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SCHOOL OF INFORMATION AND COMMUNICATION TECHNOLOGY

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IT4142E

Introduction to Data Science

Chapter 4: Introduction to Exploratory Data Analysis

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Contents of the course

- Chapter 1: Overview
- Chapter 2: Data scraping
- Chapter 3: Data cleaning, pre-processing and integration
- Chapter 4: Introduction to Exploratory Data Analysis
- Chapter 5: Introduction to Data visualization
- Chapter 6: Introduction to Machine Learning
  - Performance evaluation
- Chapter 7: Introduction to Big Data Analysis
- Chapter 8: Applications to Image and Video Analysis

Learning outcomes

- Understand key elements in exploratory data analysis (EDA)
- Explain and use common summary statistics for EDA
- Plot and explain common graphs and charts for EDA

Goals of this chapter

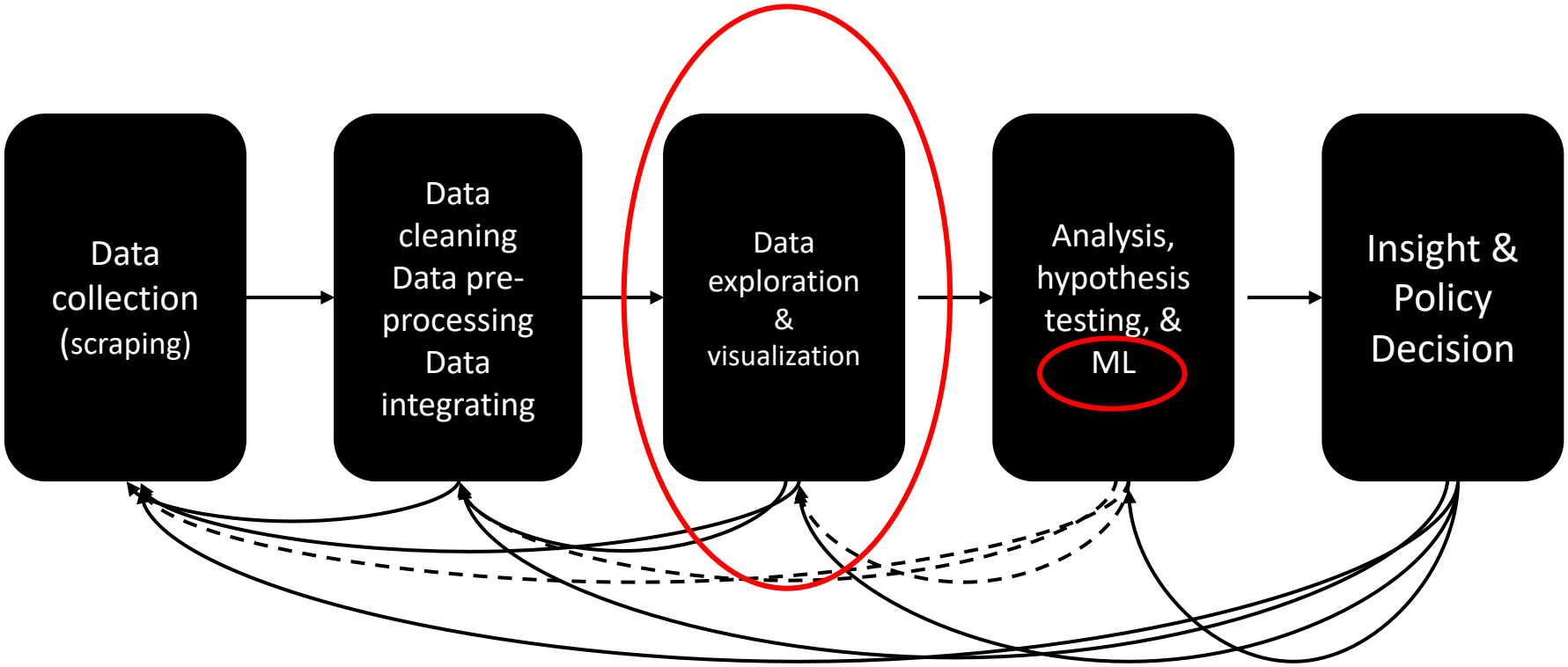
Goal	Description of the goal
M1	**Understand and be able to design and manage the systems which are based on Data Science (DS)**
M1.2	Identify, compare, and categorize the data types and systems in practice
M1.3	Be able to design systems based on DS in their future organizations
M2	**Identify and manage the opportunities from DS to boost the existing organizations, or develop new organizations**
M2.1	Understand and promote the use of DS to support their organizations
M2.2	Identify the (possible) impacts of Data Science on their organizations

Contents of this chapter

- **Chapter 4: Exploratory Data Analysis (EDA)**
  - Introduction and definitions
  - Univariate EDA measures
    - Central tendency (location)
    - Scale (data spread)
    - Shape of the distribution
  - Univariate EDA graphics
  - Multivariate EDA measures
  - Multivariate EDA graphics
  - More advanced EDA techniques
  - Summary
  - Homework

Introduction and definition

Recall: DS methodology



Motivation for EDA

- Before making inferences from data, it is essential to examine all your variables.
  - To understand your data
- Why?
  - To "listen" to the data:
    - to catch mistakes
    - to see patterns in the data
    - to find violations of statistical assumptions
    - to generate hypotheses
  - …and because if you don't, you will have trouble later

What is EDA?

- EDA **summarizes** all of the available data, so that it is **understandable by humans**
  - Summary statistics
  - Visualization (basic graphics shown in this chapter or more refined visualization in Chapter 5)
  - Dimensionality reduction
    - Principal Component Analysis (for instance)
  - Clustering and outliers - anomaly detection
    - Clustering will be seen in Chapter 6 (Machine Learning)
    - But, you can still use off-the-shelf clustering methods for EDA!

- Thanks to EDA, data scientists might find good models for the data
  - For instance, the data is / is not Gaussian
    - -> impact of the data models that can be used for data mining

EDA common questions

- What is a typical value for attribute X?
- What is the uncertainty for a typical value?
- What is a good distributional fit for attribute X / attributes X&Y?
- Does the data have outliers?
- Can we separate signal from noise in time dependent data?
- What are the most « important » attributes / combination of attributes?
- Is the data consistent or inconsistent among different data sources?

What is EDA?

- EDA is an iterative process: repeat...
  - Identify and prioritize relevant questions in decreasing order of importance
  - Ask these questions (might require data processing)
  - Construct graphics to address these questions
  - Inspect the answers and derive new questions

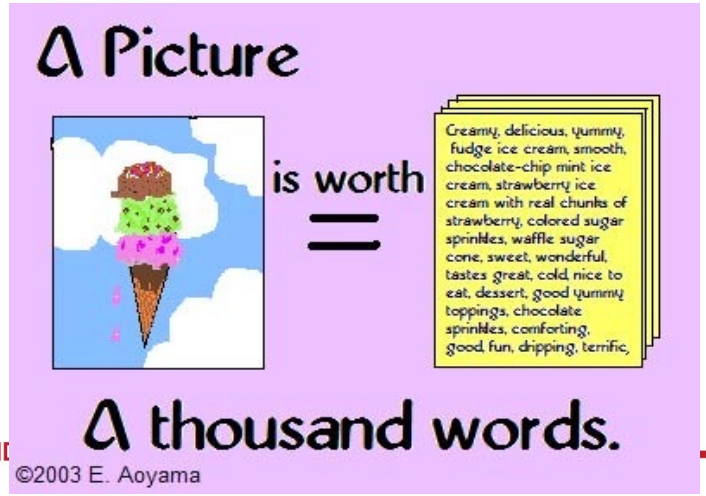
EDA strategy

- Examine variables one by one (univariate analysis)…
- … then, explore the relationships among the different variables (multivariate analysis)…
- … by applying techniques that are **adapted** to the types of the attributes (variables)
  - Categorical vs. Numeric

EDA techniques

- Quantitative techniques
  - Mostly statistics / statistical models – some ML
    - Most quantitative measures are implemented in the **pandas** library (Python)

- Graphical techniques (visualization)
  - Box plots, scatter plots, bar plots, histograms, probability plots, residual plots…
    - Most basic graphical representations, seen in this chapter, can be implemented using the **pandas / matplotlib** libraries (Python)

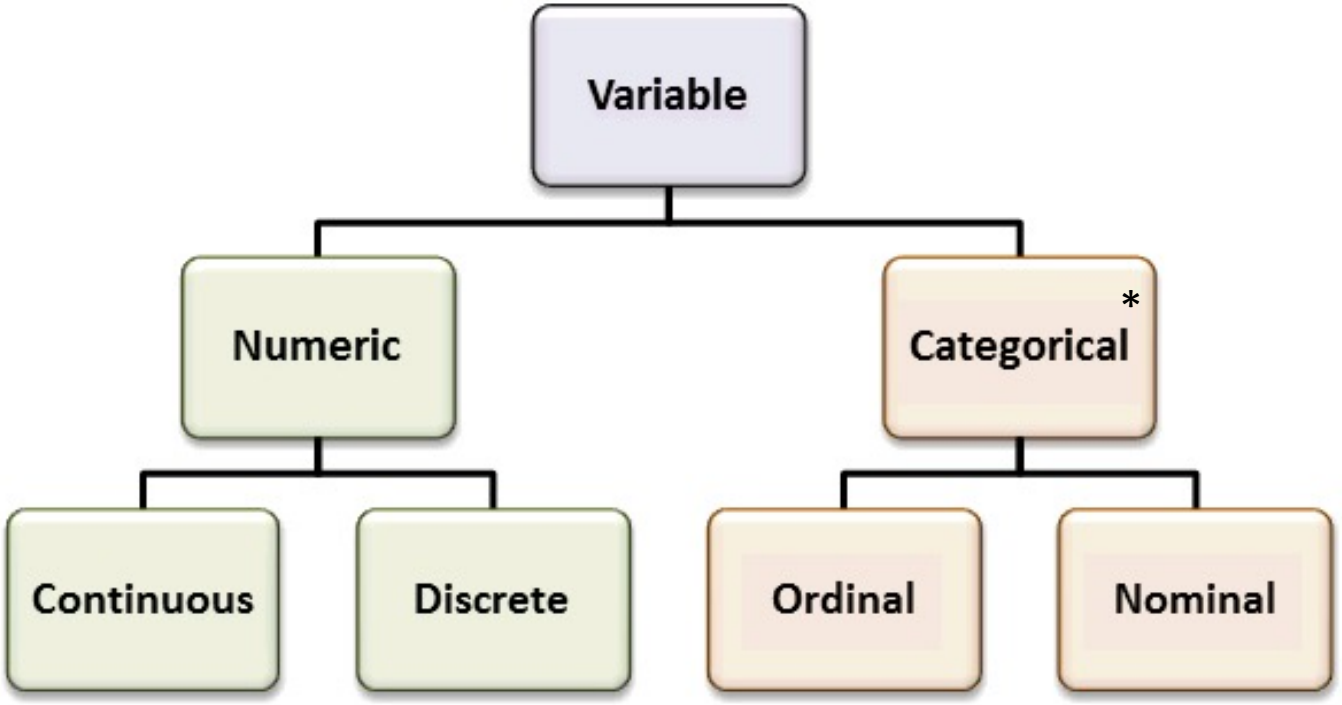


Defs: observations and variables

- Data is an collection of observations (records, subjects)
  - Rows in the data table
- An attribute is a set of values describing some aspect across all observations, it is called a variable
  - Columns in the data table

HR Information		Contact	
Position	**Salary**	**Office**	**Extn.**
Accountant	$162,700	Tokyo	5407
Chief Executive Officer (CEO)	$1,200,000	London	5797
Junior Technical Author	$86,000	San Francisco	1562
Software Engineer	$132,000	London	2558

Types of variables



*The set of possible values of categorical variables are called modalities

* Some authors call categorical variables “discrete variables”

- I do **not**, because I find this confusing, but you might find it on the web…

Dimensionality of EDA

- Univariate: analysis of **one variable**
- Bivariate: analysis of **two variable** simultaneously
- Multivariate: analysis of **several variables** simultaneously
  - Bivariate is a special case of multivariate

Univariate EDA measures

Univariate EDA measures

- Measures of central tendency (location):
  - typical or central value that best describes the data
- Measures of scale (spread):
  - estimate of the attribute's variability
- Measures of shape
  - How flat is the distribution?
  - How symmetric / asymmetric is the distribution?

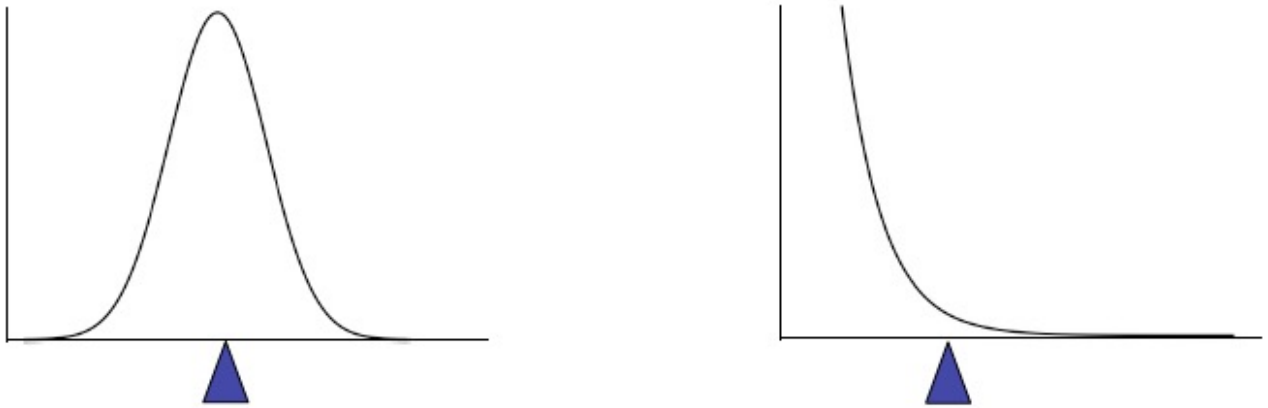
Univariate EDA measures

Central tendency (location)

Mean

- To calculate the average value of a set of observations, sum of their values divided by the number of observations:

$$\bar{x} = \frac{x_1 + x_2 + x_3 + \ldots + x_n}{n} = \frac{1}{n}\sum_{i=1}^{n} x_i$$



Median

- The median is the value having half the data smaller, and half the data larger than this value
- Calculation
  - If there are an odd number of observations, median is the middle value
  - If there are an even number of observations, find the middle two values and average them -> median
- Example
  - Age of participants: 17 19 21 22 23 23 23 38
  - **Median = (22+23)/2 = 22.5**

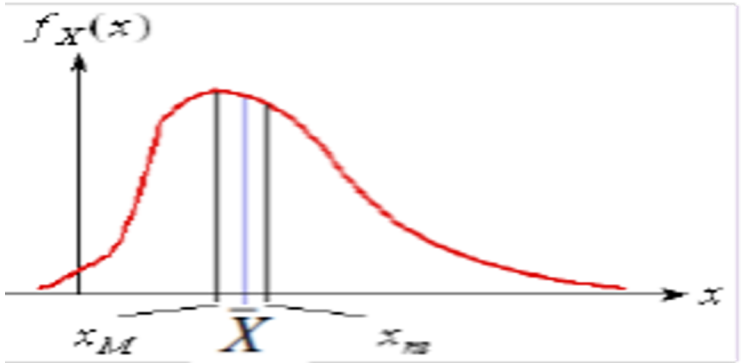
Mode

- mode is the most commonly reported value for a particular variable
  - Eg. 3, 4, 5, 6, 7, 7, 7, 8, 8, 9. Mode = 7
  - Eg. 3, 4, 5, 6, 7, 7, 7, 8, 8, 8, 9. Mode = {7, 8} = 7.5

Summary of location measures

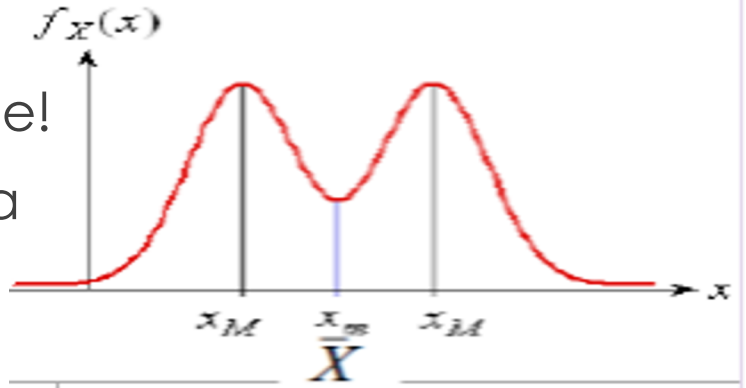
- Notations:
  - $\bar{x}$=mean
  - x_m =median
  - x_M =mode

In the general case,
$\bar{x} \neq x_m \neq x_M$

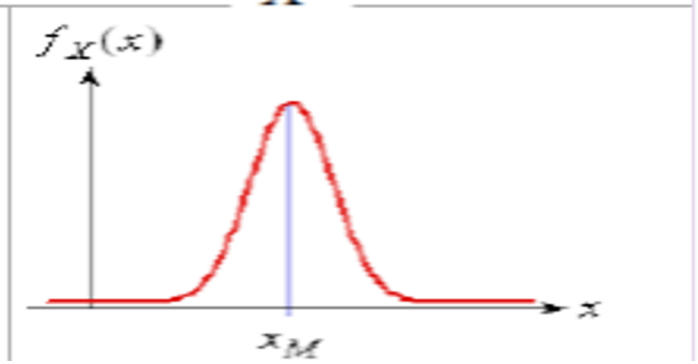


The mode is not necessarily unique!

$\bar{x} = x_m$only for symmetric data

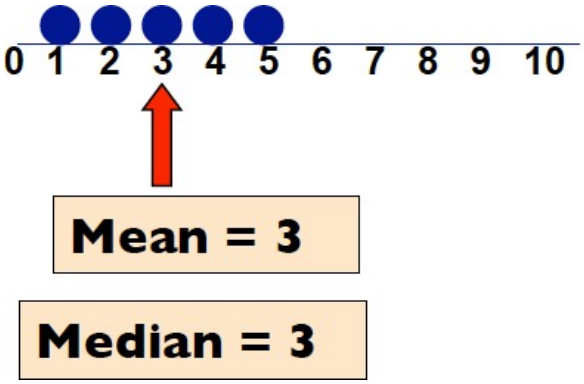


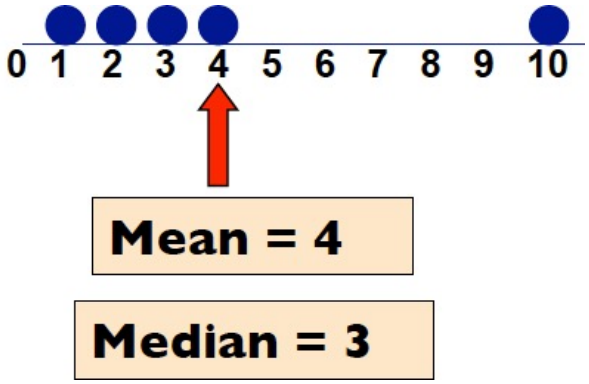
$\bar{x} = x_m = x_M$ only for symmetric, unimodal data



Which location measure is best?

- Well, it all depends on your data distribution and what you want to do with the measure!
  - Mean is best for symmetric distributions without outliers
  - But, median is more robust than mean towards outliers





  - Median is also (in general) more useful for skewed distributions

Beware – when using tools/libraries

- Sometimes, the categorical data is encoded by numbers
  - For instance, gender (male/female) can be encoded by Boolean (0/1)
  - Either because the source data was already encoded…
  - … or because, during data pre-processing (see Chapter 3-part2), we applied some **encoding** techniques
- By default, your tool (or Python library) does not "understand" your variables!!!
  - Beware: do **not** consider the mean of a categorical variable encoded as numerical!!!
  - Example of pandas .describe()

	Name	Team	Number	Position	Age	Height	Weight	College	Salary
count	364	364	364.000000	364	364	364	364.000000	364	3.640000e+02
unique	364	30	NaN	5	22	17	NaN	115	NaN
top	Cleanthony Early	New Orleans Pelicans	NaN	SG	24.0	6-9	NaN	Kentucky	NaN
freq	1	16	NaN	87	41	49	NaN	22	NaN
mean	NaN	NaN	16.829670	NaN	NaN	NaN	219.785714	NaN	4.620311e+06
std	NaN	NaN	14.994162	NaN	NaN	NaN	24.793099	NaN	5.119716e+06
min	NaN	NaN	0.000000	NaN	NaN	NaN	161.000000	NaN	5.572200e+04
20%	NaN	NaN	4.000000	NaN	NaN	NaN	195.000000	NaN	9.472760e+05
40%	NaN	NaN	9.000000	NaN	NaN	NaN	212.000000	NaN	1.638754e+06
50%	NaN	NaN	12.000000	NaN	NaN	NaN	220.000000	NaN	2.515440e+06
60%	NaN	NaN	17.000000	NaN	NaN	NaN	228.000000	NaN	3.429934e+06
80%	NaN	NaN	30.000000	NaN	NaN	NaN	242.400000	NaN	7.838202e+06
max	NaN	NaN	99.000000	NaN	NaN	NaN	279.000000	NaN	2.287500e+07

Univariate EDA measures

Scale (spread)

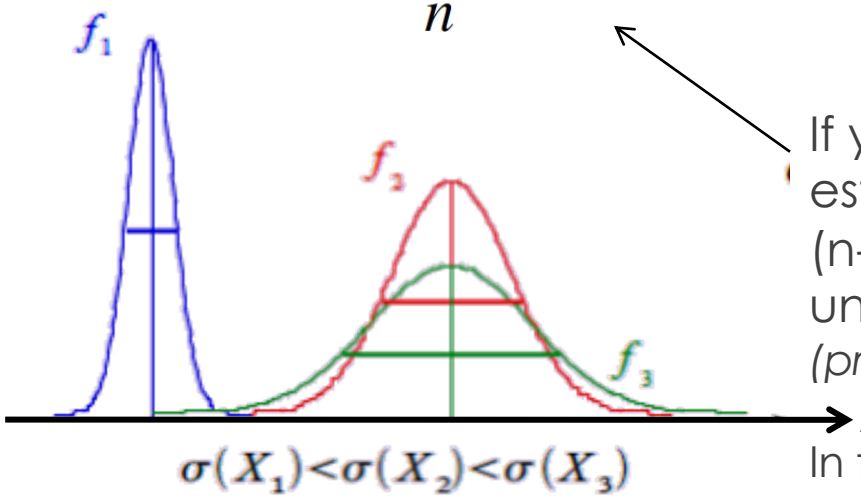
Variance and standard deviation

- Variance: the average of squared differences between the observation values and the mean

$$\hat{\sigma}^2 = \frac{\sum_i^n (x_i - \bar{x})^2}{n}$$

- Standard Deviation: just the square root of the variance

$$\hat{\sigma} = \sqrt{\frac{\sum_i^n (x_i - \bar{x})^2}{n}}$$



If you want unbiased, convergent estimations, you would have to divide by (n-1), because the actual mean is unknown (estimated using $\bar{x}$)
(proof outside of the scope of this course)

In this course, we'll use only the formulas above

Quizz

- Can variance, standard deviation be used for
  - Numeric, continuous variables?
    - Answer:
  - Numeric, discrete variables?
    - Answer :
  - Categorical, nominal variables?
    - Answer :
  - Categorical, ordinal variables?
    - Answer :
- For categorical variables: gini index, entropy…

Scale measures for categorical variables

- Gini index and entropy can measure the scale or categorical variables
  - *I.e.* how much they're spread among their *K* modalities

- Gini index:

$$Gini = 1 - \sum_{k=1}^{K} P[k]^2$$

- If *Gini* is close to 0, then the values are concentrated on one modality
- If *Gini* tends to $1 - \frac{1}{K}$, then the attribute is uniformly spread amongst modalities

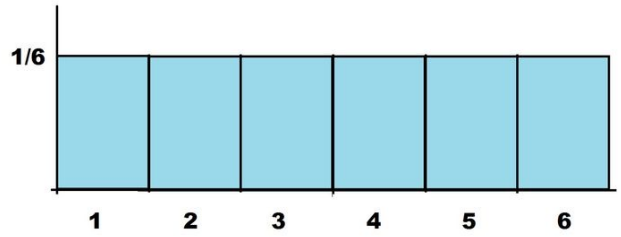
- Entropy:

$$Entropy = -\sum_{k=1}^{K} P[k] \ln(P[k])$$

- If *Entropy* is close to 0, then the values are concentrated on one modality
- If *Entropy* tends to *ln(K)*, then the attribute is uniformly spread amongst modalities

Exercises

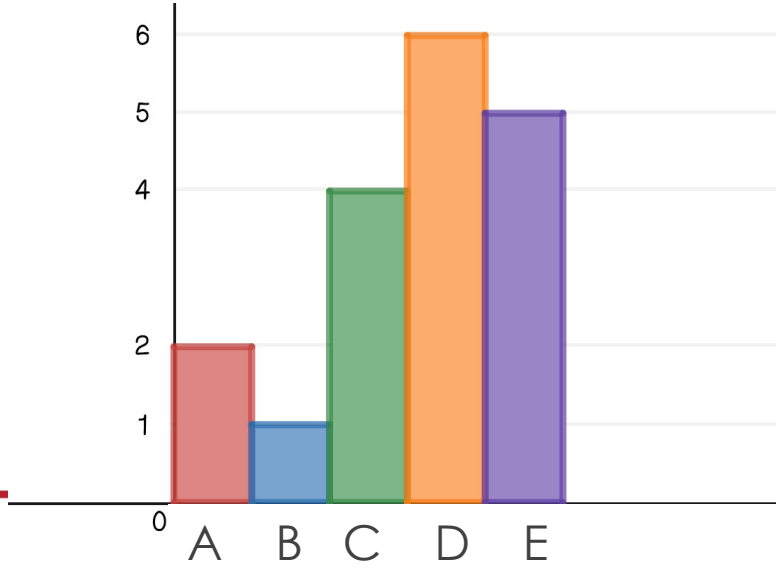
- How much are the Gini index and the entropy of a uniform distribution with 6 modalities? (*e.g.* throwing a dice)



  - Answer:

- How much are the Gini index and the entropy of this distribution?

  - Answer:



Univariate EDA measures

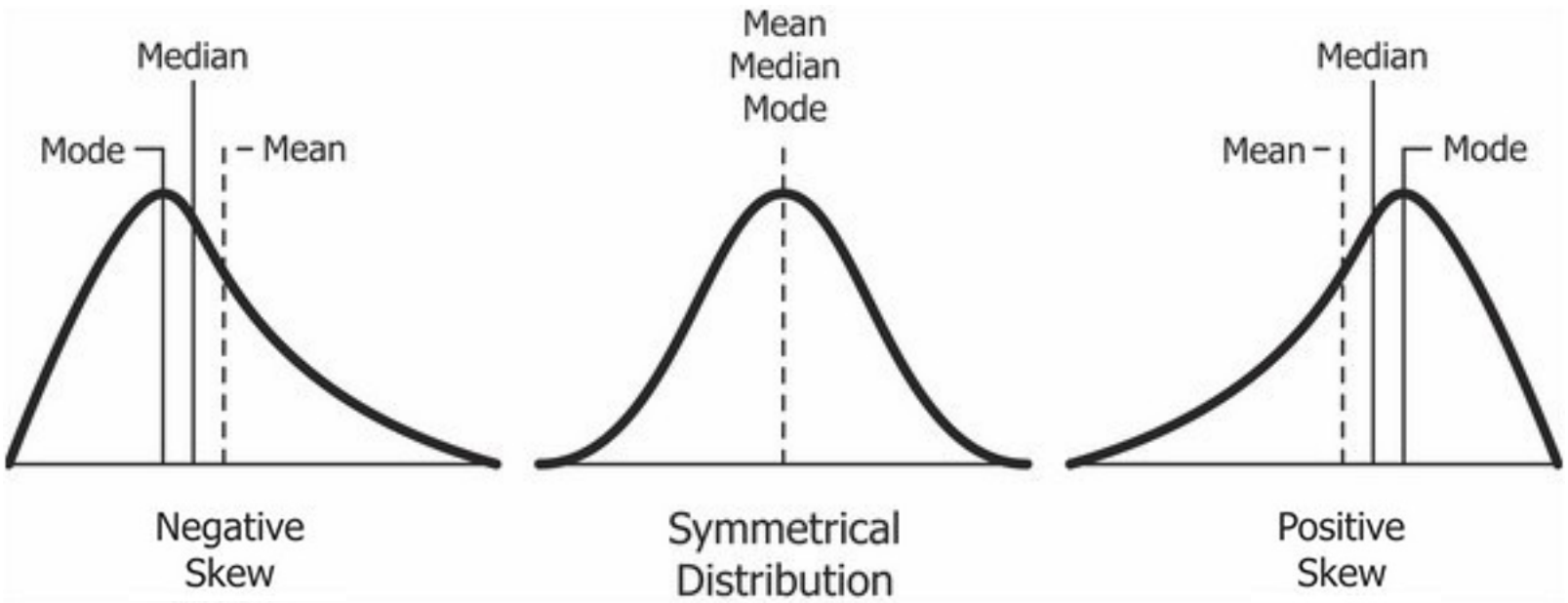
Shape of the distribution

Shape measures (for numeric variables)

- Fisher parameters characterize the shape of a distribution
  - Moment of order 1: mean $\bar{x} = \frac{x_1 + x_2 + x_3 + \ldots + x_n}{n} = \frac{1}{n}\sum_{i=1}^{n} x_i$
  - Moment of order 2: variance $\hat{\sigma}^2 = \frac{\sum_{i}^{n} (x_i - \bar{x})^2}{n}$
  - Fisher parameters=moments of order >2
    - Skewness: moment of order 3
      - Measures the **symetry / asymetry** of a distribution
    - Kurtosis: moment of order 4
      - Measures how **flat / peaky** a distribution is

Skewness

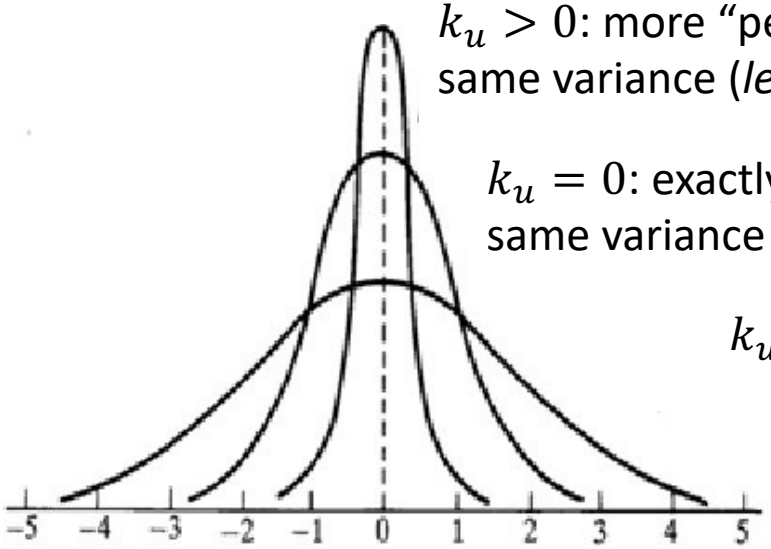
- Skewness: $s_k = \frac{\sum_{i=1}^{n}(x_i - \bar{x})^3}{n\sigma^3}$



$s_k < 0$ $s_k = 0$ $s_k > 0$

Kurtosis

- Sample excess kurtosis: $k_u = \frac{\sum_{i=1}^{n}(x_i - \bar{x})^4}{n\sigma^4} - 3$
  - Kurtosis measures peakedness / flatness of a distribution…
  - … relative to a Gaussian (normal) distribution



$k_u > 0$: more "peaky" than a Gaussian (normal) distribution with same variance (*leptokurtic* distribution)

$k_u = 0$: exactly as "peaky" as a Gaussian (normal) distribution with same variance (*mesokurtic* distribution)

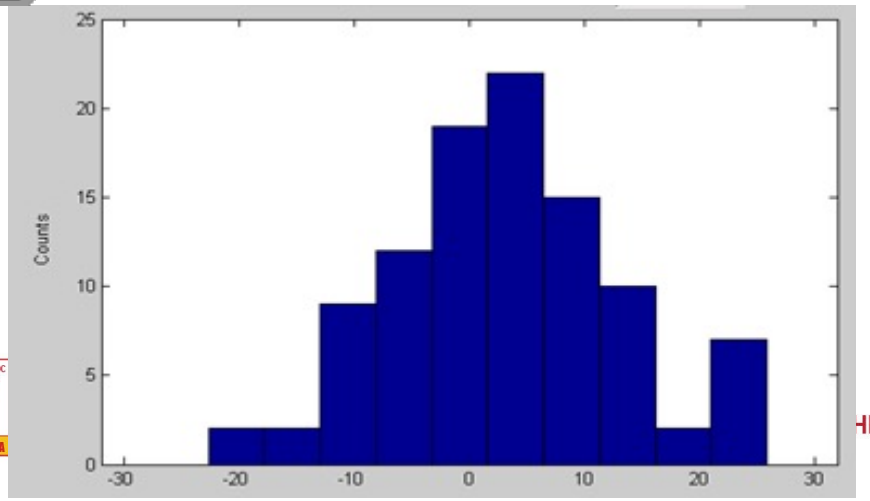
$k_u < 0$: more "flat" than a Gaussian (normal) distribution with same variance (*platykurtic* distribution)

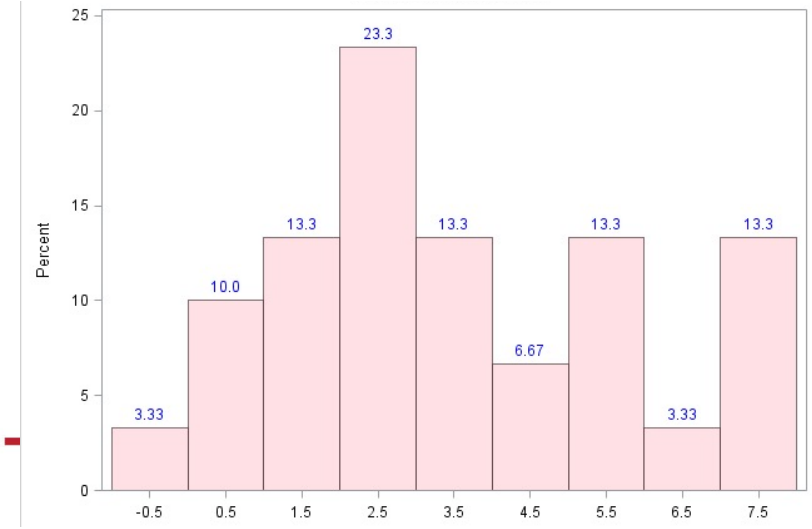
Univariate EDA graphics

Histogram plot

- An **histogram** graphically summarizes one **numeric** variable's distribution
  - The ranges used in the x-axis are called **bins**
- Histograms can be used to answer the following questions:
  - What kind of probability distribution do the data come from?
  - Where is the data located?
  - How spread out is the data?
  - Is the data symmetric or skewed?
  - Are there outliers in the data?
- Histograms can diplay either counts, or percentages

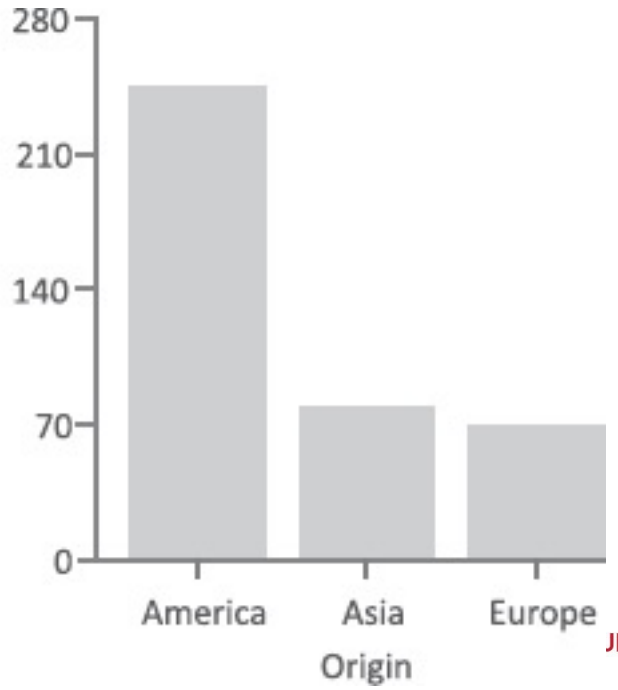
You **HAVE** to mention if it's count or percentage in the caption or y-axis

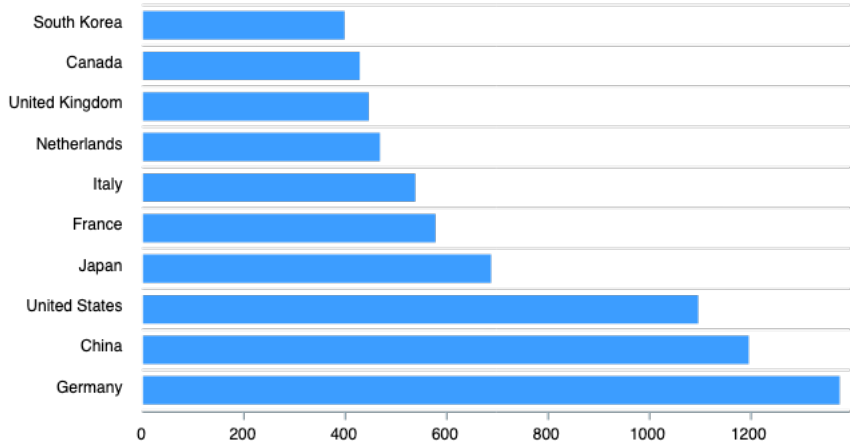




Bar charts

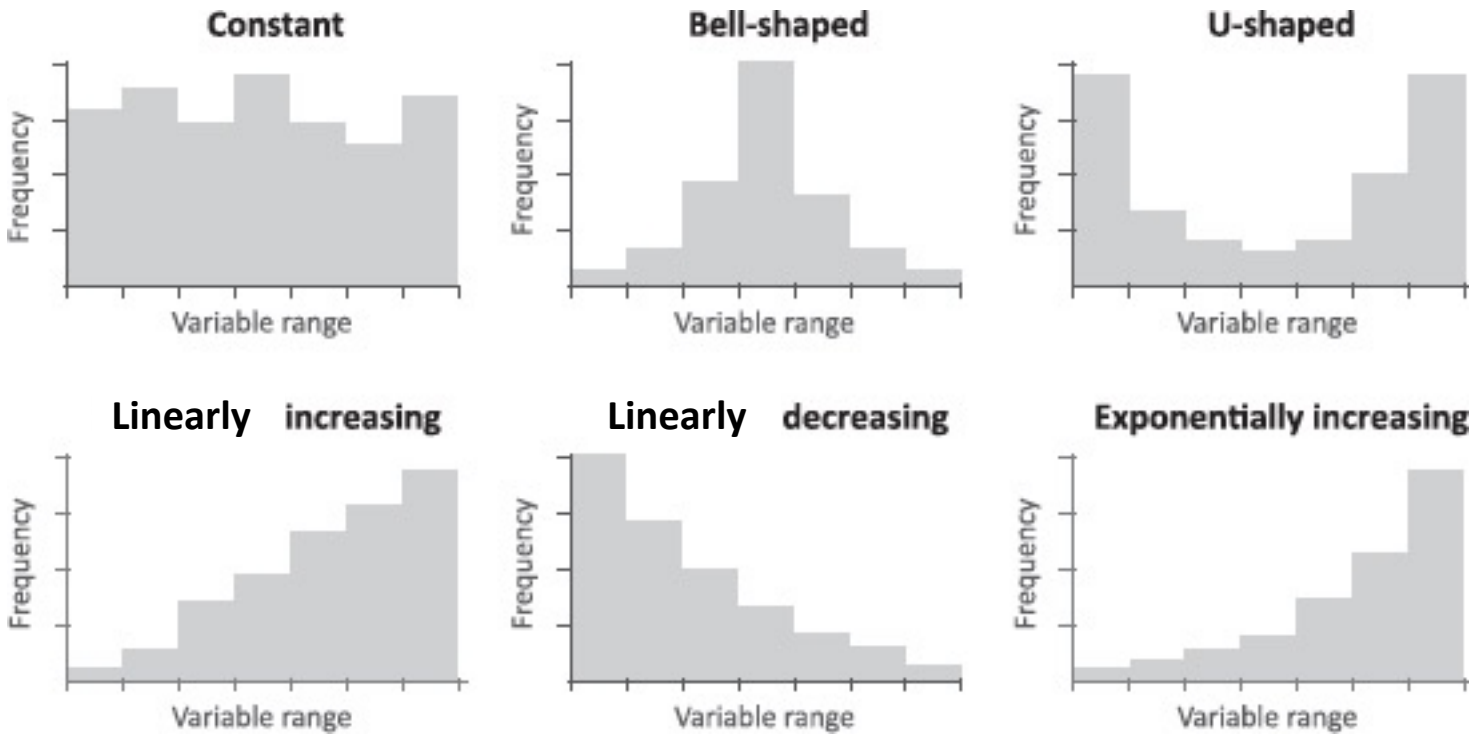
- An bar chart graphically summarizes one categorical variable's distribution
  - Similar to histograms, but for **categorical** variables
  - Instead of **bins**, bar charts use **modalities**





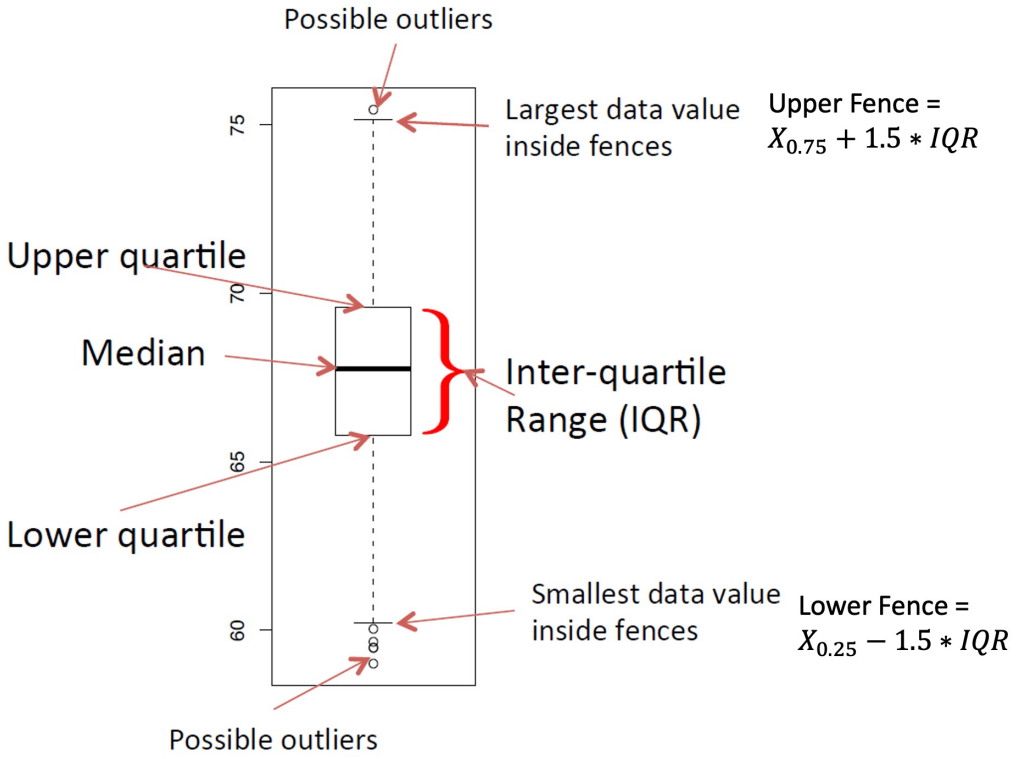
Example of distribution shapes

monotonous



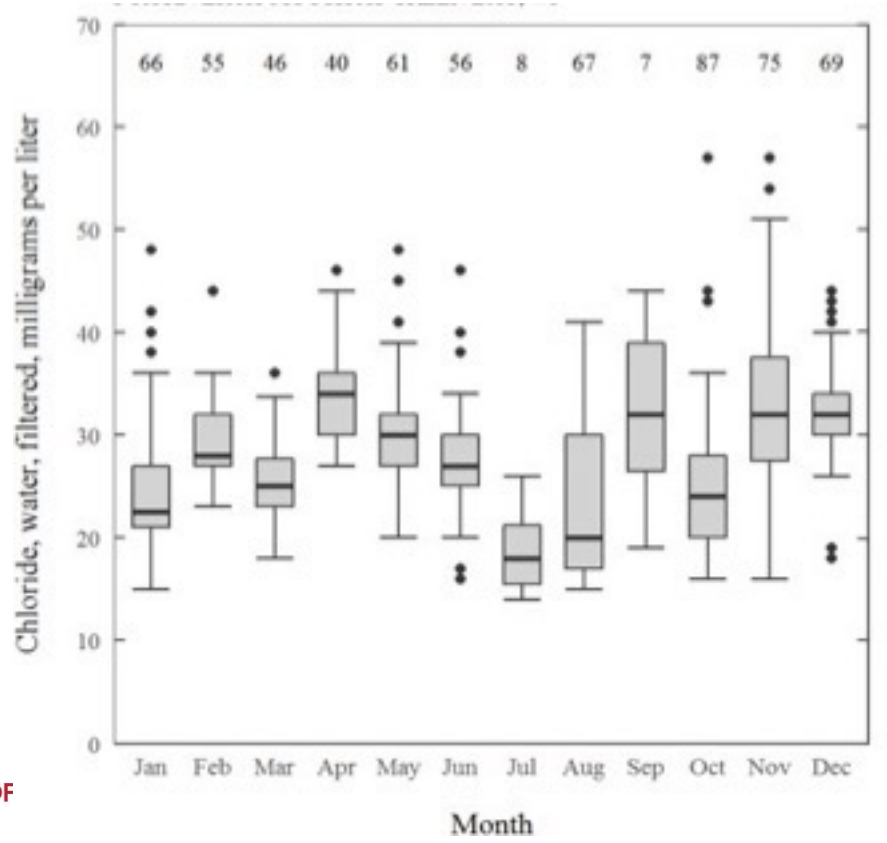
Box plot (*a.k.a.* whisker plot)

- By default in most tools/libraries, a box plot displays:
  - The lower fence value, the 25% quartile ($X_{0.25}$), the median ($X_{0.5}$), the 75% quartile ($X_{0.75}$), the upper fence value
  - Possible outliers (outside of the range between fences)



Box plot (cont'd)

- **Multiple boxplots** can provide answers to the following questions:
  - Does the central tendency differ between subgroups?
  - Does the scale differ between subgroups?
  - Are there any outliers?



Multivariate EDA **measures**

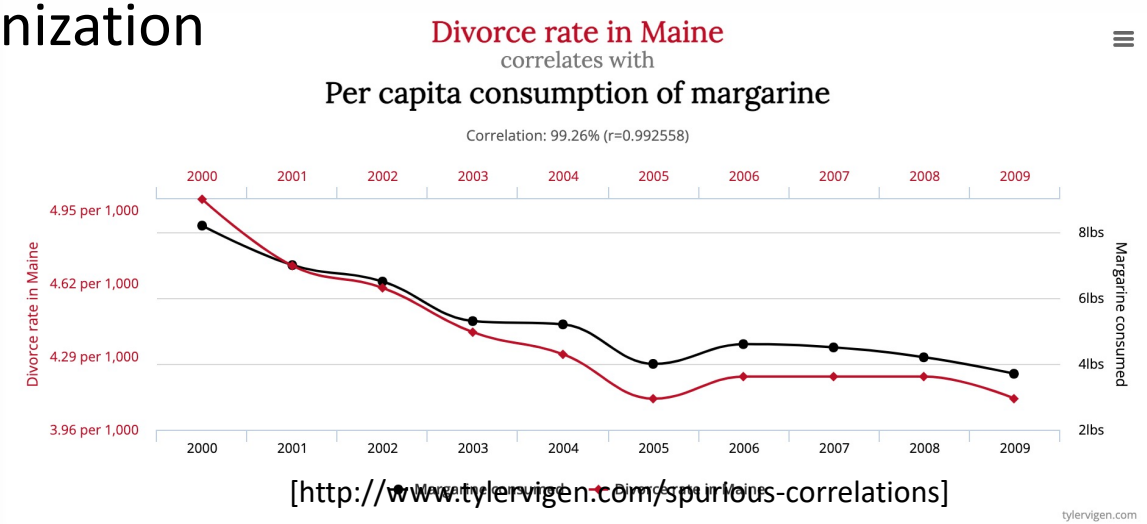
Identifying “links” (“relationships”) between multiple variables

Goal of multivariate EDA measures

- Mostly, multivariate EDA measures aim at discovering links / « relationahips » between multiple variables
  - Covariance / correlation (numeric / ordinal variables)
  - χ^2coefficient (nominal variables)

Link is **different** from causality (cause-effect)

- Link between 2 variables can be induced by other factors
  - For instance, two variables which happen to vary similarly with time/modernization



[http://www.tylervigen.com/spurious-correlations]

Covariance

- Covariance measures the linear link between numeric variables

- Covariance between 2 numeric variables *X* and *Y*

$$\sigma(X,Y)=\mathrm{cov}(X,Y)=\mathrm{cov}(Y,X) \qquad = \frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})$$

- Covariance **matrix** between *p*>2 numeric variables

$$S = \begin{pmatrix} \sigma^2(X) & \sigma(X,Y) & \sigma(X,Z) \\ \sigma(X,Y) & \sigma^2(Y) & \sigma(Y,Z) \\ \sigma(X,Z) & \sigma(Y,Z) & \sigma^2(Z) \end{pmatrix}$$

Pearson's correlation

- Problem with covariance: it is not bounded
  - Difficult to say if it's high or low: depends on the range of the variables' values
- Hence, Pearson's correlation (linear correlation) coefficient
  - Bounded in [-1, 1] -> more often used than covariance
- Pearson's correlation between 2 numeric variables *X* and *Y*

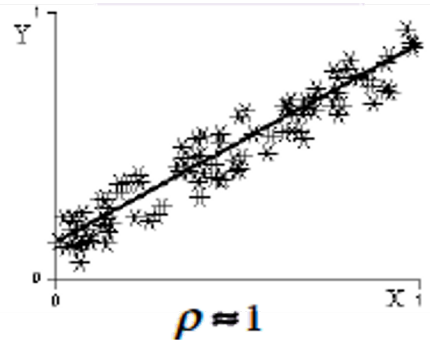
$$\rho(X,Y) = corr(X,Y) = corr(Y,X) = \frac{1}{n}\frac{\sum_{i=1}^{n}(x_i-\mu(X))(y_i-\mu(Y))}{\sigma(X)\sigma(Y)} = \frac{\sigma(X,Y)}{\sigma(X)\sigma(Y)}$$

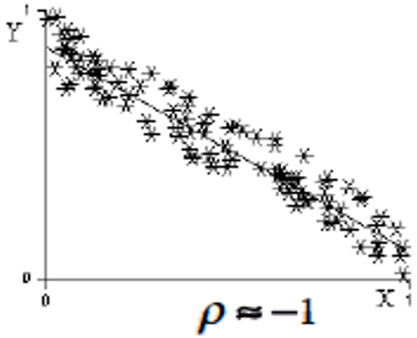
- Pearson's correlation **matrix** between *p*>2 numeric variables

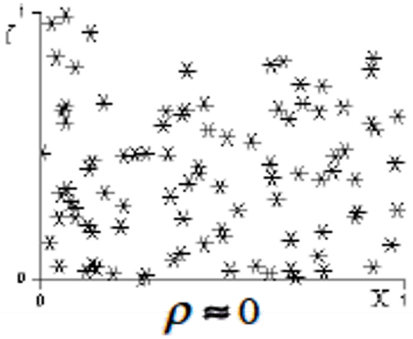
$$R = \begin{pmatrix} 1 & \rho(X,Y) & \rho(X,Z) \\ \rho(X,Y) & 1 & \rho(Y,Z) \\ \rho(X,Z) & \rho(Y,Z) & 1 \end{pmatrix}$$

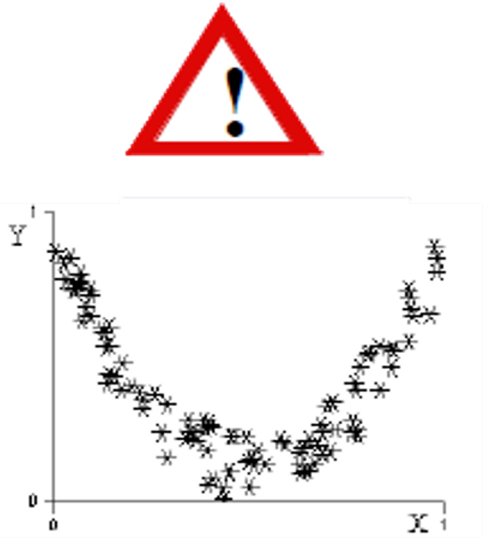
Pearson's correlation - limitations

- Pearson's correlation can **only** be applied to numeric variables
- Pearson's correlation can **only** detect linear links between variables
- Therefore, $\rho=0$ **does not imply** that the variables are statistically independent
  - Except for normal (Gaussian) variables
  - But statistically independent => $\rho=0$

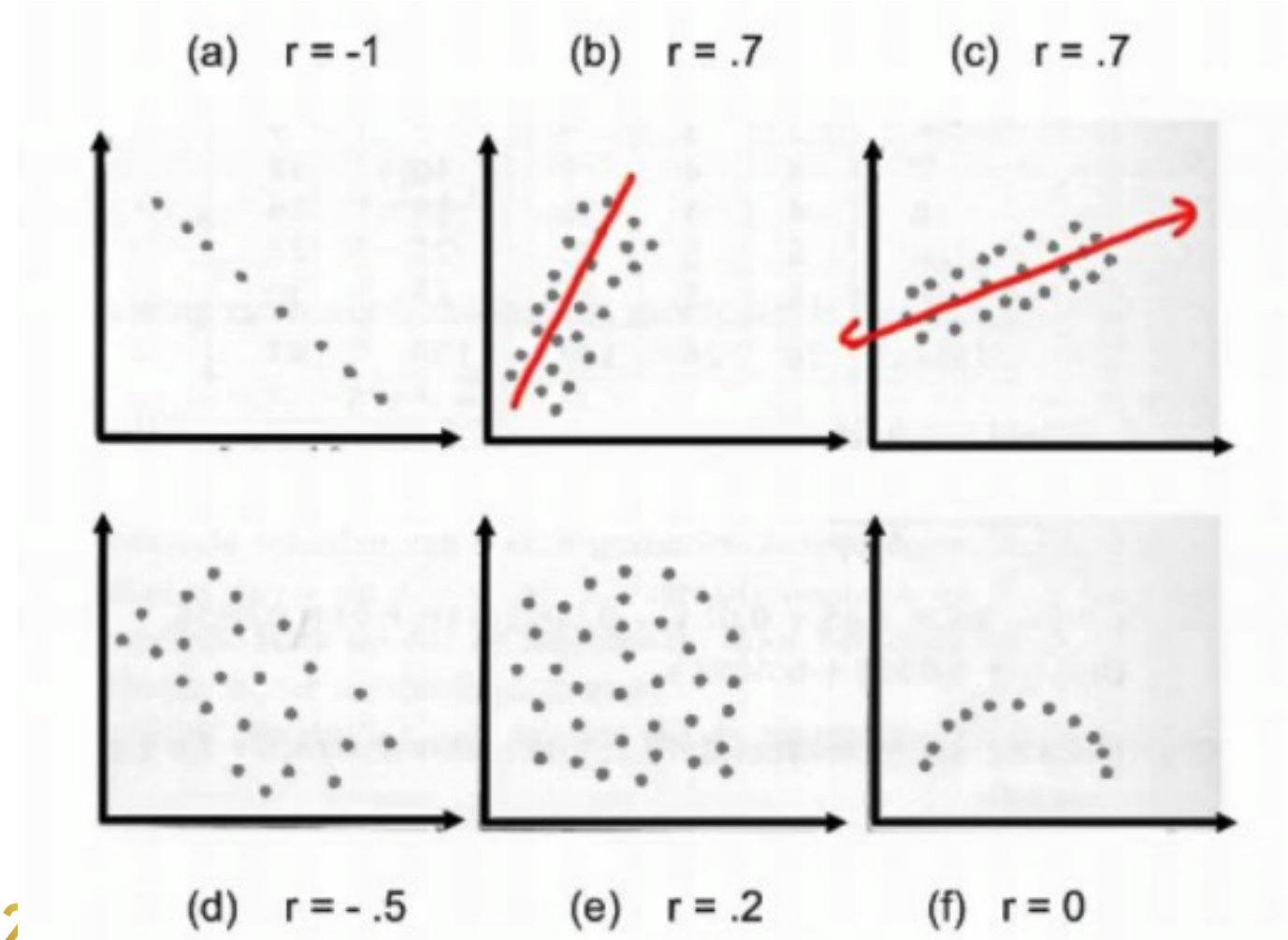






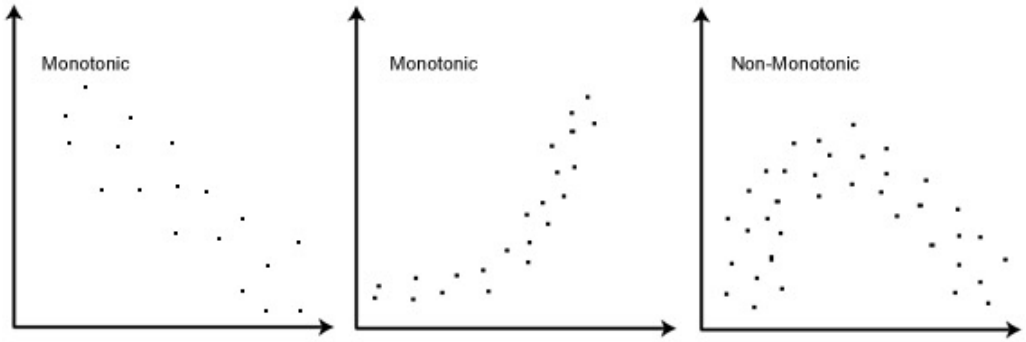


Some real examples



Spearman's correlation

- Spearman's correlation can be applied to numeric variables and to ordinal categorical variables
- Spearman's correlation
  - can detect monotonic links, whatever their shape
    - linear, exponential, ...



  - is based on the links between the **ranks** of observations

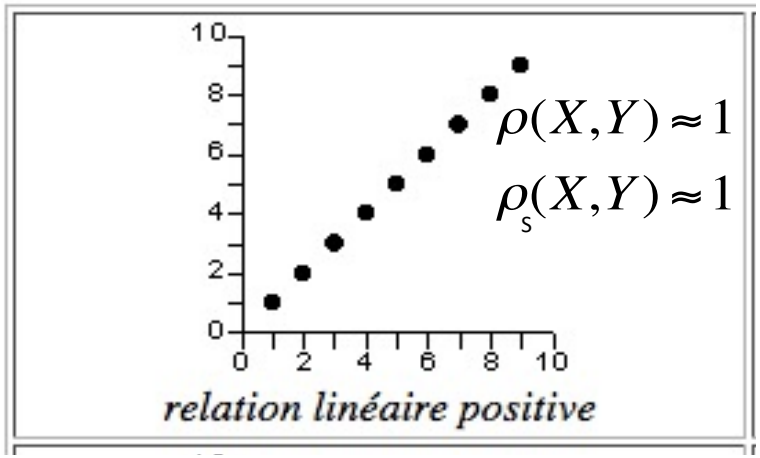
$$\rho_S(X,Y) = 1 - 6\frac{\sum_{i=1}^{N}(r(X_i) - r(Y_i))^2}{N^3 - N}$$

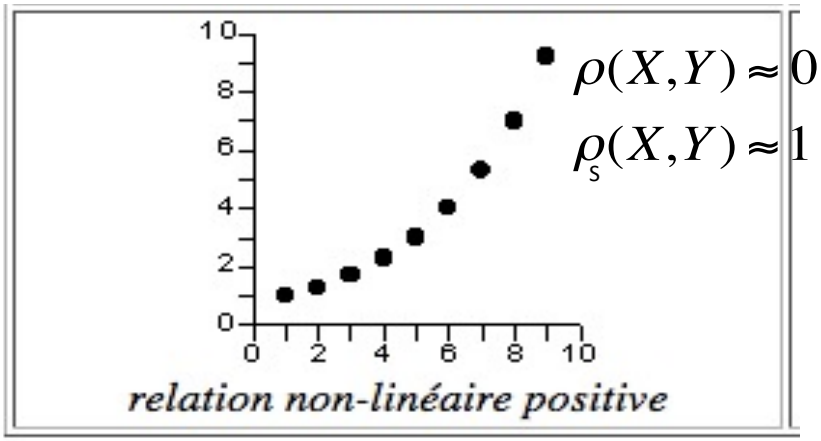
Where $r(X_i)$ is the **rank** of X_i in the distribution of $X_1, \dots X_n$ and $r(Y_i)$ is the **rank** of Y_i in the distribution of $Y_1, \dots Y_n$

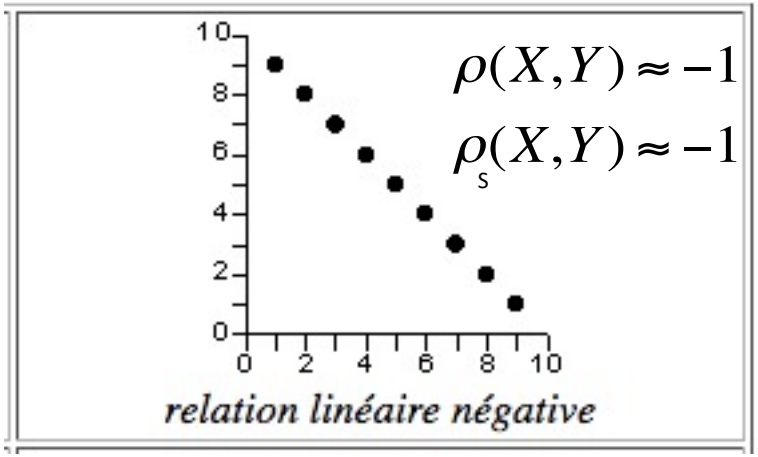
Spearman's correlation

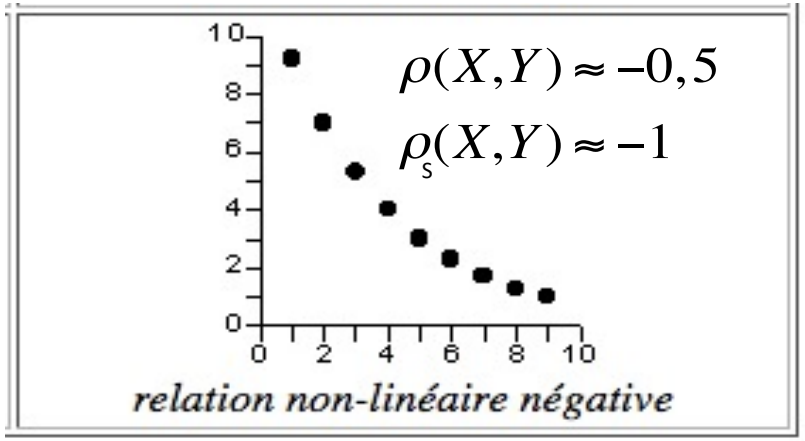
- Spearman's correlation is preferrable to Pearson's correlation if:
  - The variables are ordinal
  - The variables are numeric, but visibly non-Gaussian (*e.g.* asymmetric)
  - The link between the two variables is visibly non-linear
  - There are outliers in the distributions

Pearson *vs.* Spearman: example









Exercise 1

- Yesterday, I went to the market and bought 8 oranges
- I weighted them, wrote down their initial weight, then squizzed them for juice and weighted the waste
- So, I could determine, for each orange, the percentage of juice that each orange had
- I got the following observations:

Orange number	1	2	3	4	5	6	7	8
Orange weight	50	30	48	45	42	53	32	38
% of juice	80%	53%	70%	65%	58%	100%	53%	54.5%

Exercise 1 (cont'd)

- Draw roughly (on a piece of paper) the percentage of juice as a function of the (initial) orange weight
- By hand, calculate Pearson's correlation coefficient between the initial weight and the percentage of juice
- By hand, calculate Spearman's correlation coefficient between the initial weight and the percentage of juice
- What conclusions can you draw?

Orange number	1	2	3	4	5	6	7	8
Orange weight	50	30	48	45	42	53	32	38
% of juice	80%	53%	70%	65%	58%	100%	53%	54.5%

Exercise 1 solution

Exercise 2

- I did the same today, and I got the following observations
- Draw roughly (on a piece of paper) the percentage of juice as a function of the (initial) orange weight
- By hand, calculate Pearson's correlation coefficient between the initial weight and the percentage of juice
- By hand, calculate Spearman's correlation coefficient between the initial weight and the percentage of juice
- What conclusions can you draw?

orange number	1	2	3	4	5	6	7	8
orange weight	48	30	40	45	42	53	32	38
% of juice	73,00%	58,50%	55,00%	65,00%	58,00%	85,00%	53,00%	54,50%

Exercise 2 solution

Measuring the link between categorical variables

- When both variables are categorical and at least one is nominal, we can use the χ^2 coefficient
- Idea: measure the difference with the ***expected*** values (theoretical values, if the variables were independent)

	Like Scary Movies		
	Yes	No	Total
Girls	32	38	70
Men	30	12	42
Total	62	50	112
Percentage	55.4%	44.6%	

Question

- What are the expected values (if girls and men liked scary movies as much)?
  - N.B. The following table is called a contingency table

	Like Scary Movies		
	Yes	No	Total
Girls	32	38	70
Men	30	12	42
Total	62	50	112
Percentage	55.4%	44.6%	

Answer

- What are the expected values (if girls and men liked scary movies as much)?
  - N.B. The following table is called a contingency table

	Like Scary Movies		
	Yes	No	Total
Girls	32 *38.75*	38 *31.25*	70
Men	30 *23.25*	12 *18.75*	42
Total	62	50	112
Percentage	55.4%	44.6%	

Definition of the χ^2 coefficient

- Notations

Y / X	x_1	x_l	x_L	Σ
y_1				
y_k		n_{kl}		$n_{k.}$
y_K				
Σ		$n_{.l}$		n

- χ^2 coefficient

$$\chi^2(X,Y) = \sum_{k=1}^{K}\sum_{l=1}^{L} \frac{\left(n_{kl} - \frac{n_{k.}n_{.l}}{n}\right)^2}{\frac{n_{k.}n_{.l}}{n}}$$

Expected values

Quiz

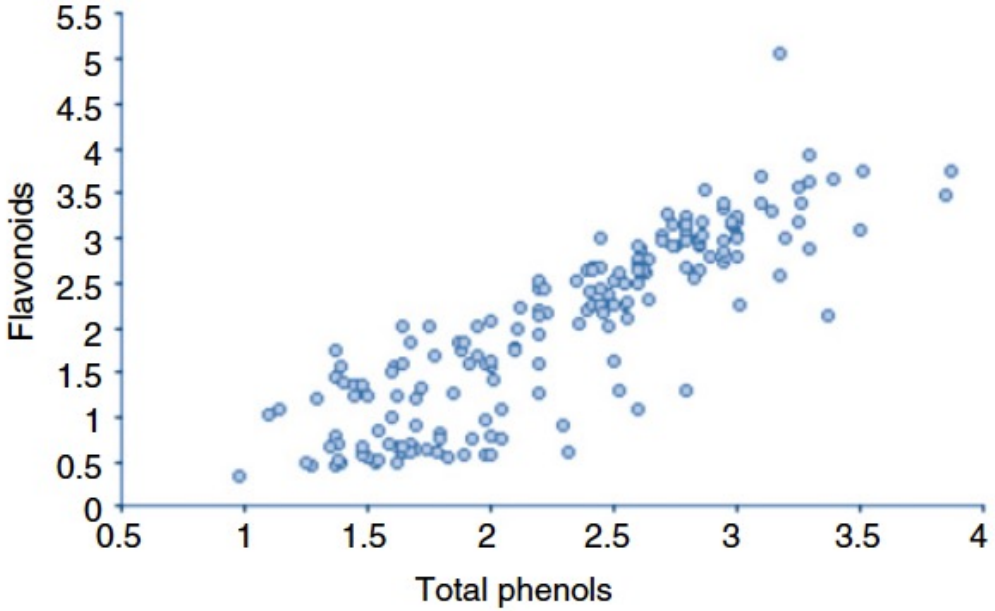
- If the χ^2 coefficient is almost 0, is there a link between the two variables, or are they not linked?
  - Answer:
- In the example of scary movies, how much is the χ^2 coefficient value?
  - Answer:
  - Homework: verify that you find the same number at home

- But, is this value **high enough** to say that liking scary movies is linked to gender, or not???
  - This is a tricky question actually, especially with few observations…
  - To answer this question, we need **hypothesis testing** (here a χ^2 test): out of the scope of this course…
    - https://en.wikipedia.org/wiki/Chi-squared_test
  - FYI: in this case, yes, liking scary movies is **significantly** linked to the gender…
  - Hypothesis testing is also required to determine if Pearson's / Spearman correlation is significant, or not
    - https://online.stat.psu.edu/stat501/lesson/1/1.9

Multivariate EDA **graphics**

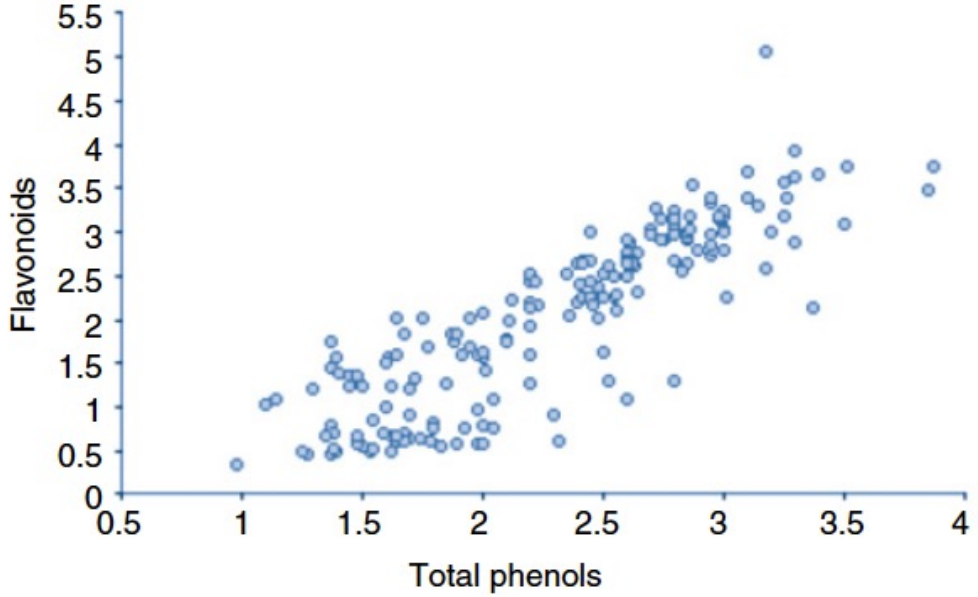
Scatter plot

- Objective: detect possible links between two **numeric, continuous** variables
  - two variables are plotted on the x-and y-axis
  - each point is a single observation.



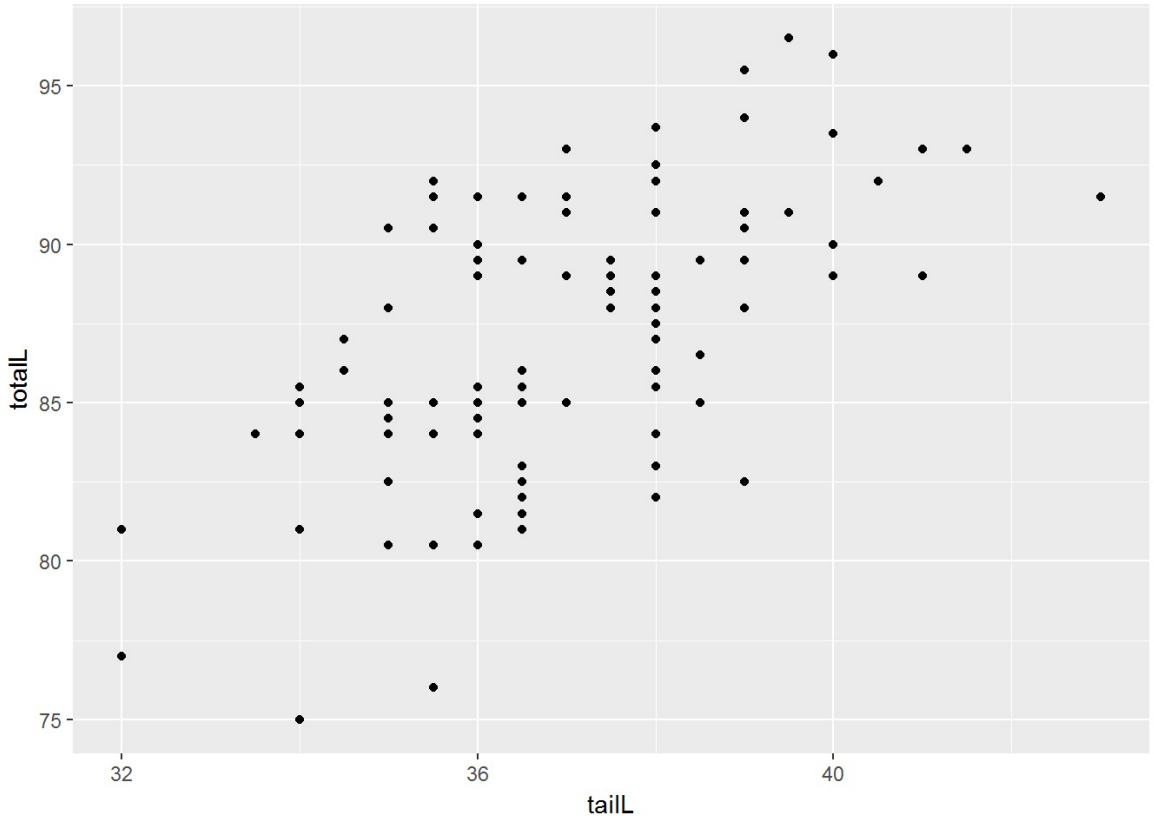
Scatter plot

- Scatter plots can provide answers to the following questions:
  - Are variables X and Y related?
  - Are variables X and Y linearly related?
  - Are variables X and Y non-linearly related?
  - Does the variation in Y change depending on X?
  - Are there outliers?



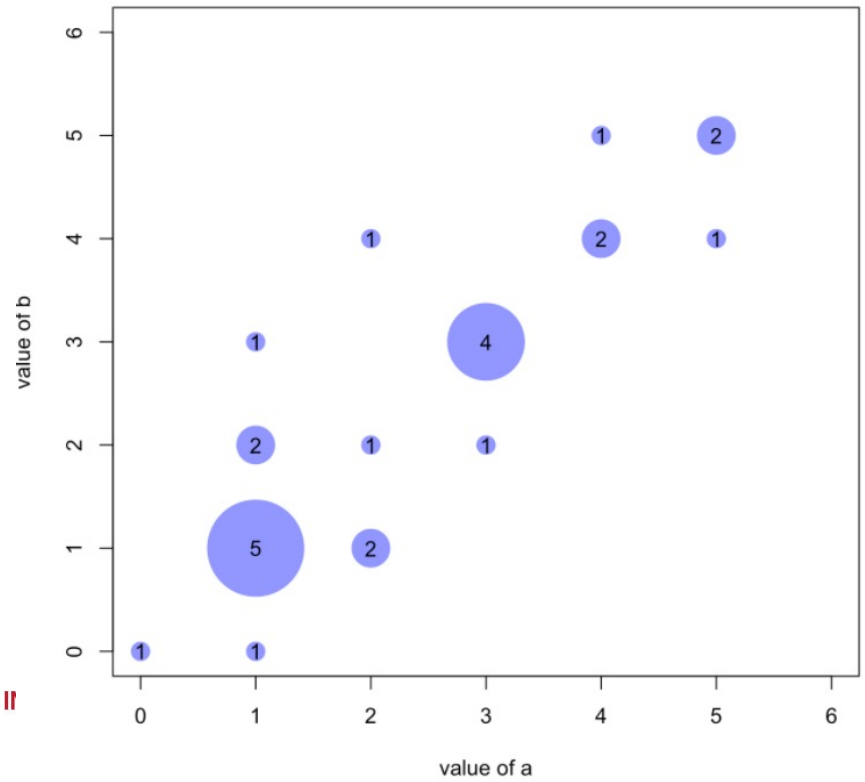
Scatter plot

- Scatter plots might also look like that
  - In particular, when one of the variables is **numeric**, but **discrete** (but not only)



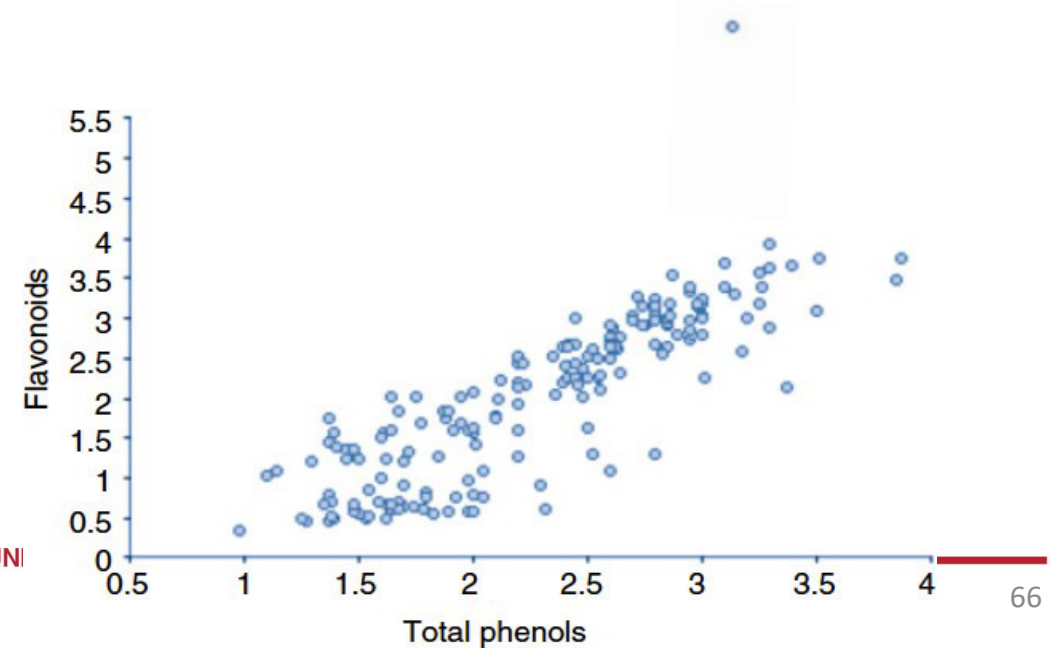
Scatter plot

- Scatter plot with **numeric, discrete** variables
  - Difficulty: if both variables are discrete, points might be cluttered
    - (overplotting)
  - Solution: Make bigger « circles » for the value sets with more data



Quiz

- With this scatter plot, do you expect Pearson's coefficient to be: close to -1, close to 1, or close to 0?
  - Answer:
- With this scatter plot, do you expect Pearson's coefficient to be: close to -1, close to 1, or close to 0?
  - Answer:
- Are there any multivariate / univariate outlier(s)?
  - Answer:



Quiz

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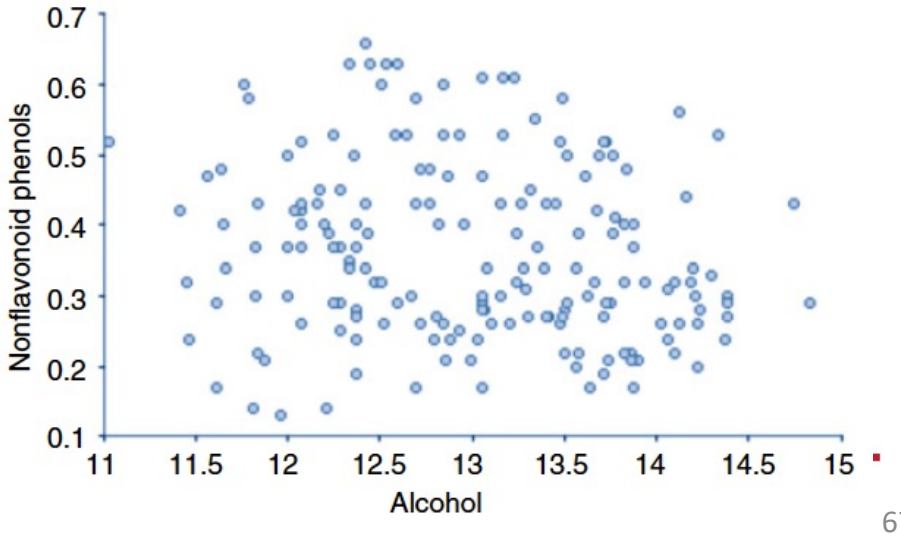
  - Answer:
- Are there any multivariate / univariate outlier(s)?
  - Answer:



Quiz

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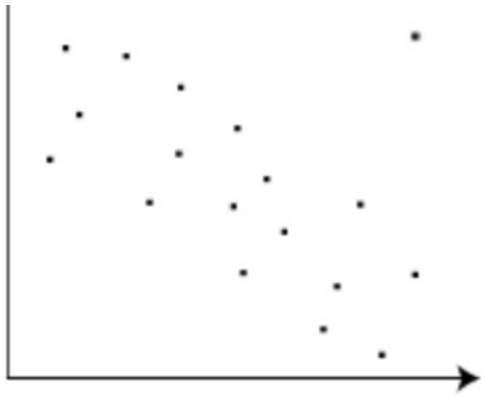
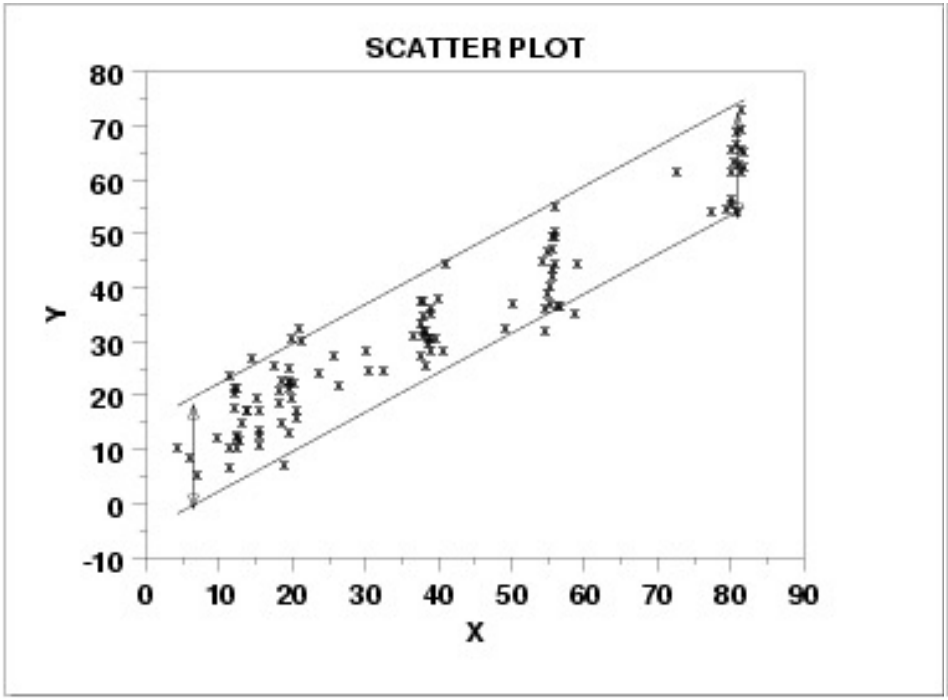
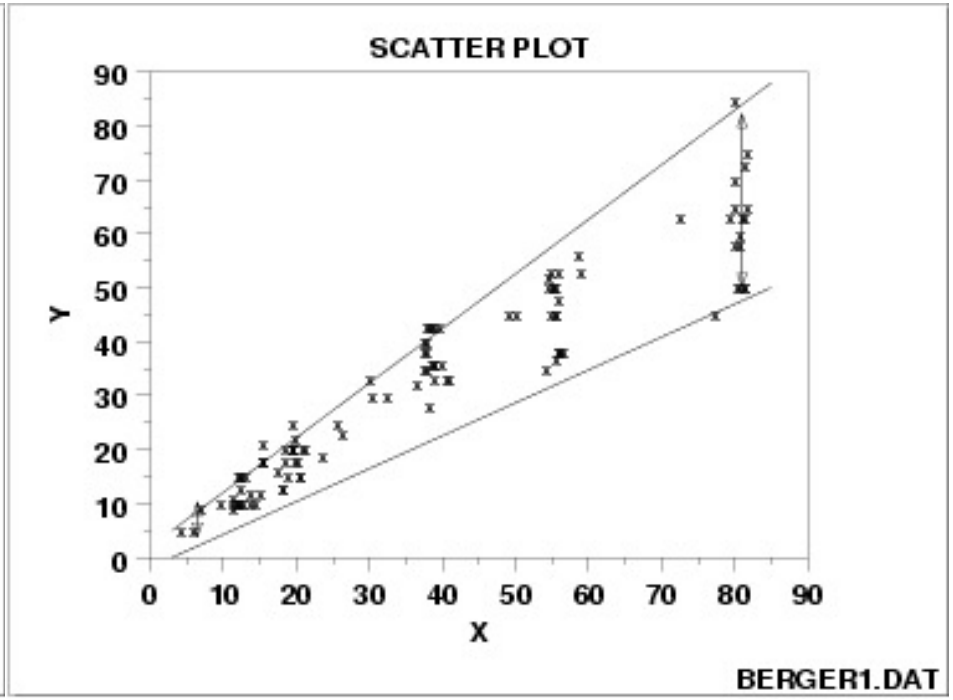
  - Answer:
- With this scatter plot, do you expect Pearson's coefficient to be: close to -1, close to 1, or close to 0?
  - Answer:
- Are there any multivariate / univariate outlier(s)?
  - Answer:



Scatter plot: variation of Y does not depend on X

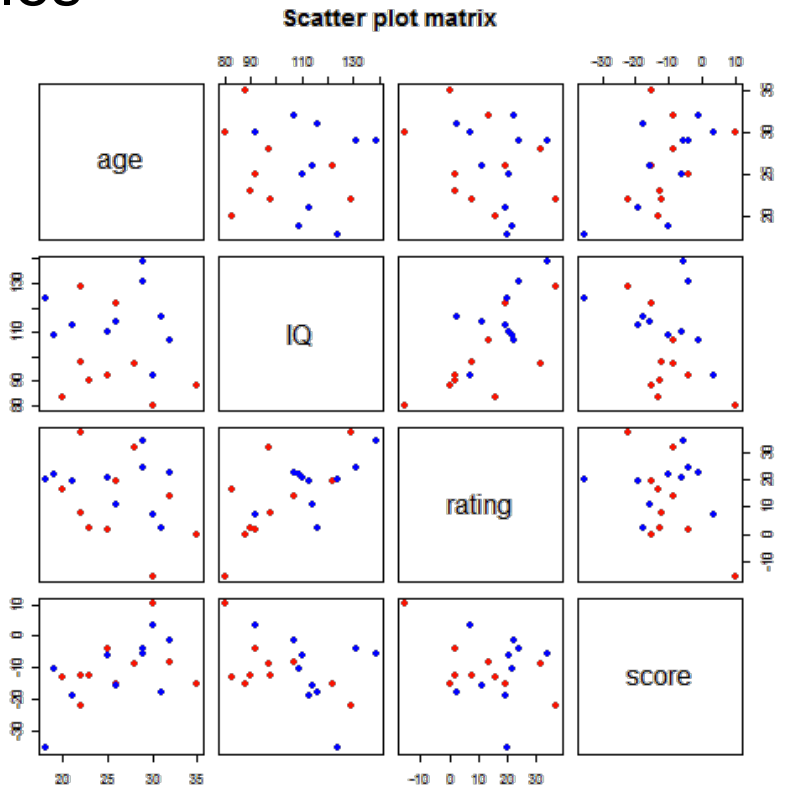
- Notion of homoscedasticity / heteroscedasticity
  - https://www.statisticshowto.com/homoscedasticity/





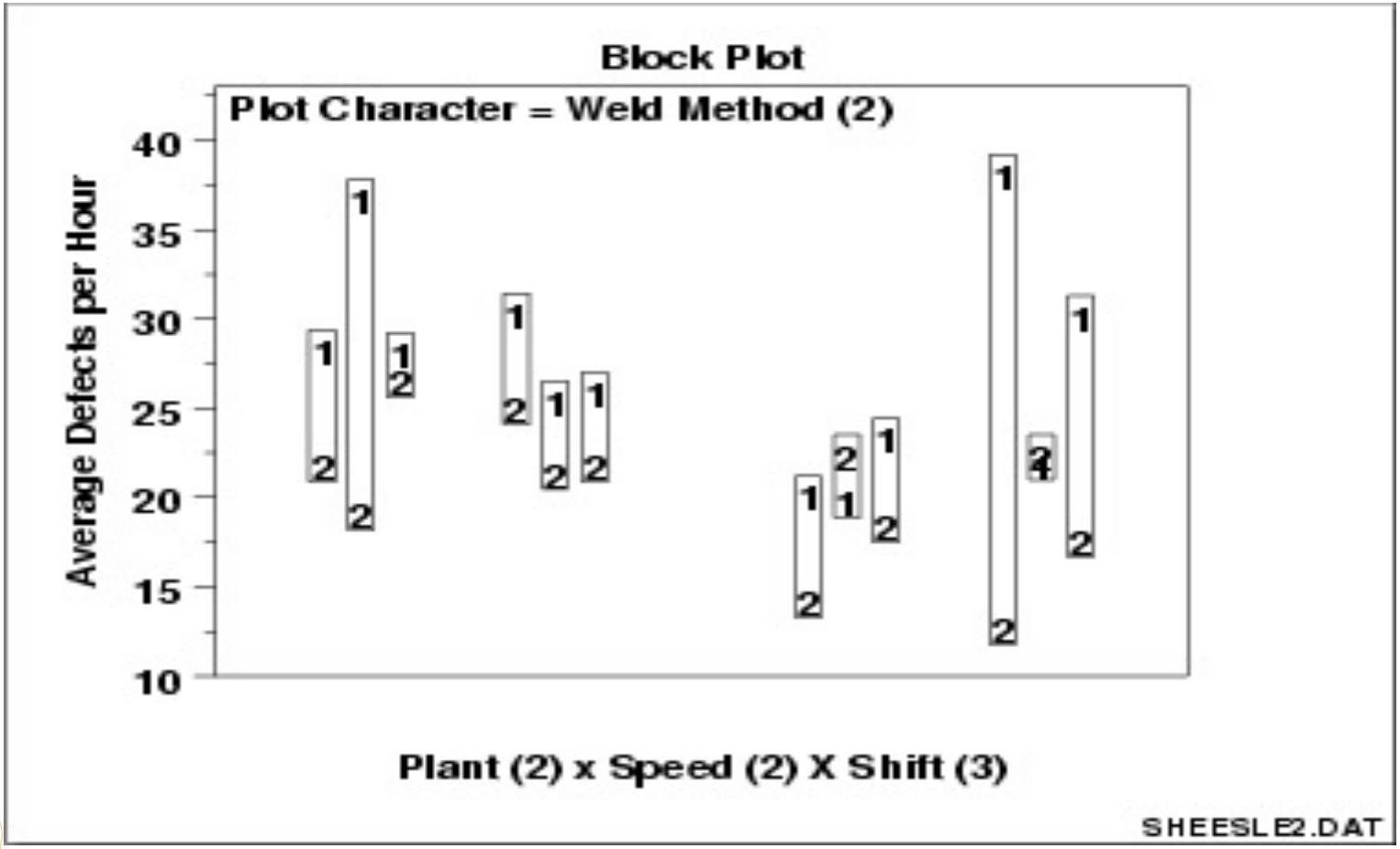
Scatterplot matrix

- Collection of **scatterplots** organized into a grid (or **matrix**)
- Each **scatterplot** shows the relationship between a pair of variables



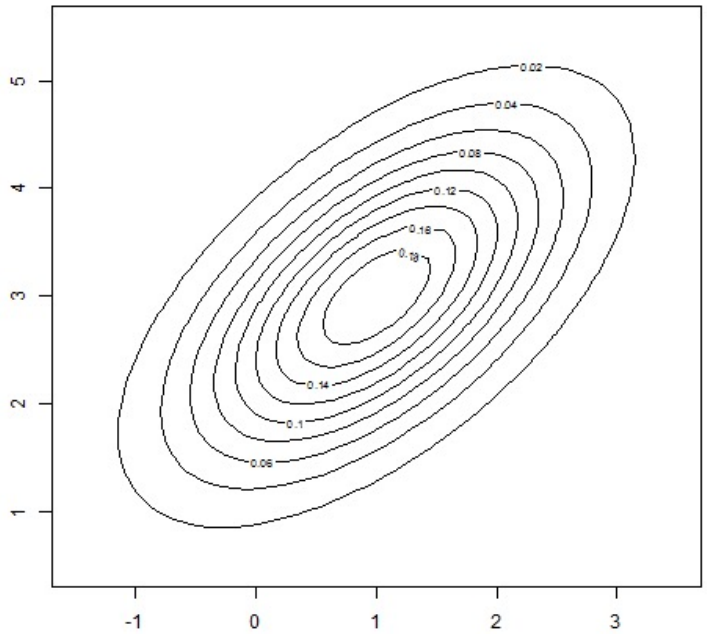
Block plot

- Useful to compare different groups of records using 2 categorical variables (with few modalities)



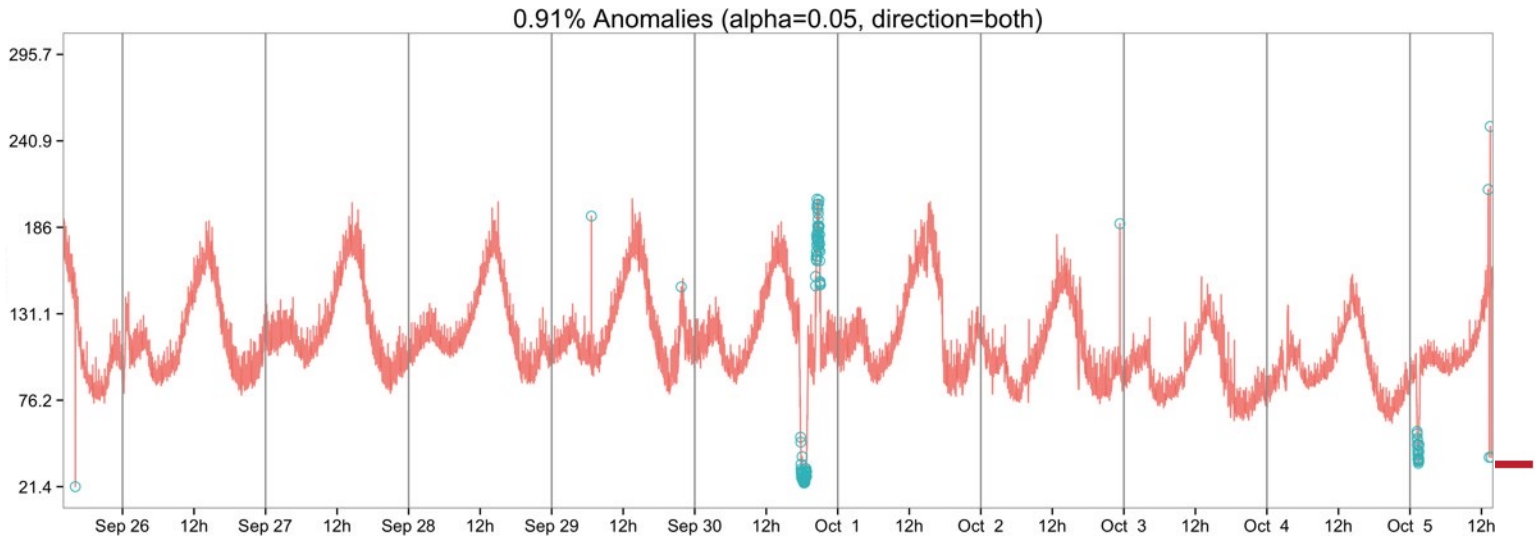
Contour plots

- Useful to visualize 3D data but on a two-dimensional plane
  - Contour lines indicate elevations that are the same
- The contour plot is used to answer the question
  - How does Z change as a function of X and Y?



Special case of time series

- Run sequence plot displays data in a time sequence
- Can be seen as a special kind of scatter plot
  - But, only one variable « of interest »: the variable on the y-axis
- The run sequence plot can be used to answer the following questions
  - Are there any shifts in central tendency (on the y-axis)?
  - Are there any shifts in variations(on the y-axis)?
  - Are there any outliers?



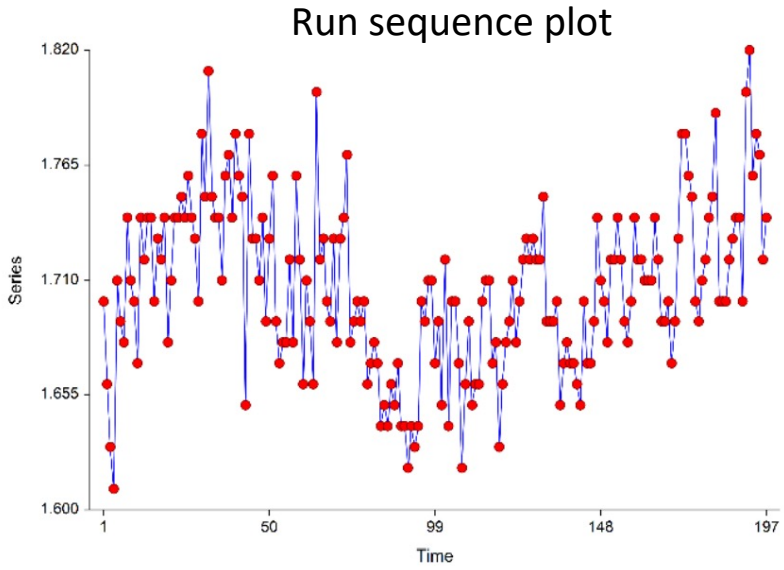
Special case of time series

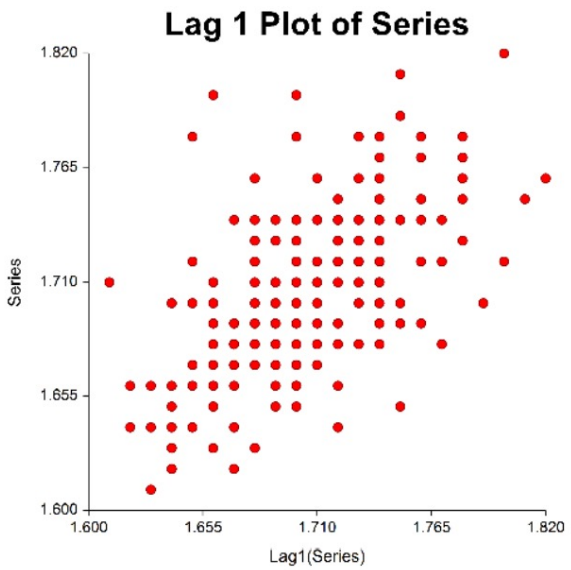
- **Autocorrelation** represents the degree of similarity between a given time series and a lagged version of itself over successive time intervals.
  - For example, in places where the weather is quite stable:
    - If it's rainy today, then it's more likely to rain tomorrow also

- Autocorrelation is conceptually similar to the correlation between two different time series, but autocorrelation uses the same time series twice (1x original, 1x lagged)

Special case of time series

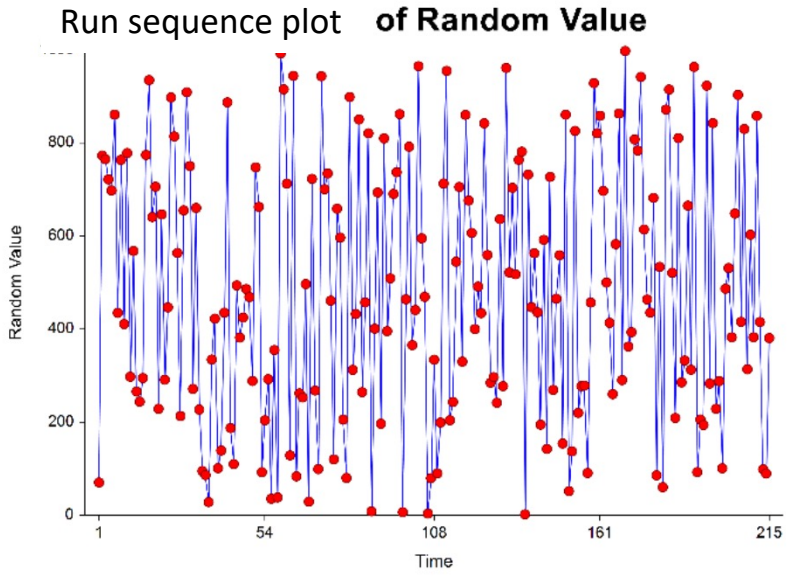
- To detect **auto-correlation** in a time series, one might use **lag plot**
  - The time interval (lag=k) is fixed for all data
    - If Y_i = value of the y-axis variable at time *I*, $\text{Lag}_k(Y_i) = Y_{i-k}$
    - For example, $\text{Lag}_1(Y_2) = Y_1$ and $\text{Lag}_3(Y_{10}) = Y_7$

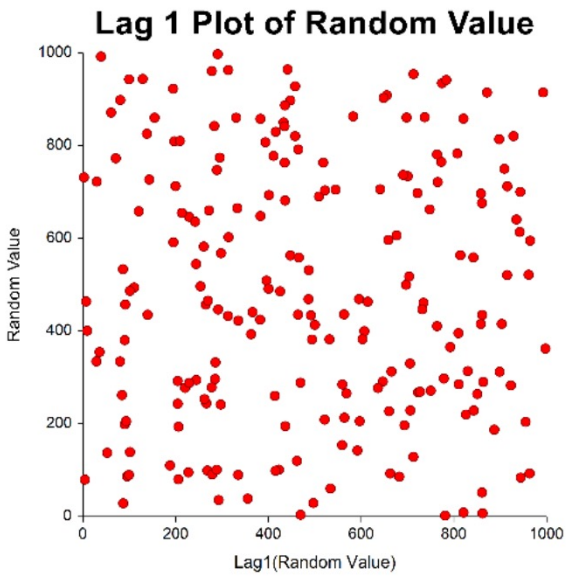




Example of lag plot

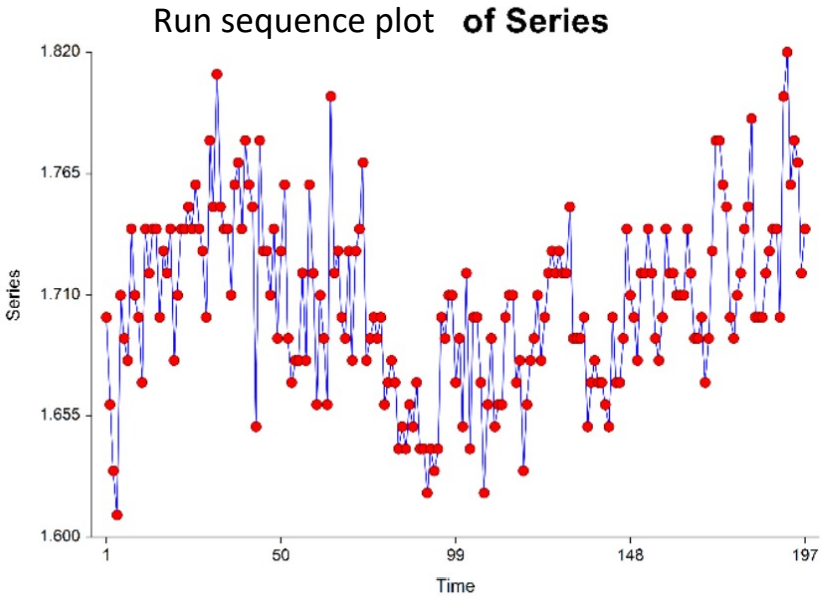
- Random Data (no autocorrelation)

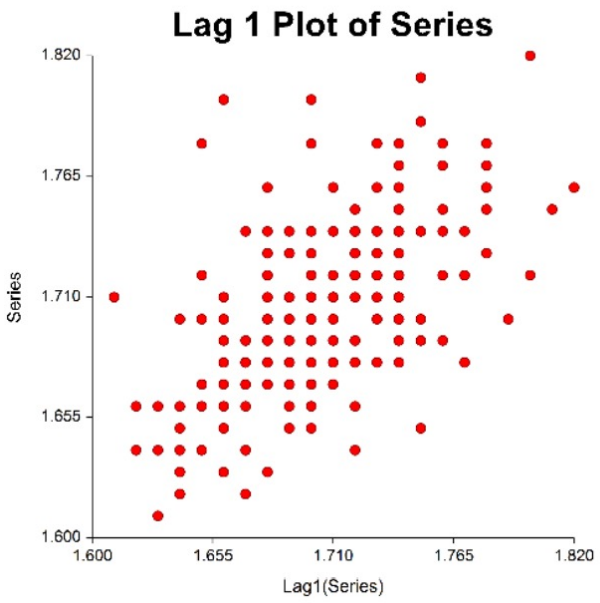




Example of lag plot

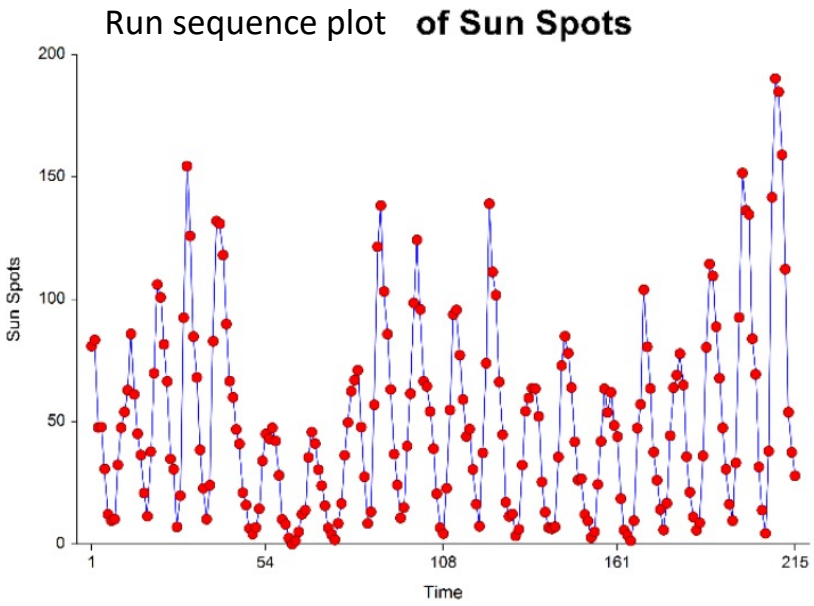
- Data with weak autocorrelation

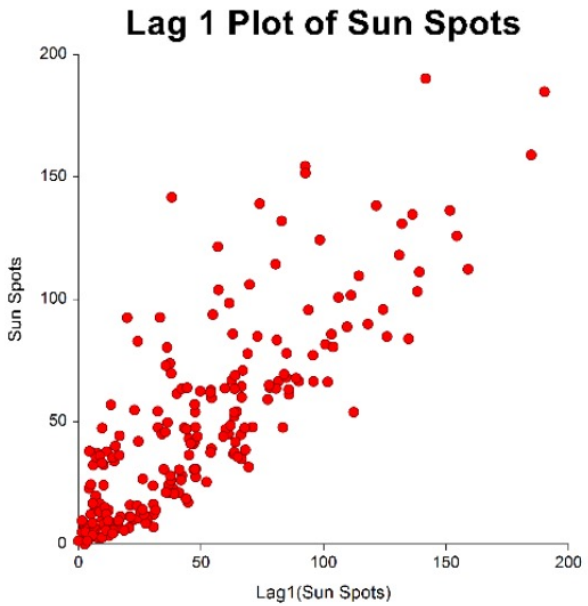




Example of lag plot

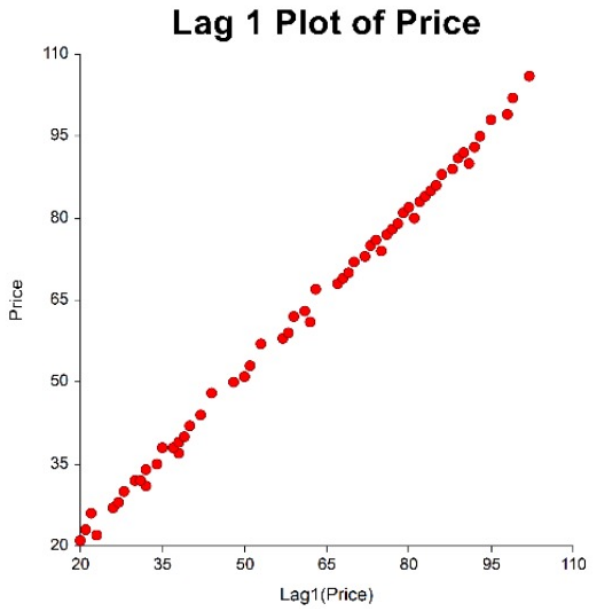
- Data with moderate autocorrelation





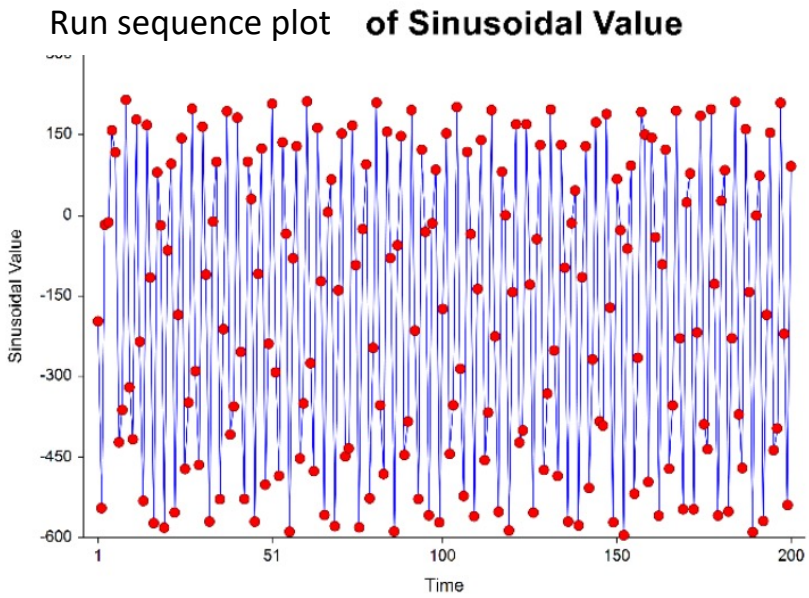
Example of lag plot

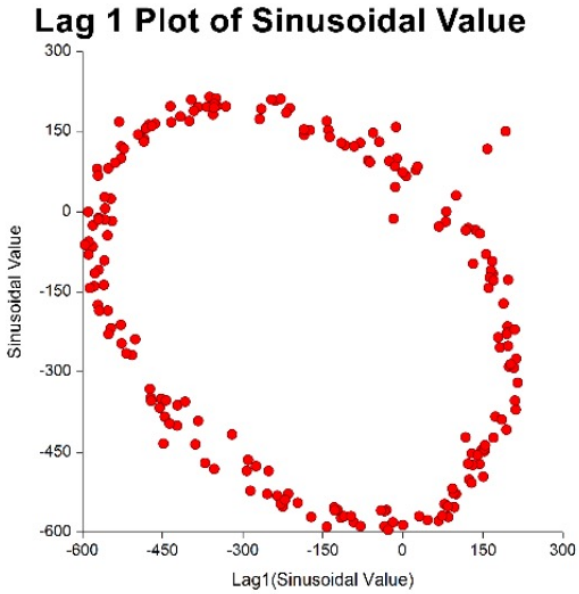
- Data with moderate autocorrelation



Example of lag plot

- Lag-plot of sinusoidal data



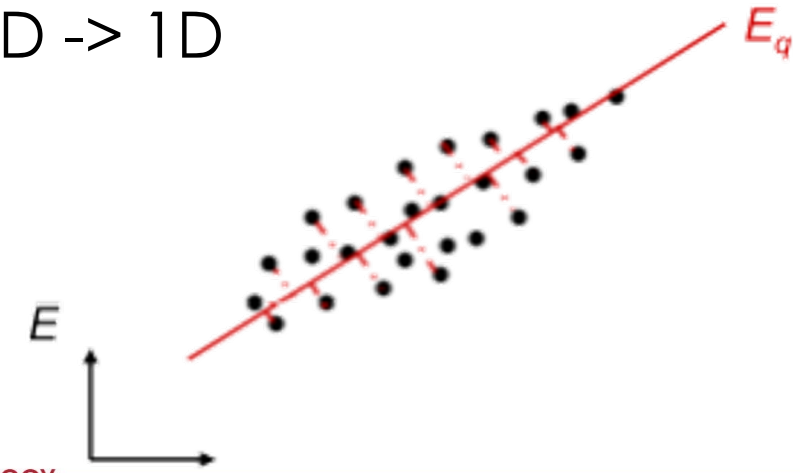


More advanced EDA techniques

Motivations

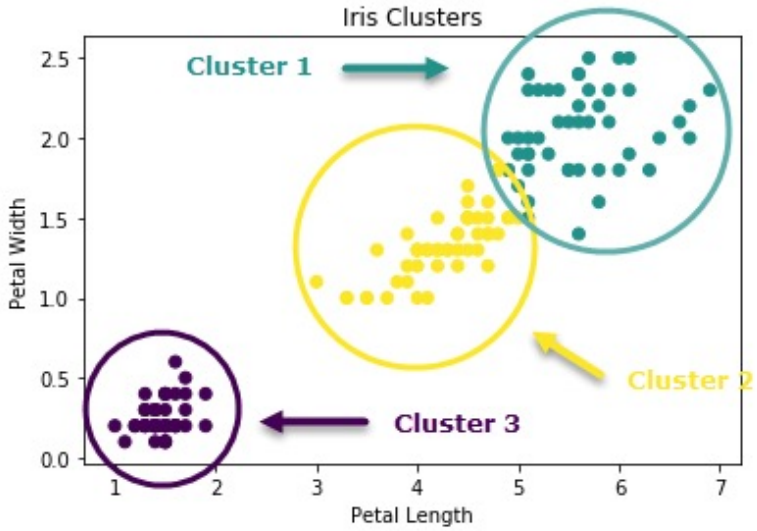
- Contour plots are fine with 3 variables, but what if we have 12 variables for instance?
  - Advanced **visualization** techniques (chapter 5)
  - **Dimensionality reduction** techniques (chapter 6)
    - *E.g.* Principal Component Analysis (**PCA**)
      - Finds the optimal hyperplane Eq of reduced dimensions that best represents the « shape » of the data (minimizes MSE)
      - Example: PCA for 2D -> 1D

MSE = $\sqrt{\frac{\sum_{i=1}^{n} ei^2}{n}}$; ei=distance between x_i in *E* and its projection on Eq



Motivations

- What if some scatter-plots show different *clusters* of data?
  - Might be interesting to observe in order to summarize the data (create customer groups for instance)
  - Clustering techniques are unsupervised Machine Learning techniques (Chapter 6)



Summary

Summary

- In this lecture, you've learned (1/2):
  - Univariate EDA **measures**
    - Central tendency (location)
      - Mean, median, mode
    - Scale (data spread)
      - Variance, standard deviation (for numeric variables)
      - Gini index, entropy (for categorical variables)
    - Shape of the distribution
      - Kurtosis, skewness (for numeric variables)
  - Univariate EDA **graphics**
    - Histogram, boxplot (for numeric variables)
    - Bar chart (for categorical variables)

Summary

- In this lecture, you've learned (2/2):
  - Multivariate EDA **measures**
    - Covariance and Pearson's coeffcient (for numeric variables)
    - Spearman coefficient (for numeric and categorical, ordinal variables)
    - Chi2 coefficient (for categorical variables)
  - Multivariate EDA **graphics**
    - Scatter plot and contour plots (for numeric variables)
    - Block plots (for categorical variables with few modalities)
    - Run sequence plot and lag plot (for time series)

Summary

- In this lecture, you've had an overview about:
  - More advanced EDA techniques
    - Visualization (see chapter 5)
    - Dimensionality reduction (see chapter 6)
    - Clustering (see chapter 6)

Homework

Homework (for next lesson)

- By hand:
  - If not finished yet, make the exercises on page 31 and 51-55
- Using a specific software (Tableau Public)
  - Register on Tableau Public
  - Do the following tutorial: https://help.tableau.com/current/guides/get-started-tutorial/en-us/get-started-tutorial-home.htm
  - Because this tutorial is based on Tableau Desktop (paying version) and not Tableau Public (free version), there are a few things that cannot be done, such as:
    - At the very end of "Step 3: Focus your results", File -> Save As
    - In "Step 5: Drill down into the details", some hierarchy-based actions are not possible to perform using the Public version
    - In "Step 8: Share your findings with others", do the section "Use Tableau Public" only

EDA: to be continued in the next chapters…

Questions

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Thank you for your attention!!!