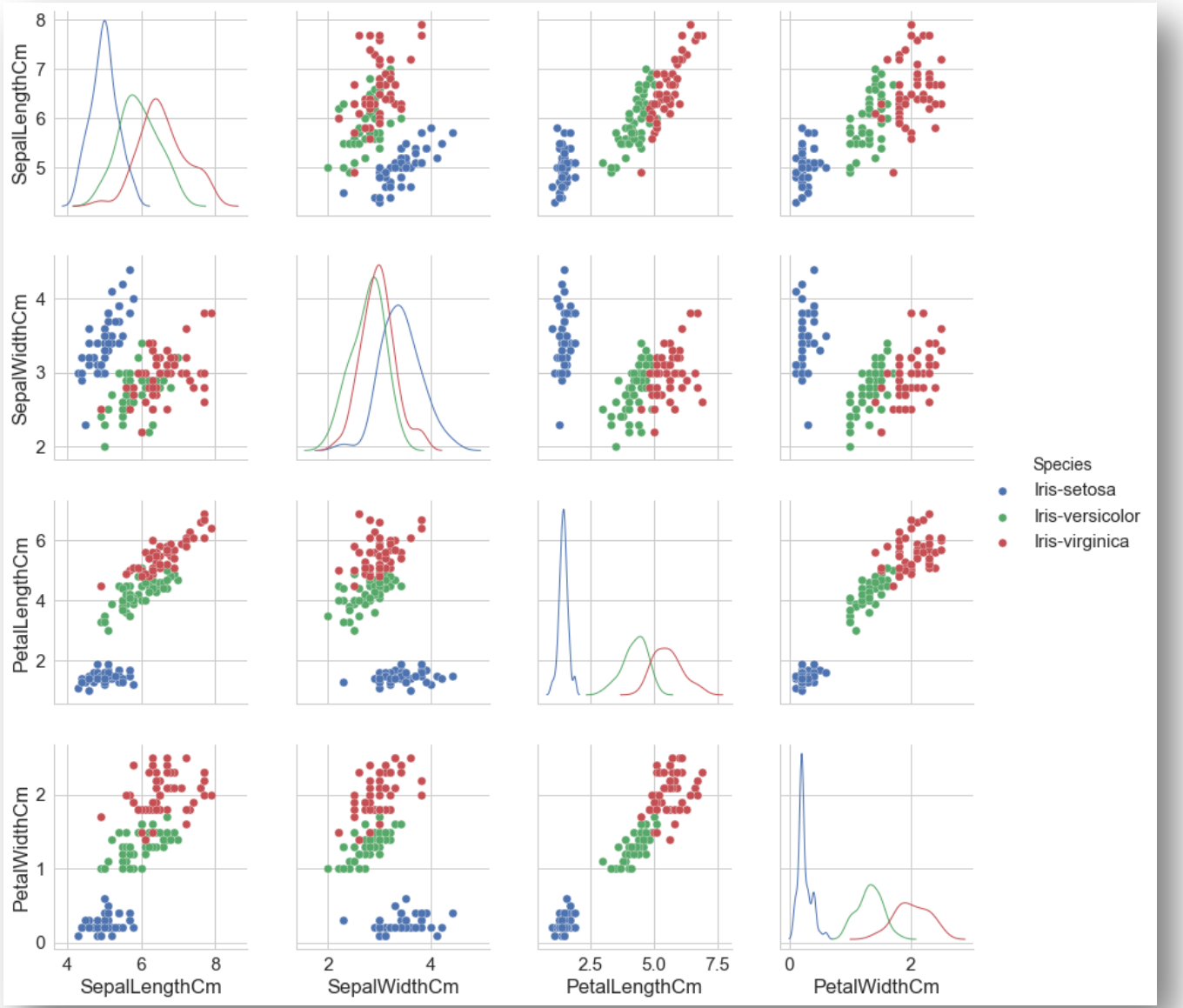

SepalWidthCm
SepalLengthCm
4.5
4.0
3.5
3.0
2.5
2.0
5
6
7
8
Species
Iris-setosa
Iris-versicolor
Iris-virginica


Sepal Length
8.0
7.5
7.0
6.5
6.0
5.5
5.0
4.5
1
2
3
4
5
6
7
Petal Length


class
Iris-setosa
Iris-versicolor
Iris-virginica
Enhanced Scatter Plot
Sepal Length
4.5
5.5
6.5
7.5
1
2
3
4
5
6
7
Petal Length

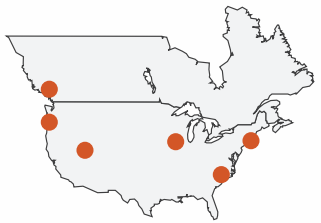

pearsonr = -0.11; p = 0.18
SepalWidthCm
SepalLengthCm
4.5
4.0
3.5
3.0
2.5
2.0
5
6
7
8

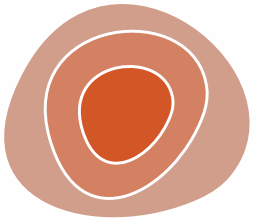

SepalLengthCm
SepalWidthCm
PetalLengthCm
PetalWidthCm
Species
Iris-setosa
Iris-versicolor
Iris-virginica

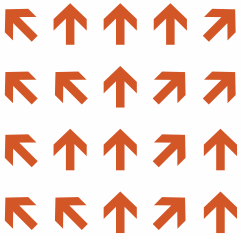

SepalLengthCm
SepalWidthCm
PetalLengthCm
PetalWidthCm
Species
Iris-setosa
Iris-versicolor
Iris-virginica

Visualizing Spatial Data

- Geometry
  - Geographic
  - Others
- Scalar fields (one value per cell)
  - Isocontours
  - Direct volume rendering
- Vector and tensor fields (many values per cell)
  - Flow glyphs
  - Geometric (sparse seeds)
  - Textures (dense seeds)
  - Features (globally derived)



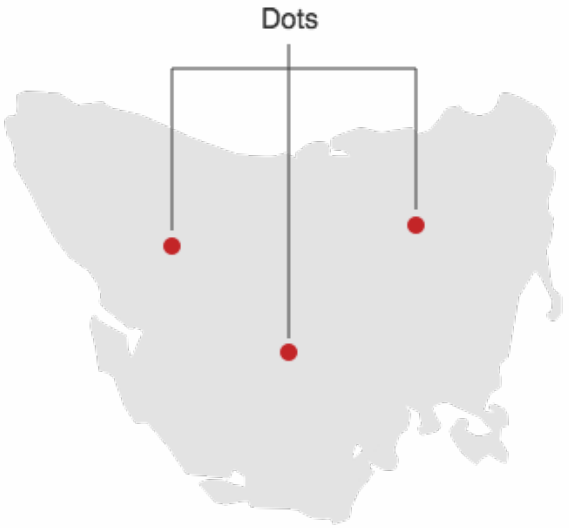


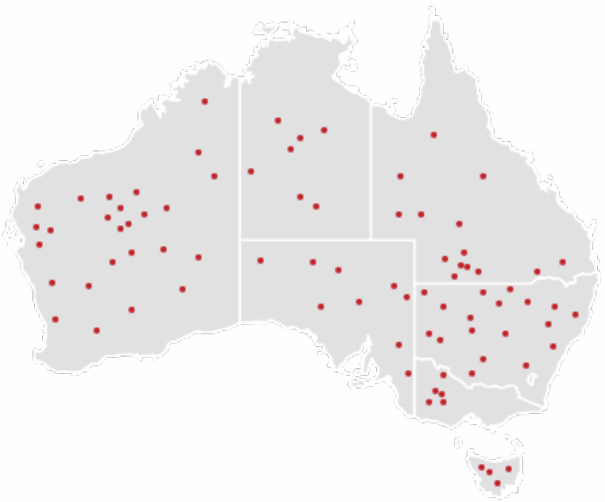


Geometry

Dot Maps

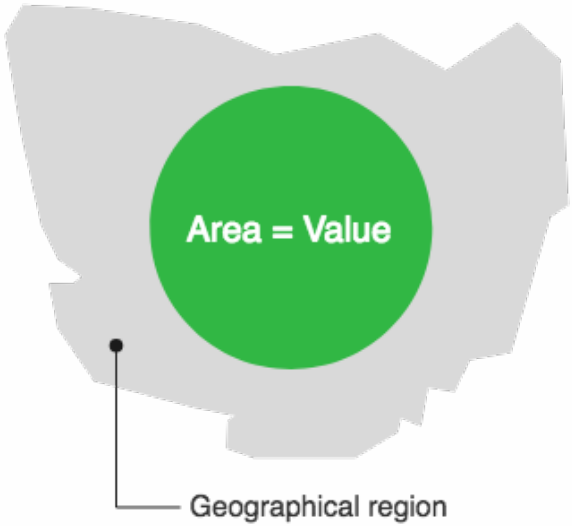
- What?
  - Geometry (position)
- Why?
  - Locate data in space
- Remarks
  - Scale up to hundreds of items
  - Color/shape can encode an additional categorical attribute (reduce scalability)

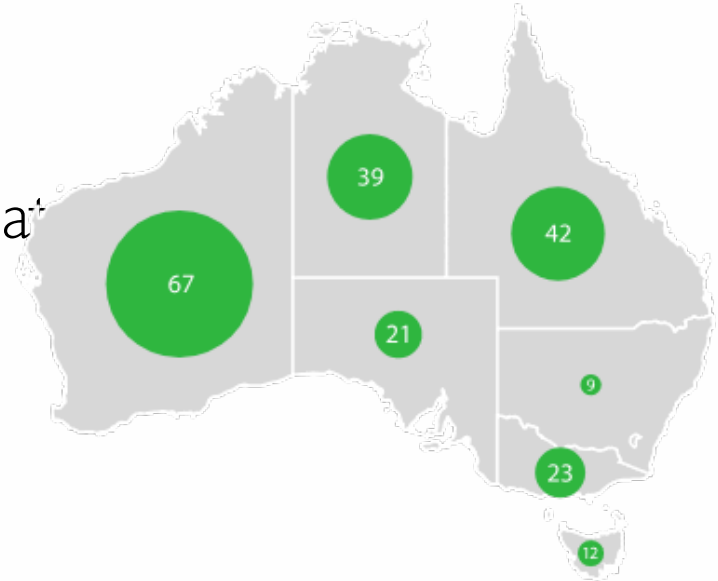




Bubble Maps

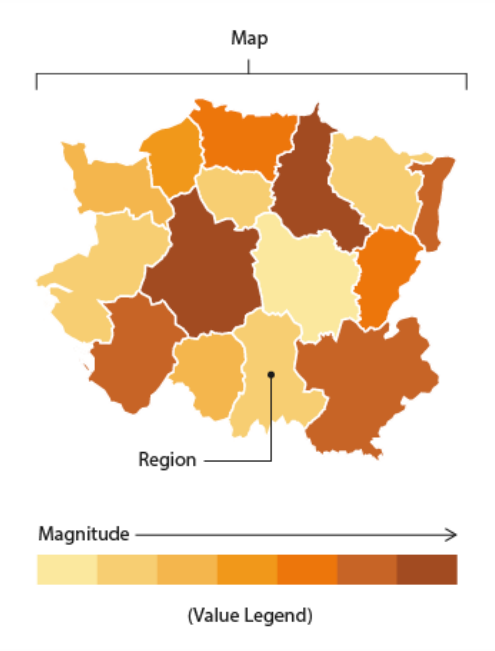
- What?
  - Geometry (position)
  - One quantitative attribute
- Why?
  - Locate data in space
  - Lookup and compare
- Remarks
  - Scale up to hundreds of items
  - Color can encode an additional ca
    (interaction with size).

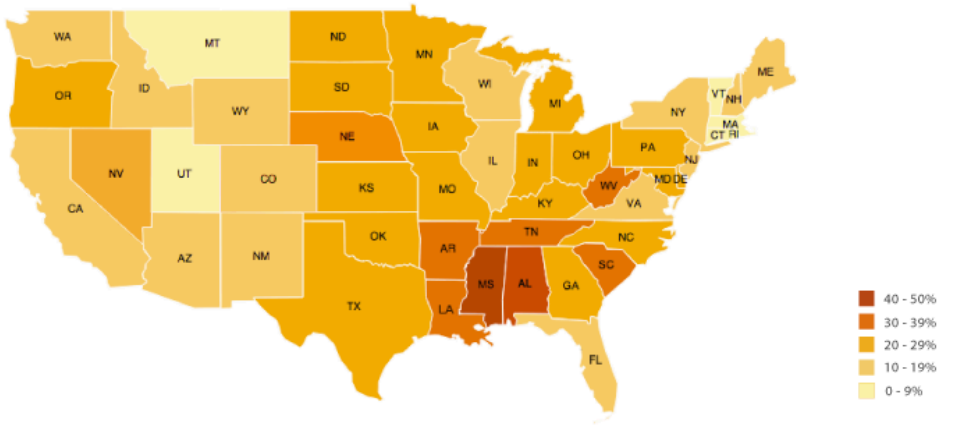




Choropleth Map

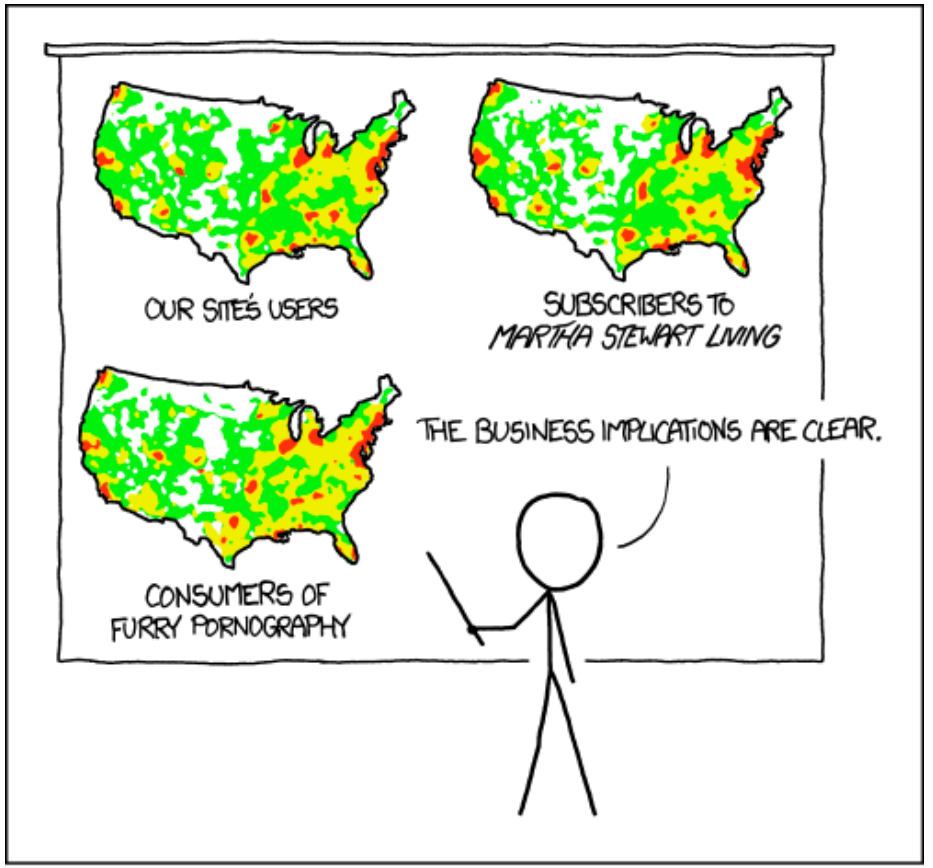
- What?
  - Geometry (position)
  - One quantitative attribute
- Why?
  - Locate data in space
  - Lookup and compare
- Remarks
  - Scale up to ~1000 items
  - Hue can encode an additional categorical attribute (better if binary





Bias of Population-related Maps

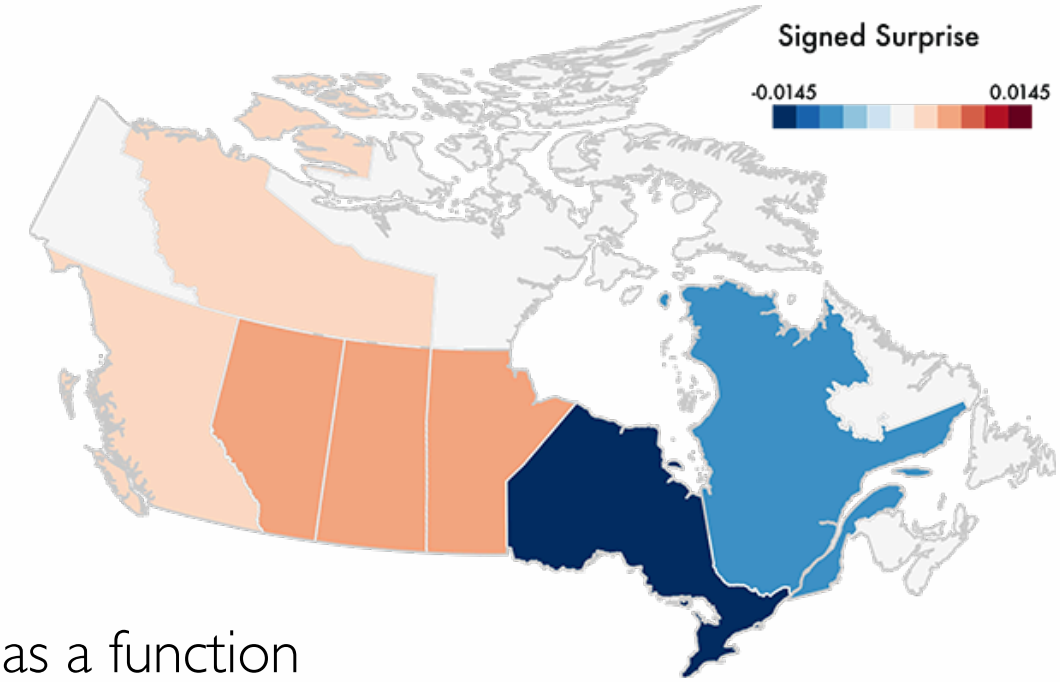
- Using absolute values is dangerous!
- Any map would show population distributionS
- How to deal with this?
  - Visualize per capita (relative)
  - Use statistical models
- See the example at https://xkcd.com/1138



PET PEEVE #208:
GEOGRAPHIC PROFILE MAPS WHICH ARE BASICALLY JUST POPULATION MAPS

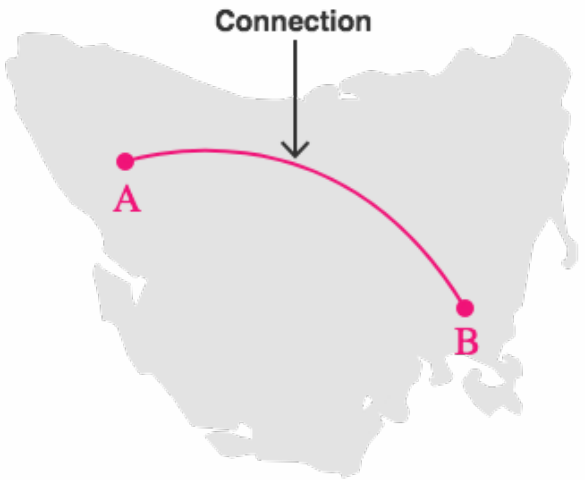
Surprise Maps

- What?
  - Geometry (position)
  - One quantitative attribute
  - One derivative attribute
- Why?
  - Locate data in space
  - Lookup and compare
- Remarks
  - The surprise is computed as a function prior and posterior probability of data distribution.
  - Prior probability is generated with a family of standard models.
- Illustration from https://medium.com/@uwdata/surprise-maps-showing-the-unexpected-e92b67398865



Connection Maps

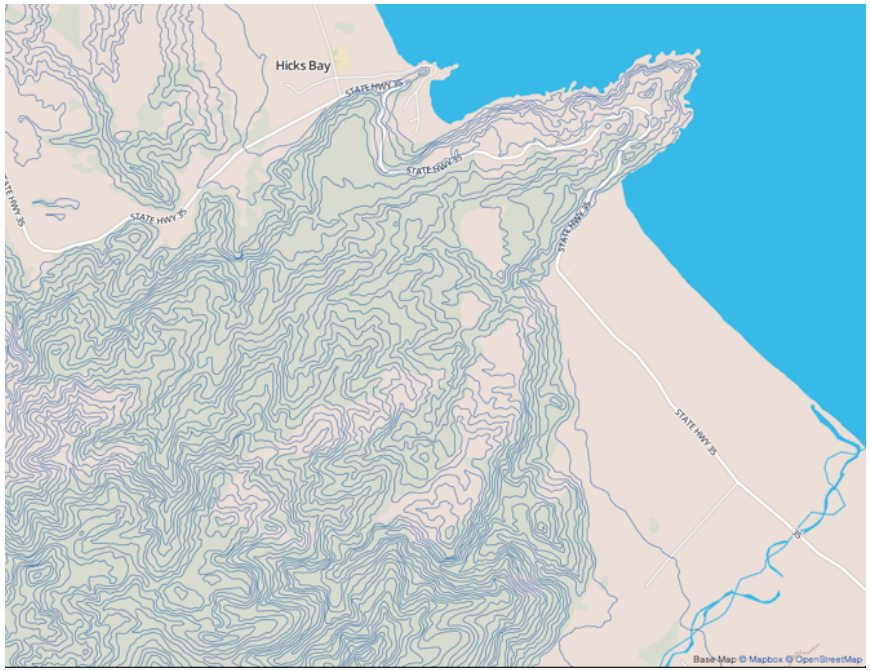
- What?
  - Network and positions
- Why?
  - Lookup path
  - Identify patterns
- Remarks
  - Size of links can encode an additional ordered attribute (3-4 bins at max)



Scalar Fields

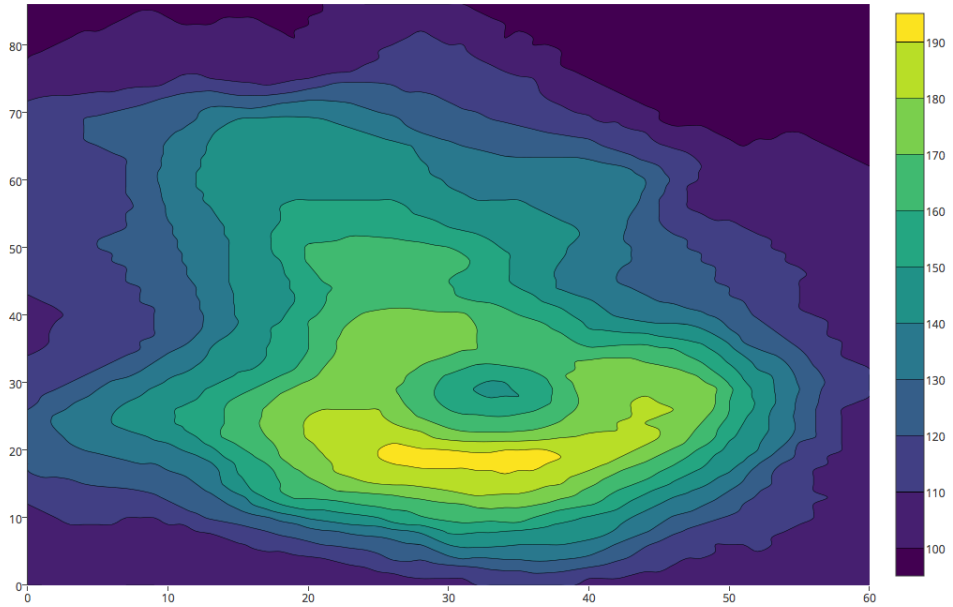
Isocontour Maps

- What?
  - Geographic data
  - One quantitative attribute
  - Derived positions
- Why?
  - Shape
- Remarks
  - The lines are computed from the values of scalar field
  - Area can be filled and color encoded



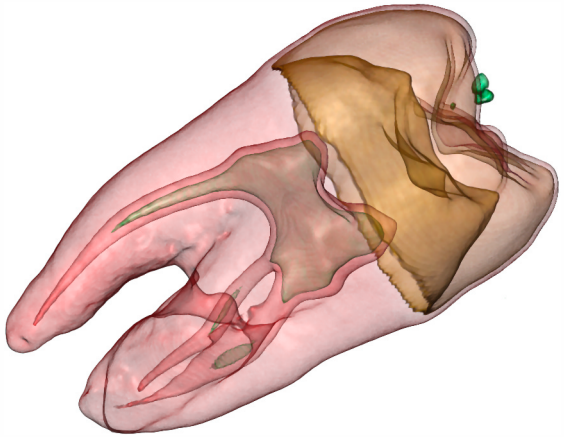
Isocontour Plots

- What?
  - 2D spatial field
  - One quantitative attribute
  - Derived geometry
- Why?
  - Shape and patterns
- Remarks
  - The lines are computed from the values of scalar field
  - Area can be empty or filled and color encoded



Isosurface Plots

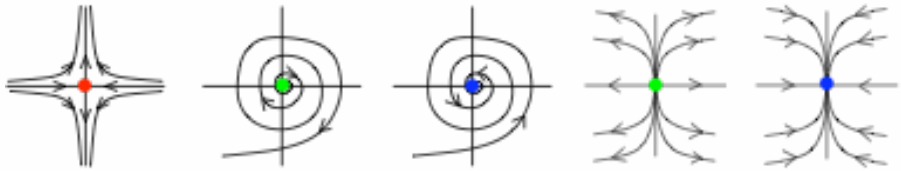
- What?
  - 3D spatial scalar field
  - 1 quantitative attribute
  - derived geometry
- Why?
  - Shape
- Remarks
  - Tree of isosurfaces: positions computed for specific values of the scalar field

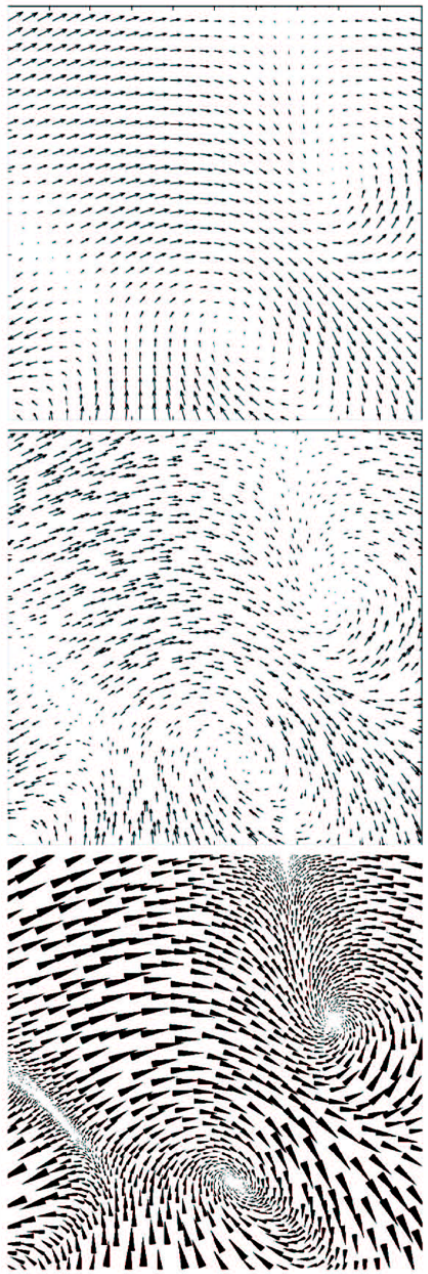


Vector Field

Glyph Flow

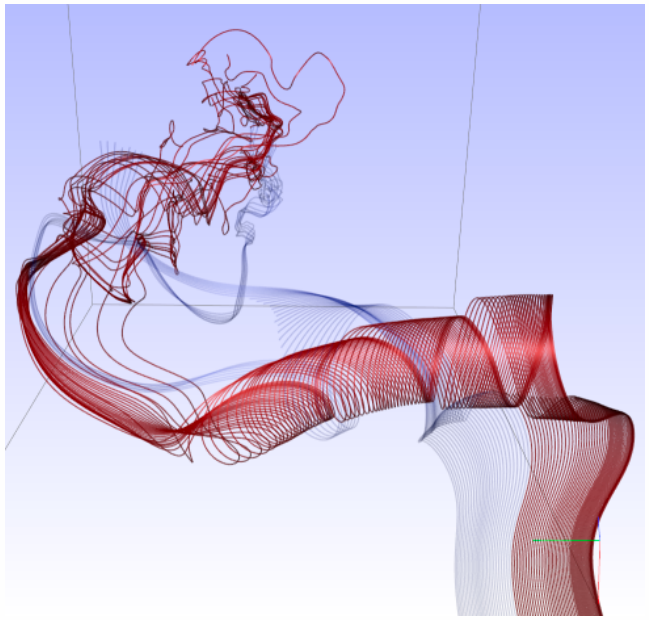
- What?
  - 2D vector fields
- Why?
  - Shape and patterns
  - Identify critical points
- Remarks
  - Different glyphs can be used to represent vectors
  - Density of grid and jittering





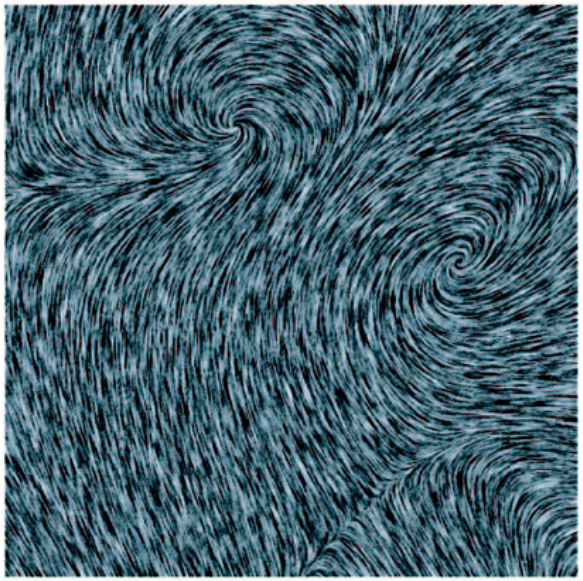
Geometric Flow

- What?
  - 2D/3D vector field
  - Derived geometry
- Why?
  - Shape and patterns
  - Identify critical points
- Remarks
  - Seeding strategy affects the outcome
  - Usage of clustering and color coding improves readability



Texture Flow

- What?
  - 2D vector field
- Why?
  - Shape and patterns
  - Identify critical points
- Remarks
  - Similar to glyphs flow,
    but computes the flow of
    a continuous distribution of particles



Feature flow: anatomy

- What?
  - 2D vector fields
- Why?
  - Shape and patterns
  - Identify critical points
- Remarks
  - Similar to glyphs flow
  - But seeding is based on global computing strategy to identify areas with similar behaviors

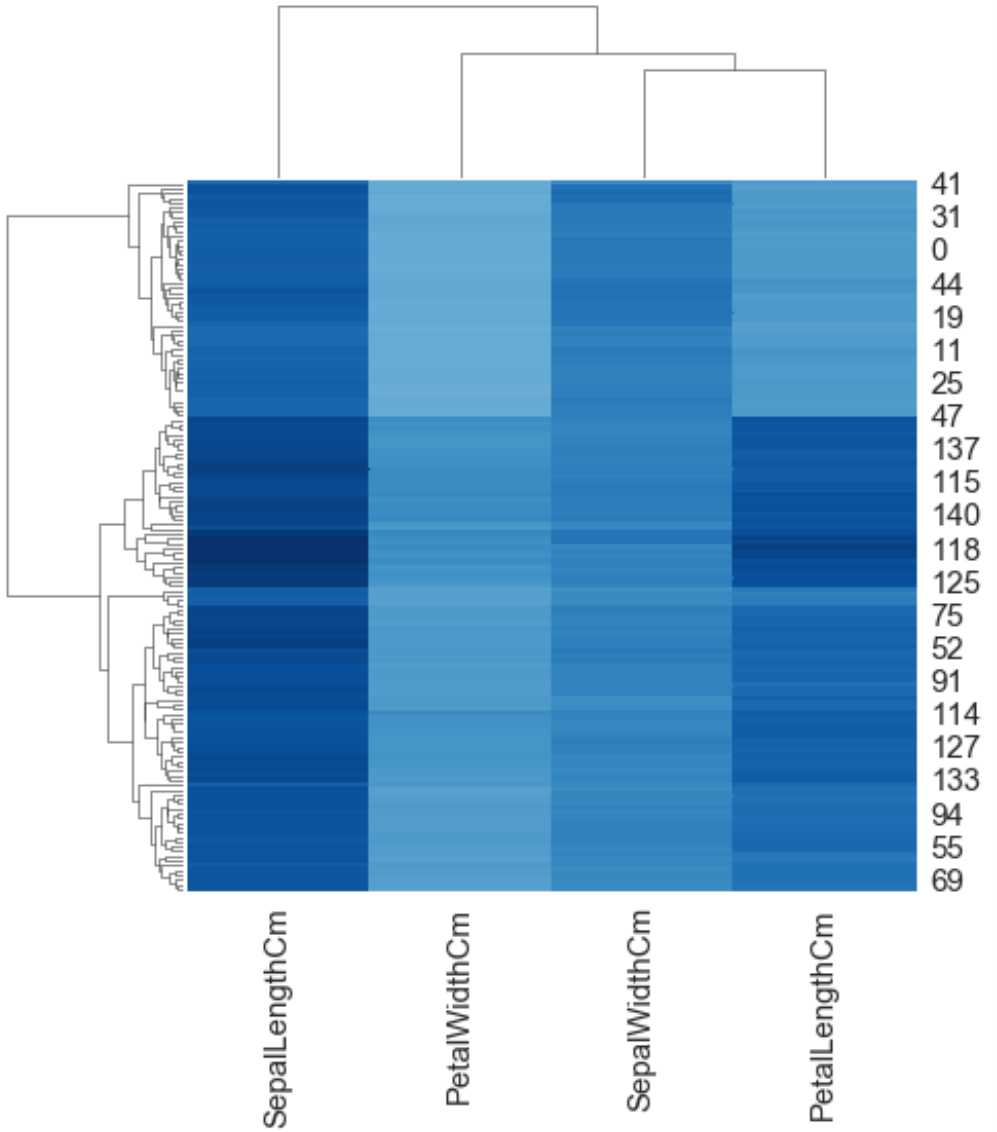
More than Two Dimensions at Once

Two main approaches

Visualize all the dimensions at once
(e.g., heatmaps, spider plots, and Chernoff)

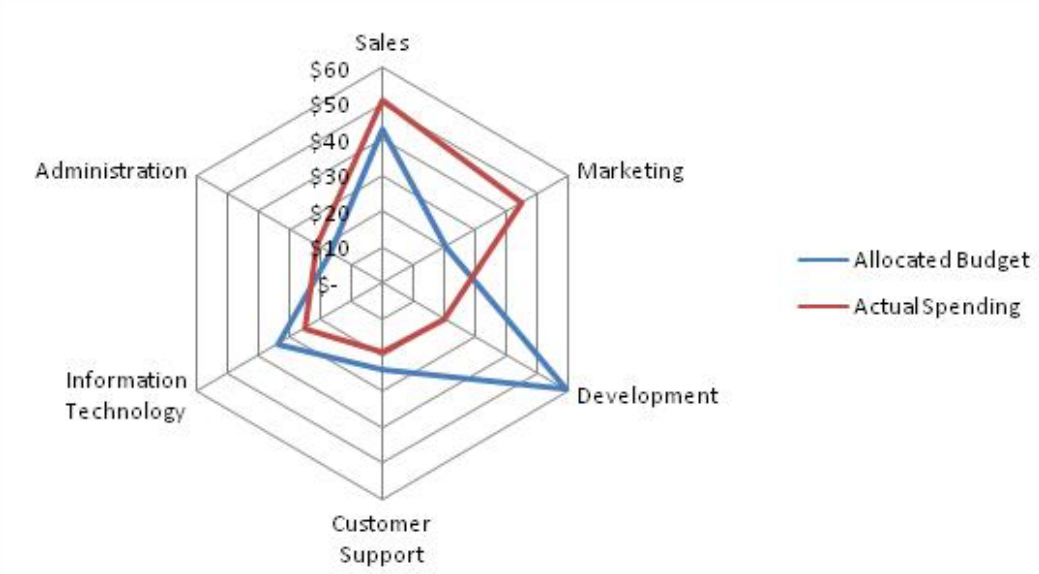
Project the data into a smaller space
and visualize the the projected data

Heat Maps


41
31
0
44
19
11
25
47
137
115
140
118
125
75
52
91
114
127
133
94
55
69
SepalLengthCm
PetalWidthCm
SepalWidthCm
PetalLengthCm

Spider plots, Radar Plots, and Star Plots

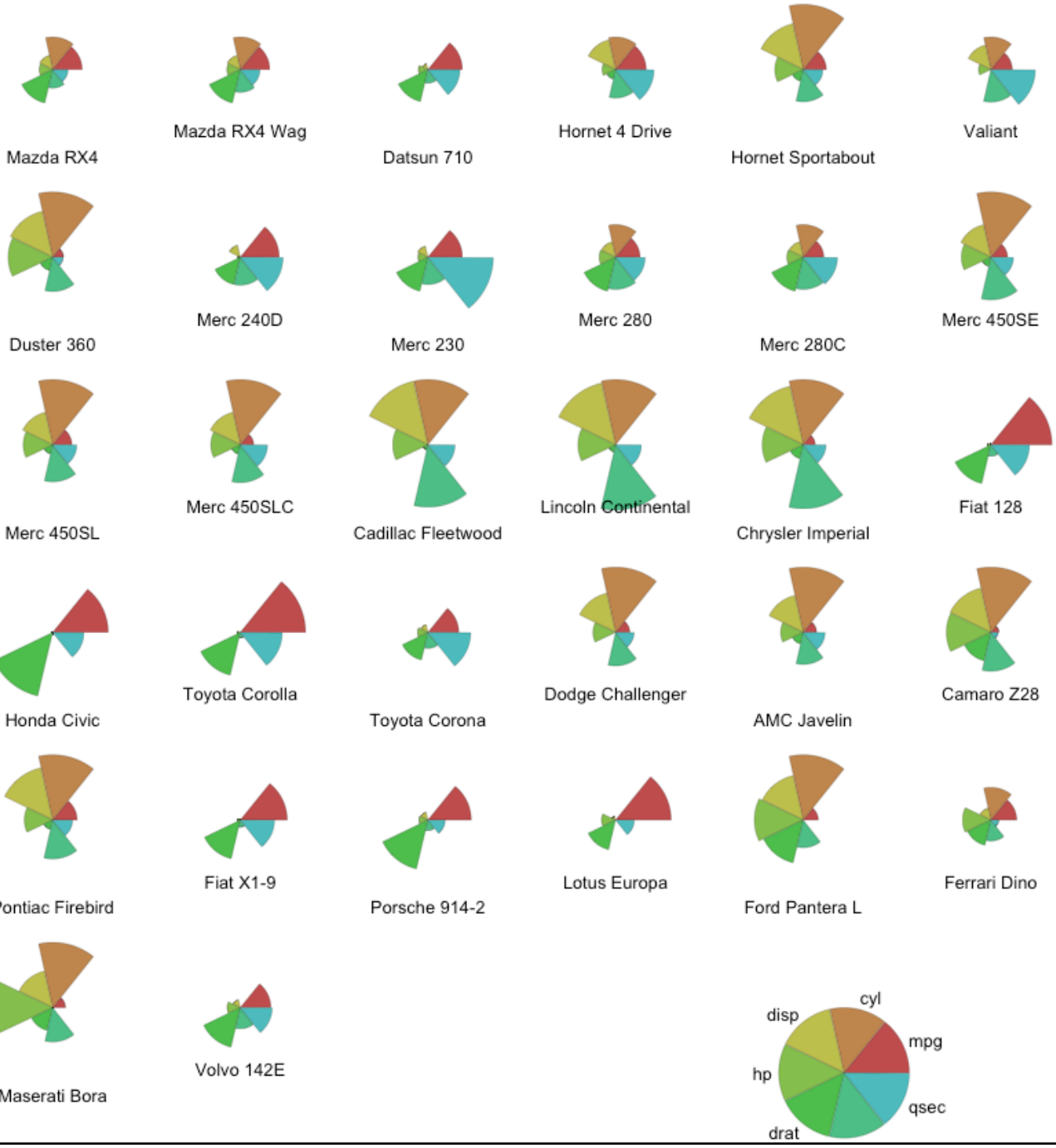
- Information radiates outward from central point
- The line connecting the values of an object is a polygon



Example Spider Chart by David Clement

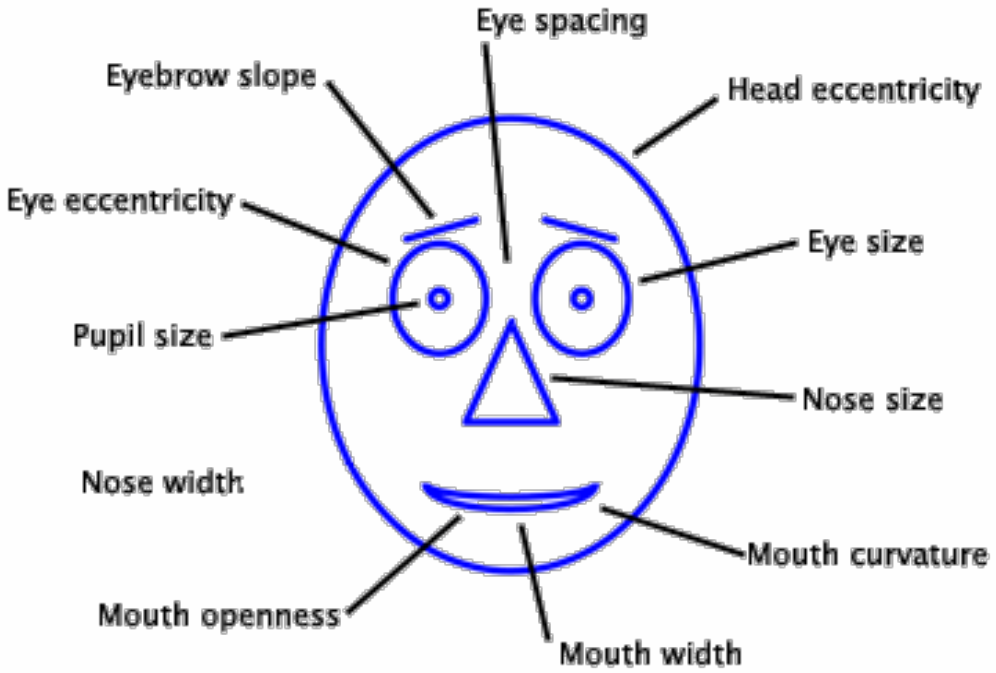
Motor Trend Cars : stars(*, full = F)

Motor Trend Cars

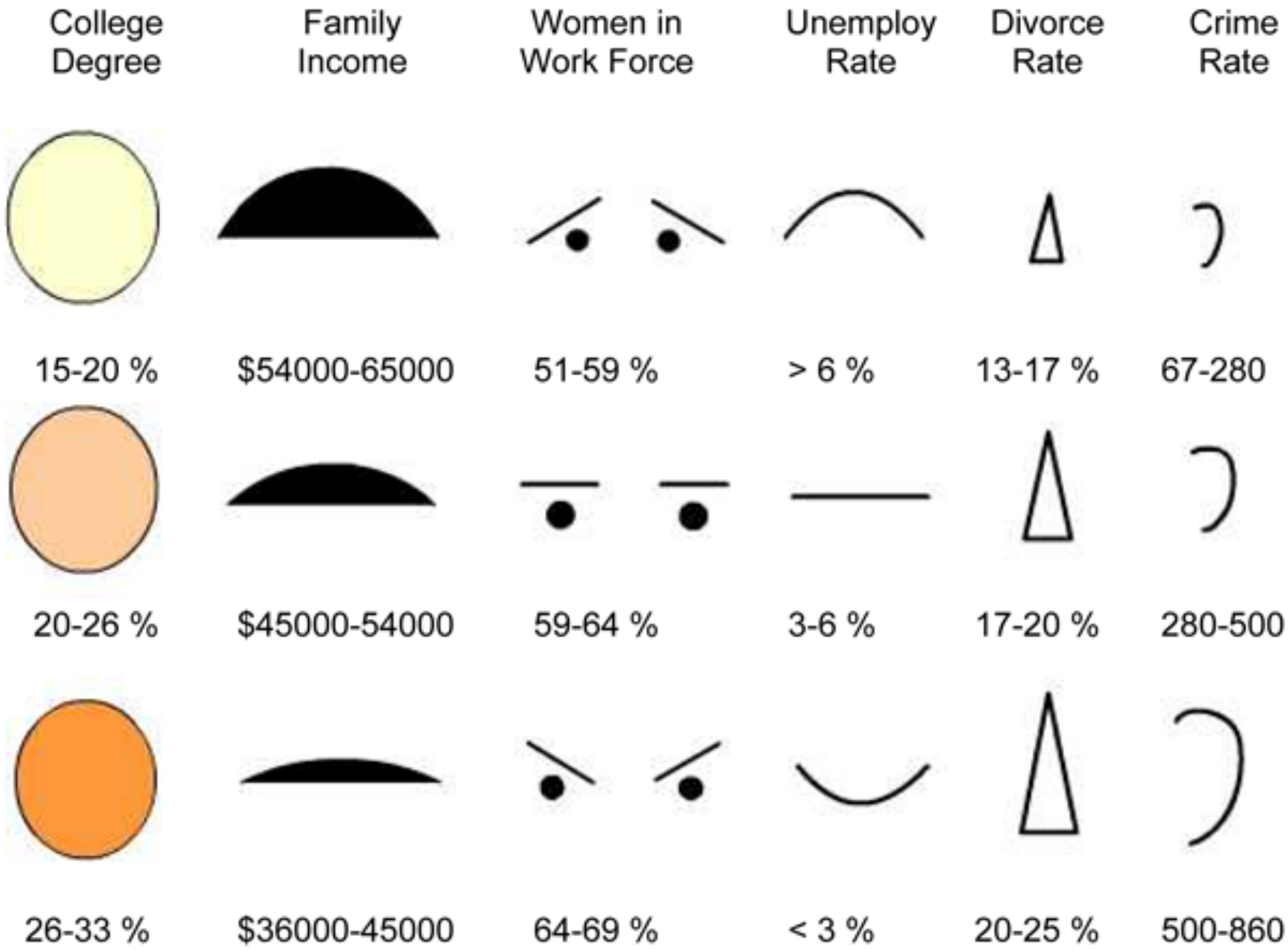


Chernoff Faces

- Approach created by Herman Chernoff
- Associates each attribute with a characteristic of a face
- The values of each attribute determine the appearance of the corresponding facial characteristic



- Each example becomes a separate face
- Relies on human's ability to distinguish faces



http://cartastrophe.files.wordpress.com/2010/06/spinelli.png

Mazda RX4

Mazda RX4 Wag

Datsun 710

Hornet 4 Drive

Hornet Sportabout

Valiant

Duster 360

Merc 240D

Merc 230

Merc 280

Merc 280C

Merc 450SE

Merc 450SL

Merc 450SLC

Cadillac Fleetwood

Lincoln Continental

Chrysler Imperial

Fiat 128

Honda Civic

Toyota Corolla

Toyota Corona

Dodge Challenger

AMC Javelin

Camaro Z28

Pontiac Firebird

Fiat X1-9

Porsche 914-2

Lotus Europa

Ford Pantera L

Ferrari Dino

Maserati Bora

Volvo 142E

Projecting Data into a Lower Dimensional Space

When projecting high-dimensional data into fewer dimensions we can either

Find a linear projection

e.g. use Principle Component Analysis

Find a non-linear projection

e.g. use t-distributed Stochastic Neighbor Embeddings (t-SNE)

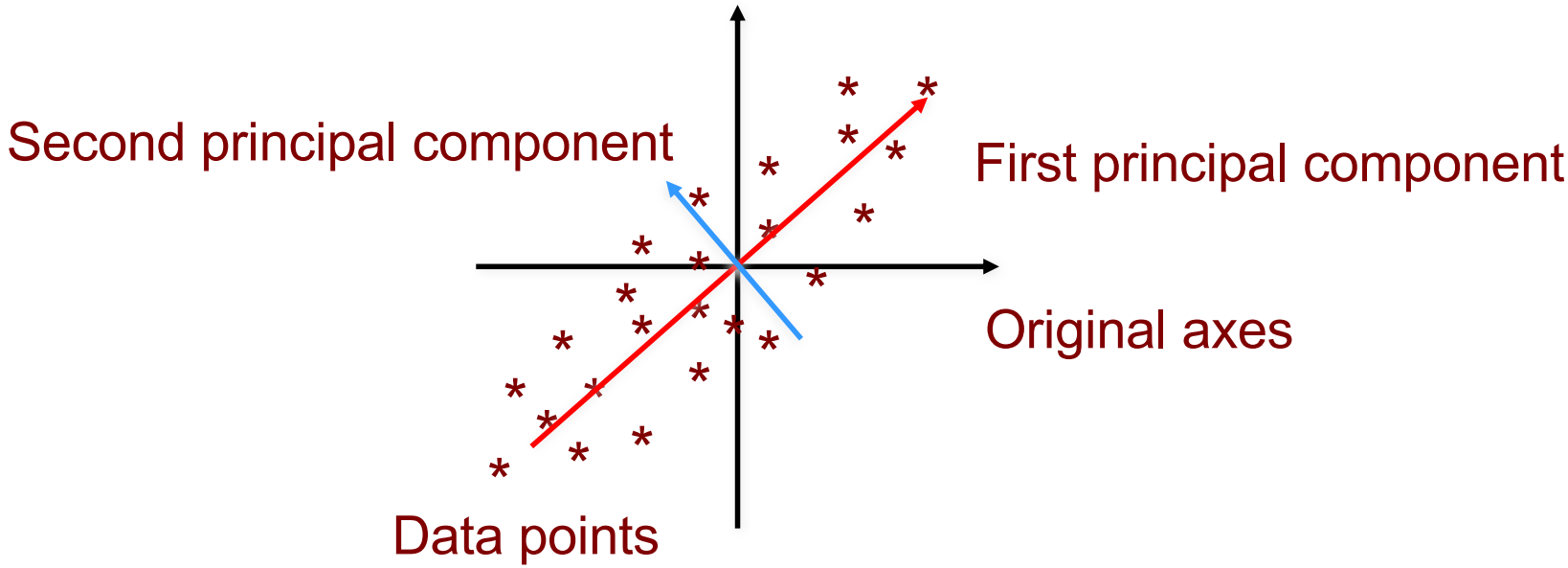
Principal Component Analysis

Principal Component Analysis (PCA)

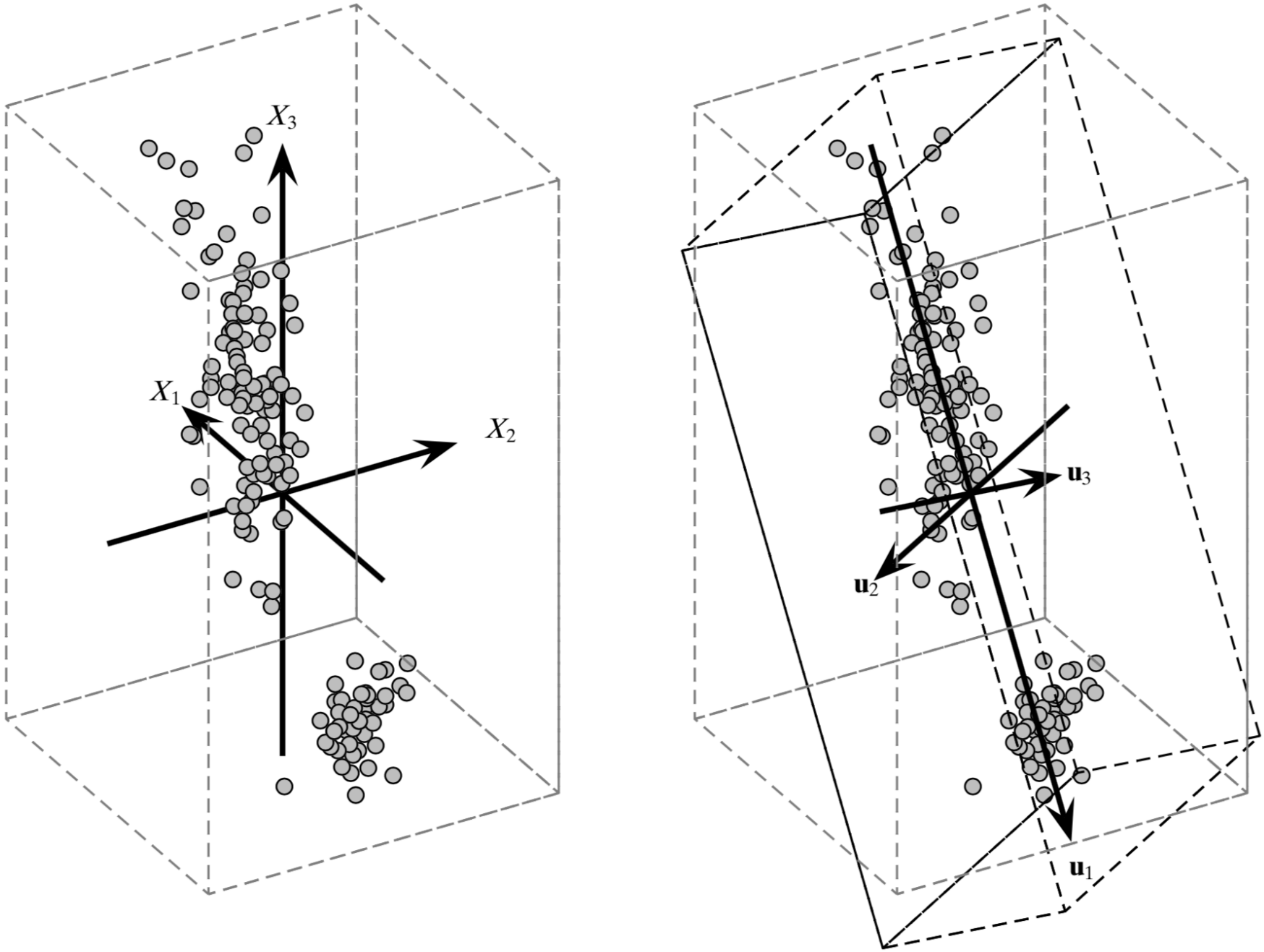
- Typically applied to reduce the number of dimensions of data (feature selection)
- The goal of PCA is to find a projection that captures the largest amount of variation in data
- Given N data vectors from n-dimensions, find k<n orthogonal vectors (the principal components) that can be used to represent data
- Works for numeric data only and it is affected by scale so data usually need to be rescaled before applying PCA

Principal Component Analysis (PCA)

- Steps to apply PCA
  - Normalize input data
  - Compute k orthonormal (unit) vectors, i.e., principal components
  - Each input data point can be written as a linear combination of the k principal component vectors
- The principal components are sorted in order of decreasing "significance" or strength
- Data size can be reduced by eliminating the weak components, i.e., those with low variance.
- Using the strongest principal components, it is possible to reconstruct a good approximation of the original data)


Second principal component
First principal component
Original axes
Data points

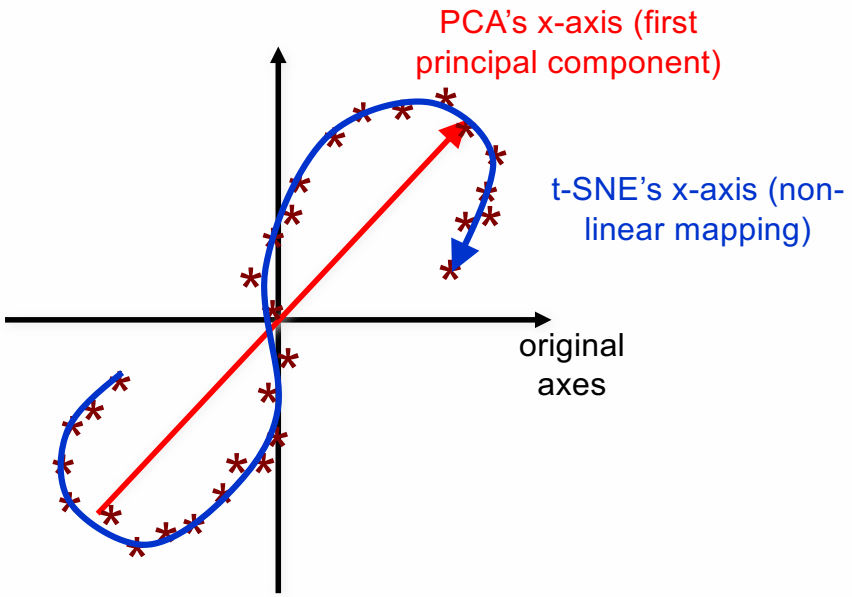
http://scikit-learn.org/stable/auto_examples/preprocessing/plot_scaling_importance.html


X_3
X_1
X_2
$\mathbf{u}_3$
$\mathbf{u}_2$
$\mathbf{u}_1$

t Distributed Stochastic Neighbor Embedding

Non-linear Dimensionality Reduction

- Data in high dimensions never fills the entire space and always lives within some lower-dimensional manifold



- t-SNE is a non-linear dimensionality reduction technique used to map high-dimensional data into 2 or 3 dimensions

- Points from original space mapped onto "map points" in 2D/3D

- Unlike PCA, the mapped points are not linear combination of original attribute values and the axes of mapped space are not linear combination (rotation) of original axes

t Distributed Stochastic Neighbor Embedding

- t-SNE tries hard to preserve local distances to nearby points
- Unlike PCA which tries to preserve global (long range) distances between points as much as possible
- t-SNE converts distances between data points to joint probabilities then models orignal points by mapping them to low dimensional map points such that position of map points conserves the structure of the data
- i.e. similar data points are modeled by nearby map points while dissimilar data points are modeled by distant map points

t Distributed Stochastic Neighbor Embedding

- The t-SNE algorithm has two main steps

1. Define a probability distribution over pairs of high-dimensional data points so that:
   - Similar data points have a high probability of being picked
   - Dissimilar points have an extremely small probability of being picked
2. Define a similar distribution over the points in the map space
   - Minimize the Kullback–Leibler divergence between the two distributions with respect to the locations of the map points
   - To minimize the score, it applies gradient descent

Physical Analogy

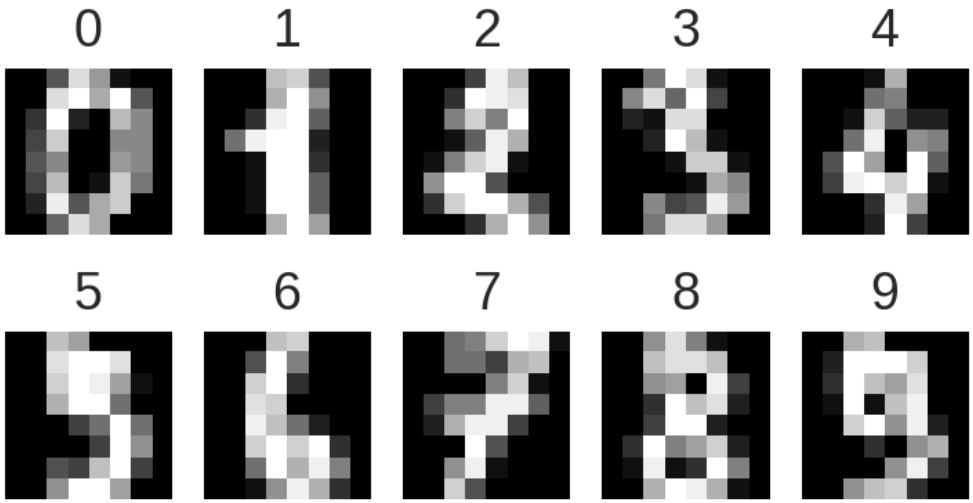
- Assume that map points are all connected with springs.
  - The stiffness of a spring connecting two points depends on the mismatch between the similarity of the two data points and the similarity of the two map points
- Let the system evolve according to the laws of physics
  - If two map points are far apart while the data points are close, they are attracted together
  - If they are nearby while the data points are dissimilar, they are repelled.
- The final mapping is obtained when the equilibrium is reached.

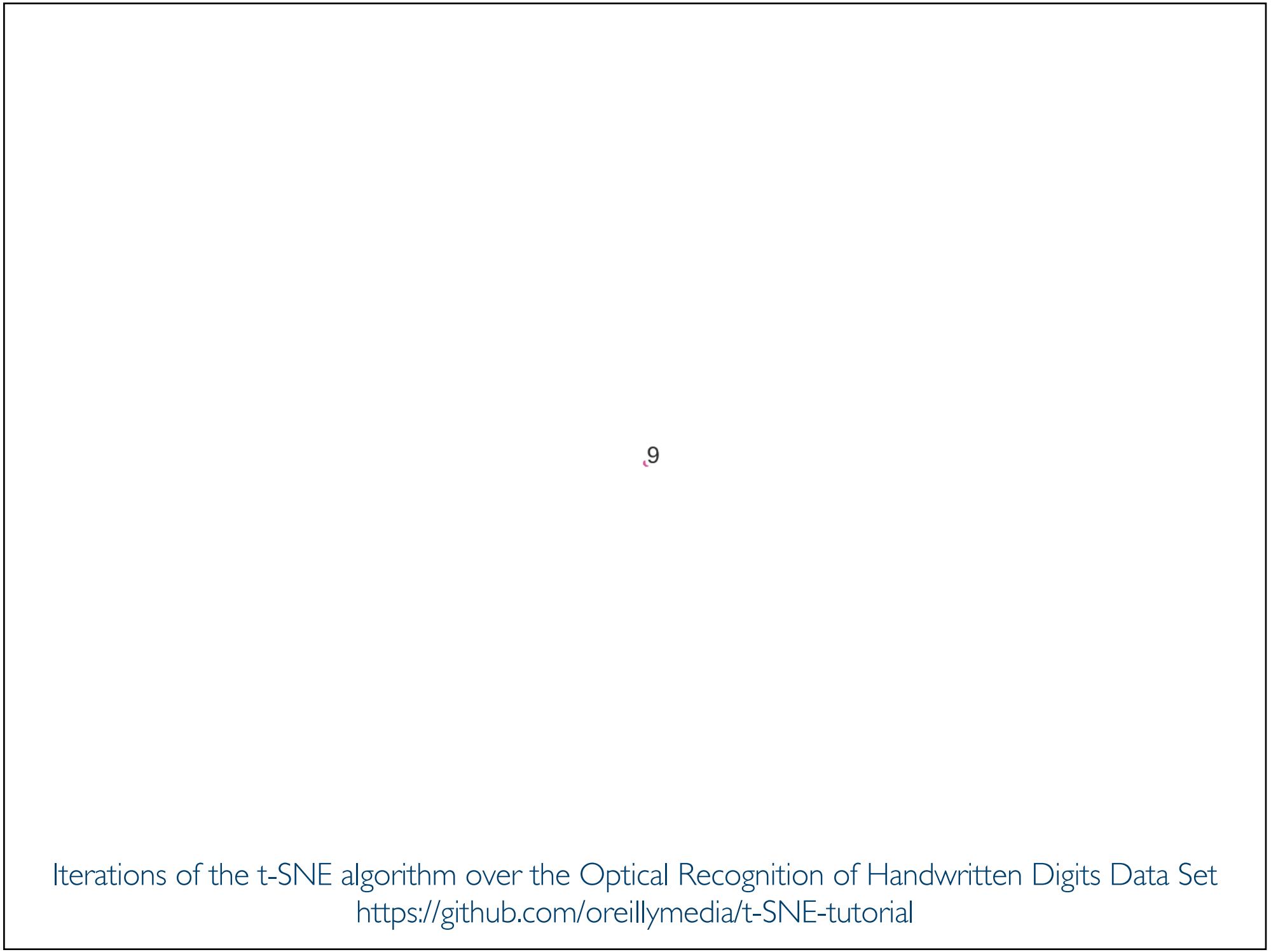
Example: Handwritten Digit Dataset

- Optical Recognition of Handwritten Digits Data Set from the UCI machine learning repository

  http://archive.ics.uci.edu/ml/datasets/Optical+Recognition+of+Handwritten+Digits

- Contains 1797 images with 8x8 pixels each





Iterations of the t-SNE algorithm over the Optical Recognition of Handwritten Digits Data Set
https://github.com/oreillymedia/t-SNE-tutorial

t-SNE Caveats

- The parameter perplexity says (loosely) how to balance attention between local and global aspects of the data
- Different initializations will lead to different results
- Should be applied to data with a "reasonable" number of dimensions (e.g. 30-50)
- If the data have more dimensions, another dimensionality reduction algorithm should be applied

Force-directed Layout

- Idea of mapping complicated data into 2D is not limited to high dimensional data ….
- We can map any graph of data points into 2D provided we have some (dis)similarity value between pairs of nodes
  - Such as the Euclidean distance between them in higher dimensional space
  - Or their joint probability under a Gaussian kernel (in case of t-SNE)
  - Or Pearson's correlation, Spearman's Rank correlation, chi-squared, etc.
- It works by moving points around in the mapped 2D space until convergence
- Technique is called force-directed layout. There are many algorithms implemented in Gephi (https://gephi.org), on next slide we have an example of a graph generated using it

Other Visualizations


Visualization of retweets during the
2013 Boston Marathon on April 15, 2013
obtained using Gephi and the Twitter API

Some Interesting Pages

- https://python-graph-gallery.com
- https://python-graph-gallery.com/category/seaborn/
- https://github.com/matplotlib/AnatomyOfMatplotlib
- https://github.com/rasbt/matplotlib-gallery
- https://seaborn.pydata.org/examples/index.html
- http://bokeh.pydata.org/en/latest/

Study Material

- "Data Mining and Analysis" – Chapter 2 & 3
- t-Distributed Stochastic Neighbor Embedding (t-SNE)
  - http://lvdmaaten.github.io/tsne/
  - https://www.youtube.com/watch?v=RJVL80Gg3lA
  - http://alexanderfabisch.github.io/t-sne-in-scikit-learn.html
  - http://jmlr.csail.mit.edu/papers/volume9/vandermaaten08a/vandermaaten08a.pdf
  - https://distill.pub/2016/misread-tsne/
- Principal Component Analysis
  - "Data Mining and Analysis" – Chapter 7
  - http://sebastianraschka.com/Articles/2015_pca_in_3_steps.html
- Data Visualization
  - PhD Course by Daniele Loiacono