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MISSING DATA

Missing data

- Missing data is very common
- · Main reasons behind missing data:
 - Person did not want to share his/her personal data
 - Data loss during data transfer
 - Lack of information, etc
- Important: some algorithms will ignore missing values, while others will not even run if missing data exists

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Approaches for handling missing data

We will analyze a couple of ideas to handle missing data:

- Removing rows with missing values
- 2. Removing rows where most part of the values are missing
- 3. Ignoring columns with too many missing values
- 4. Data imputation
- 5. Data imputation using machine learning

#1: Removing rows with missing values

- Sometimes, the number of rows with missing values is not too big (< 5%)
- If this is the case, we can think about removing the rows with missing values
- Important: we should try to avoid data removal as much as possible

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#2: Removing rows where most of the values are missing

- An often better approach is to remove instances in which most of the values are missing
- The threshold may change here, e.g., 70%, 75%, 80%, etc
- How do we pick this threshold up?
 - Feeling
 - We check how much data we will lose

#3: Ignoring columns with too many missing values

- If the number of missing values is too high for a column, perhaps we should get rid of the column
- Again: what is the threshold for flagging a column removal?

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#4: Data imputation

- If you don't have too many missing values, we can replace these values with a "generic" value
- This is not necessarily the best approach, as we are not sure whether this "generic" value is a common behavior in data

More on imputation

- Static value
 - Replace missing values with a 0, +99999999 or -99999999
 - Do these values make sense? What is their impact when using machine learning?
- Statistic
 - Replace missing values with the mean/median/mode of the remainder of the values
 - Mean: what if the data has outliers?
- Predictive model
 - We can infer the missing values based on the present values for the remainder of the columns

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Summing up

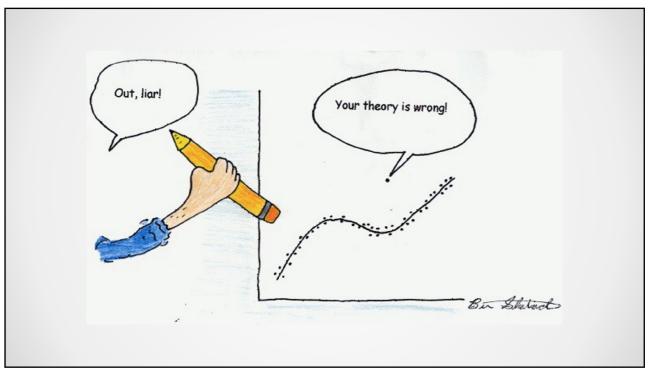
- If you don't have many missing values, we may ignore them
- If a column has too many missing values, we may remove it
- · Imputation is a viable option, but requires testing

Activity

 Let's identify and handle missing values using the Titanic dataset

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OUTLIERS



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Outlier

- · An outlier is a value that is very "far" from the others
- · It can be much smaller or bigger than the rest
- · Does not exhibit the same behavior as the other data
- It is hard to identify, as what is an outlier to a dataset might be different in other datasets

Reasons for Outliers

- · Mistakes in data acquisition
- · Data may be corrupted
- · Or maybe, the outlier is true

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Example

Do you see any outliers in this table?

Gender	Age	Height
М	20	159
F	21	191
М	24	173
М	24	181
F	28	156
М	26	192
F	19	280
F	22	162
М	26	190

Another example

What about in this table? Note that all of the data is correct, yet, Michael Phelps is still an outlier

Athlete	# of medals
Michael Phelps	28
Larisa Latiynina	18
Marit Bjorgen	15
Nikolai Andrianov	15
Ole Eimar Bjorndalen	13
Boris Shakhlin	13
Edoardo Mangiarotti	13

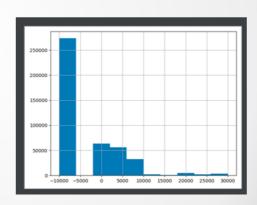
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FINDING OUTLIERS WITH HISTOGRAMS

Finding outliers with histograms

Histogram

- Univariate plot that allows us to analyze the data distribution of a single variable
- Let's plot the "MAIORRENDACASA" variable histogram and see what happens:)



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USING BOX-PLOTS FOR OUTLIER ANALYSIS

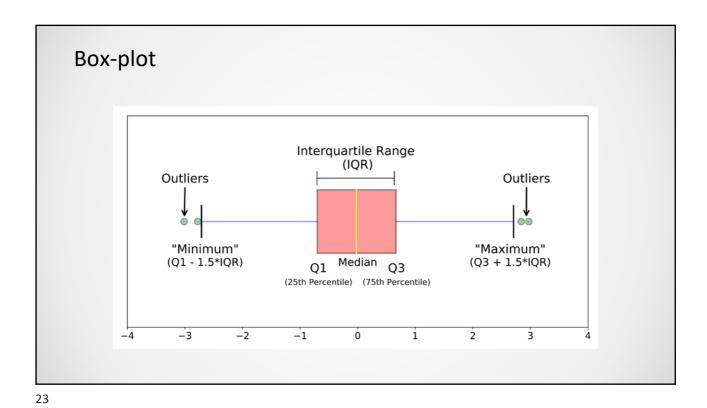
Agenda

- · We will use Tukey's method to identify outliers
- Tukey's method is based on quartiles, more specifically on the Inter-quartile range, or IQR
- · Overview:
 - Apply Tukey's method in each variable individually
 - If an instance is flagged as an outlier n times, then it should be removed
 - How do we define n?

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Inter-quartile Range

- The interval between the 1st and 3rd quartiles
- IQR = Q3 Q1
- If a value is greater than 1.5 * IQR + Q3 or smaller than Q1 1.5
 * IQR, then it is flagged as an outlier
- 1.5 is a "rule of thumb" proposed by Tukey
- 3 is a threshold for determining "far out" values
- Let's analyze this using boxplots



Using box-plots for outlier analysis

- · Be cautious
- There is no guarantee that data outside the IQR are, indeed, outliers
- · Approaches:
 - Check the data that has been flagged
 - Verify the IQR results for multiple variables, and if it is flagged multiple times, then it is very likely that this data point is an outlier

Activity

Let's use box-plots to analyze the variables available in the **OMMLBD_FAMILIAR.csv** file

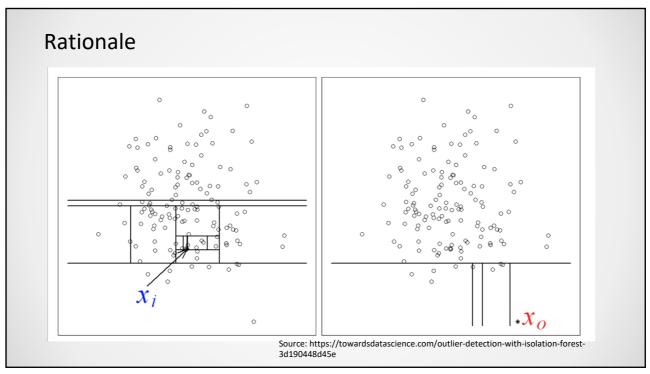
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ISOLATION FORESTS

Rationale

- · Outliers are less frequent than regular observations
- If the data is randomly partitioned, outliers will require, in average, less partitions to be **isolated** from the rest of the data points

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Isolation Forest

- A set of isolation trees are created, and each tree randomly partitions the data points
- An "anomaly score" is obtained for a data point as follows:
- · A score close to 1 stands for an outlier
- · A score smaller than 0.5 indicates normal observations
- If all scores are close to 0.5, the entire sample does not contain distinct anomalies

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Example

Let's use isolation forests in a toy example and understand it visually

ACTIVITY

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Enron

- Back in the 2000s, Enron was one of the biggest companies in USA
- In 2002, it went bankrupt due to frauds
- Most of the data has been made public
- And today we will work with the data on salaries and emails



Outlier analysis

- Using the Enron dataset, try and identify individuals with weird (outlier) behavior
- The rationale here is that if someone has an outlier behavior, it is likely to be a fraudster
- Use any tools you wish, but we expect you to find at least 3 major outliers
- Data is available at: http://www.ppgia.pucpr.br/~jean.barddal/datascience/e nron.csv