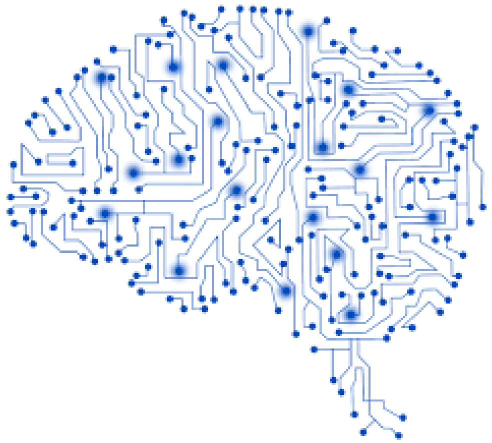
University of Minho
School of Engineering



Dados e Aprendizagem Automática

Data Exploration and Preparation

DAA @ MEI/1º ano – 1º Semestre

Data Quality

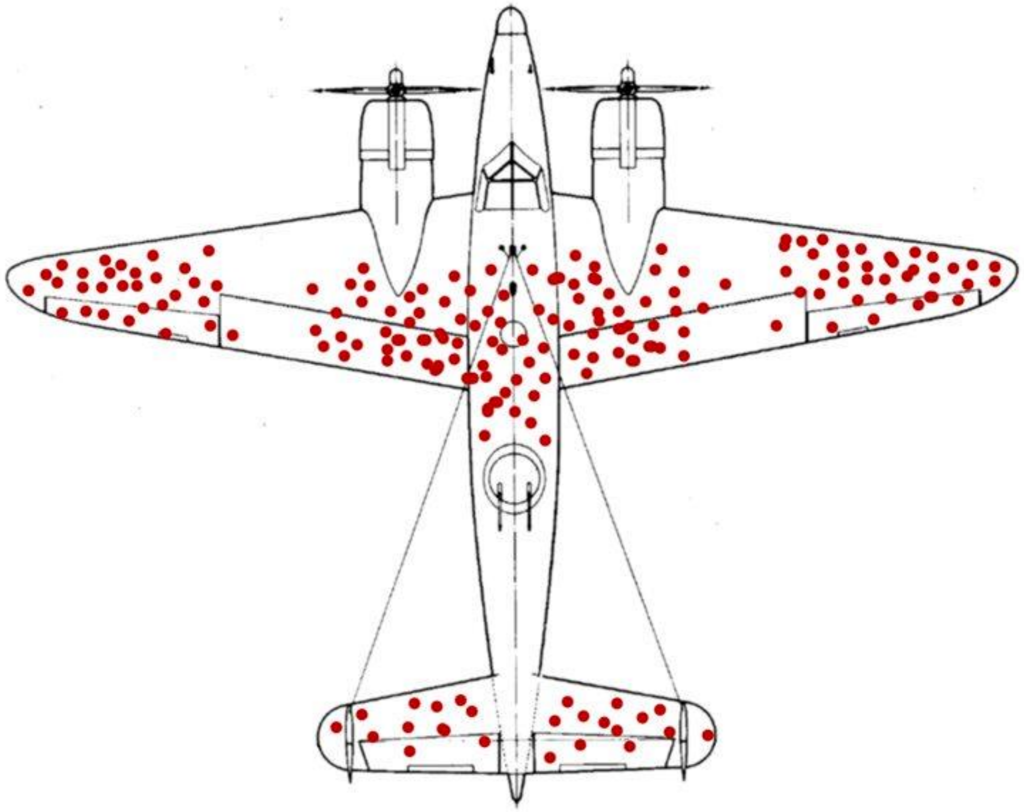
Think clearly…

During WWII, the US Navy tried to determine where they needed to armor their aircraft to ensure they came back home. They ran an analysis of where planes had been shot up.

Everybody told that, obviously, the places that needed to be up-armored are the wingtips, the central body, and the elevators. That’s where the planes were all getting shot up!

Abraham Wald, a statistician, disagreed.

Why?



Contents

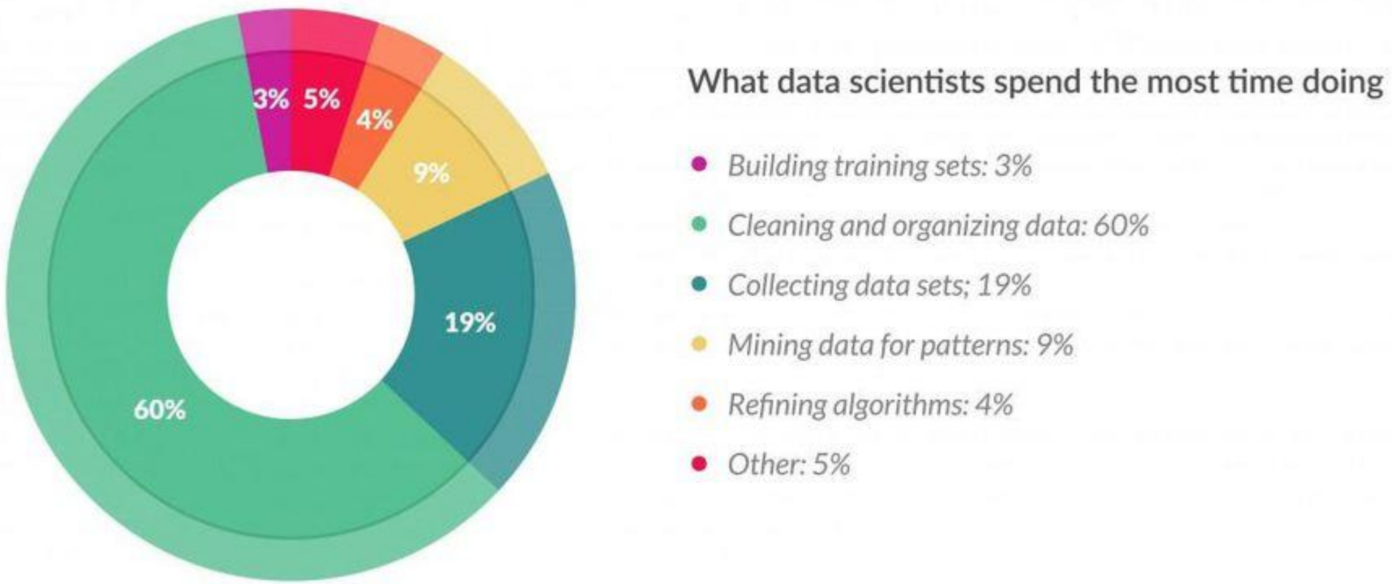
Why Prepare Data?

- The main objective of data preparation is to transform the data sets so that the information contained in them is properly exposed to the Knowledge Extraction tool;
- Data preparation “also prepares the preparer” in order to select the most suitable KE models;
- Data has to be formatted to suit a given KE tool;
- Data collected from the "real world":
  - are incomplete;
  - contain garbage;
  - may contain inconsistencies.

Data Quality

Indeed… Cleaning and manipulating data may be considered as the:

- Most Time-Consuming task
- Least Enjoyable task (by some!)



(https://www.forbes.com/sites/gilpress/2016/03/23/data-preparation-most-time-consuming-least-enjoyable-data-science-task-survey-says/#1594bda36f63)

Data Quality

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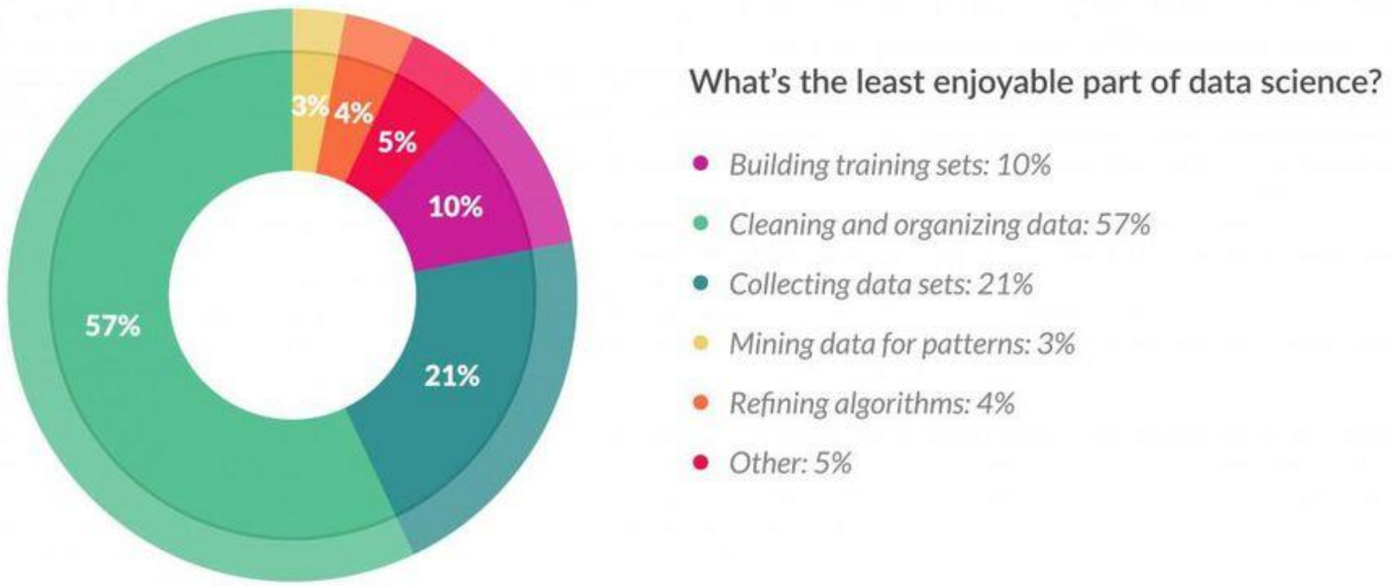
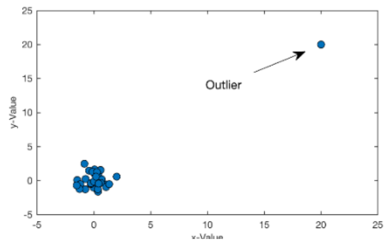
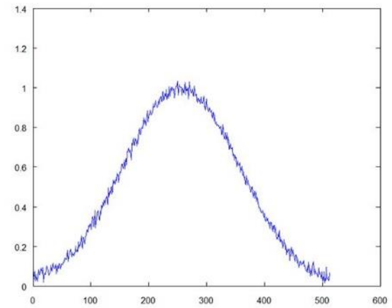


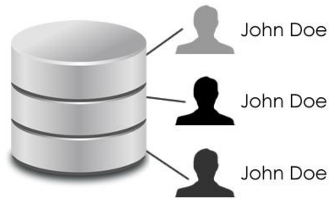
(https://www.forbes.com/sites/gilpress/2016/03/23/data-preparation-most-time-consuming-least-enjoyable-data-science-task-survey-says/#1594bda36f63)

Data Quality

- Poor data quality negatively affects many data processing efforts;
- Example: a classification model for detecting people who are loan risks is built using poor data;
  - Some credit-worthy candidates are denied loans;
  - More loans are given to individuals that default.
- What kinds of data quality problems?
- How can we detect problems with the data?
- What can we do about these problems?
- Examples of data quality problems:
  - Noise and outliers;
  - Wrong data;
  - Fake data;
  - Missing values;
  - Duplicate data.



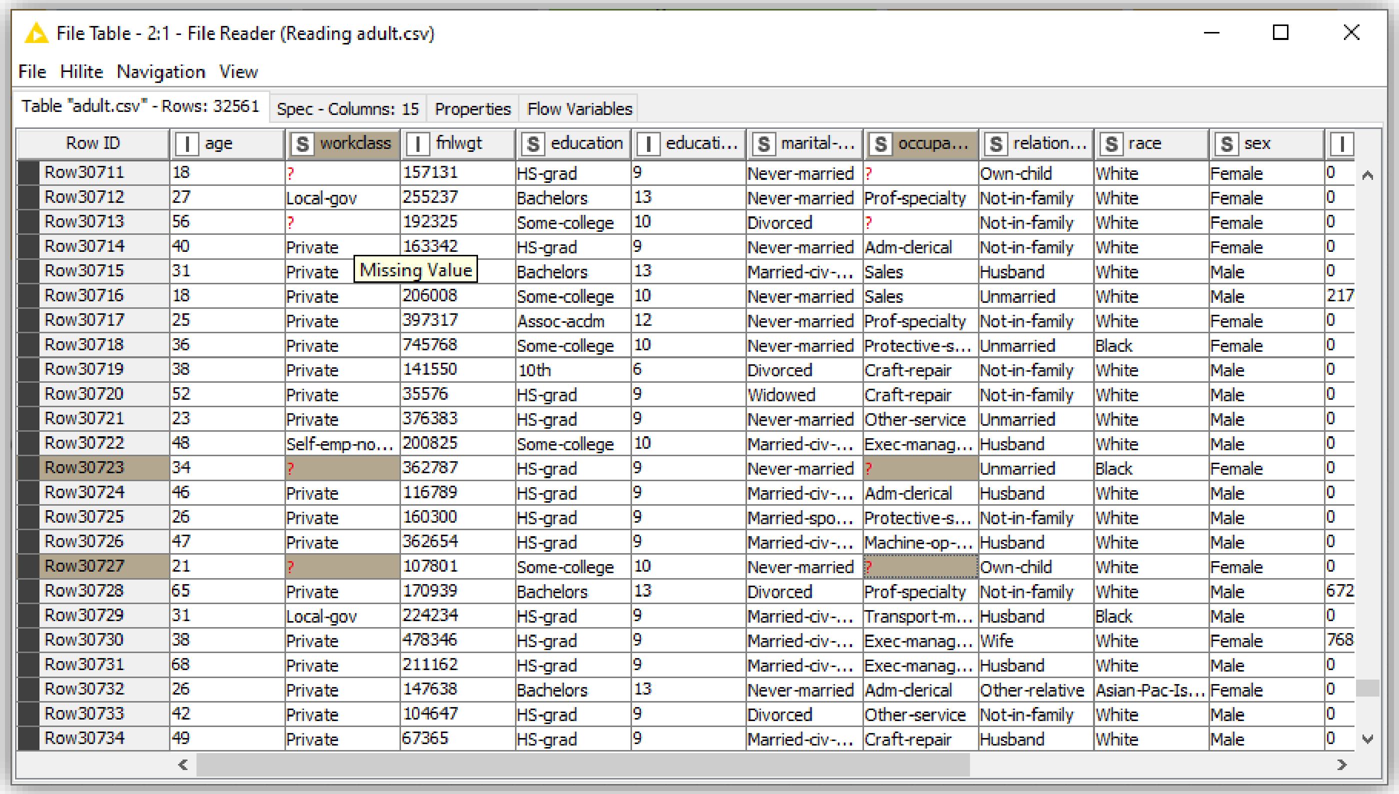




Data Quality

A few problems… How to solve them?

- Missing values
  - Information that is not available because it wasn’t collected or because it consisted of sensitive information
  - Features that are not applicable in all cases
- Duplicated Records
  - Same (or similar) data collected from different sources



File Table - 2:1 - File Reader (Reading adult.csv)

File Hilite Navigation View

Table "adult.csv" - Rows: 32561 | Spec - Columns: 15 | Properties | Flow Variables

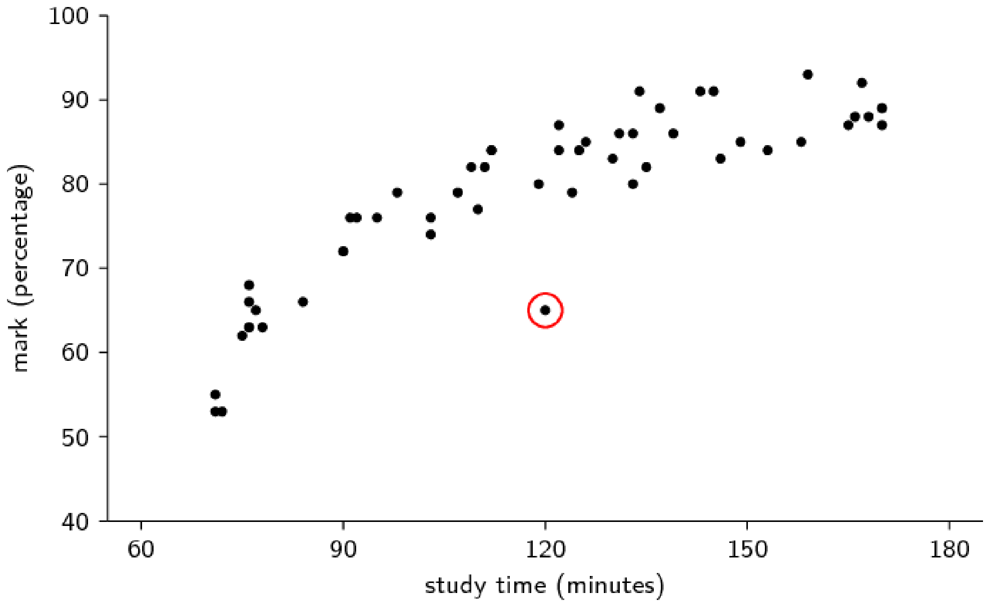
Row ID	I age	S workclass	I fnlwgt	S education	I educati…	S marital-…	S occupa…	S relation…	S race	S sex	I
Row30711	18	?	157131	HS-grad	9	Never-married	?	Own-child	White	Female	0
Row30712	27	Local-gov	255237	Bachelors	13	Never-married	Prof-specialty	Not-in-family	White	Female	0
Row30713	56	?	192325	Some-college	10	Divorced	?	Not-in-family	White	Female	0
Row30714	40	Private	163342	HS-grad	9	Never-married	Adm-clerical	Not-in-family	White	Female	0
Row30715	31	Private	Missing Value	Bachelors	13	Married-civ-…	Sales	Husband	White	Male	0
Row30716	18	Private	206008	Some-college	10	Never-married	Sales	Unmarried	White	Male	217
Row30717	25	Private	397317	Assoc-acdm	12	Never-married	Prof-specialty	Not-in-family	White	Female	0
Row30718	36	Private	745768	Some-college	10	Never-married	Protective-s…	Unmarried	Black	Female	0
Row30719	38	Private	141550	10th	6	Divorced	Craft-repair	Not-in-family	White	Male	0
Row30720	52	Private	35576	HS-grad	9	Widowed	Craft-repair	Not-in-family	White	Male	0
Row30721	23	Private	376383	HS-grad	9	Never-married	Other-service	Unmarried	White	Male	0
Row30722	48	Self-emp-no…	200825	Some-college	10	Married-civ-…	Exec-manag…	Husband	White	Male	0
Row30723	34	?	362787	HS-grad	9	Never-married	?	Unmarried	Black	Female	0
Row30724	46	Private	116789	HS-grad	9	Married-civ-…	Adm-clerical	Husband	White	Male	0
Row30725	26	Private	160300	HS-grad	9	Married-spo…	Protective-s…	Not-in-family	White	Male	0
Row30726	47	Private	362654	HS-grad	9	Married-civ-…	Machine-op-…	Husband	White	Male	0
Row30727	21	?	107801	Some-college	10	Never-married	?	Own-child	White	Female	0
Row30728	65	Private	170939	Bachelors	13	Divorced	Prof-specialty	Not-in-family	White	Male	672
Row30729	31	Local-gov	224234	HS-grad	9	Married-civ-…	Transport-m…	Husband	Black	Male	0
Row30730	38	Private	478346	HS-grad	9	Married-civ-…	Exec-manag…	Wife	White	Female	768
Row30731	68	Private	211162	HS-grad	9	Married-civ-…	Exec-manag…	Husband	White	Male	0
Row30732	26	Private	147638	Bachelors	13	Never-married	Adm-clerical	Other-relative	Asian-Pac-Is…	Female	0
Row30733	42	Private	104647	HS-grad	9	Divorced	Other-service	Not-in-family	White	Male	0
Row30734	49	Private	67365	HS-grad	9	Married-civ-…	Craft-repair	Husband	White	Male	0

Data Quality

A few problems… How to solve them?

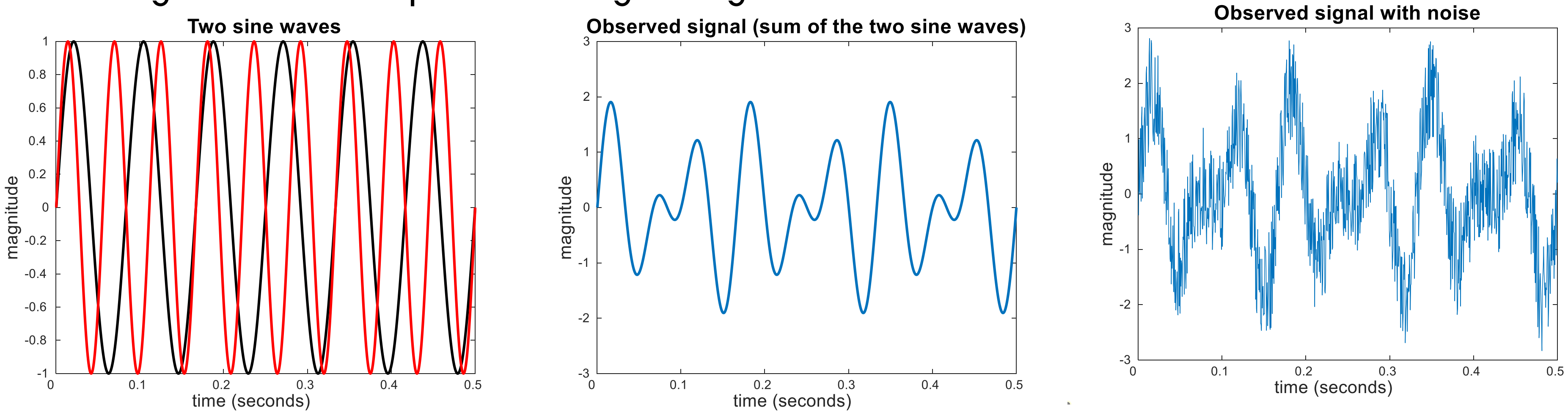
- Noise
  - Modifications to the original records (data that is corrupted or distorted) due to technological limitations, sensor error or even human error

- Outliers
  - A data point that differs significantly from other observations



Noise

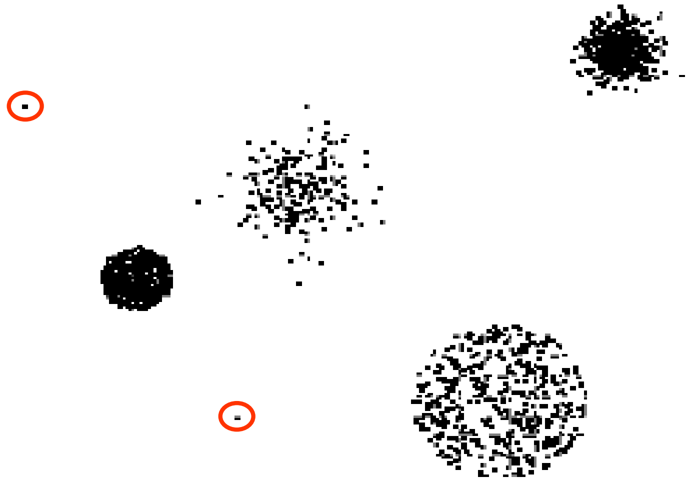
- Noise is an extraneous object;
- For attributes, noise refers to modification of original values;
  - Examples: distortion of a person's voice when talking on a poor phone and "snow" on television screen;
  - The figures below show two sine waves of the same magnitude and different frequencies, the waves combined, and the two sine waves with random noise;
    - The magnitude and shape of the original signal is distorted.

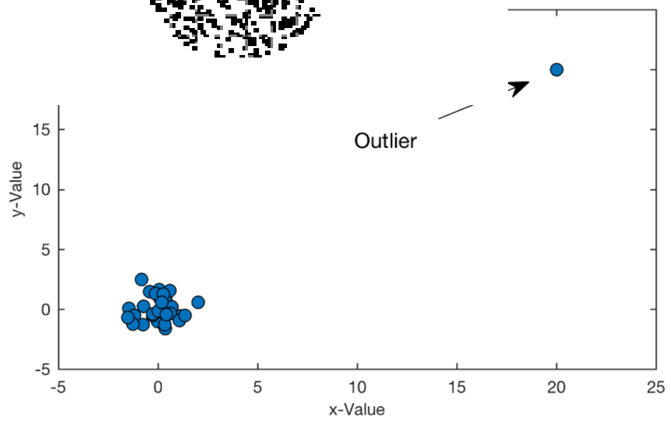


Source: Introduction to Data Mining, Pang Ning Tan, Michael Steinbach, Anuj Karpatne, Vipin Kumar, ISBN 9780133128901, 2018.

Outliers

- ***Outliers*** are data objects with characteristics that are considerably different than most of the other data objects in the data set;
  - **Case 1:** Outliers are noise that interferes with data analysis
  - **Case 2:** Outliers are the goal of our analysis
    - Credit card fraud
    - Intrusion detection
- Causes?





Source: Introduction to Data Mining, Pang Ning Tan, Michael Steinbach, Anuj Karpatne, Vipin Kumar, ISBN 9780133128901, 2018.

Missing Values

- Reasons for missing values:
  - Information is not collected;
    (e.g., people decline to give their age and weight)
  - Attributes may not be applicable to all cases.
    (e.g., annual income is not applicable to children)

- Handling missing values:
  - Eliminate data objects or variables;
  - Estimate missing values;
    - Example: time series of temperature
    - Example: census results
  - Ignore the missing value during analysis.

Source: Introduction to Data Mining, Pang Ning Tan, Michael Steinbach, Anuj Karpatne, Vipin Kumar, ISBN 9780133128901, 2018.

Duplicate Data

- Data set may include data objects that are duplicates, or almost duplicates of one another;
  - Major issue when merging data from heterogeneous sources
- Examples:
  - Same person with multiple email addresses
- Data cleaning;
  - Process of dealing with duplicate data issues
- When should duplicate data not be removed?

Source: Introduction to Data Mining, Pang Ning Tan, Michael Steinbach, Anuj Karpatne, Vipin Kumar, ISBN 9780133128901, 2018.

Data Exploration

Why?

- Understand the data and its characteristics
- Evaluate its quality
- Find patterns and relevant information

Data Exploration

How?

- Central Tendency: average, mode, median…
- Statistical dispersion: variance, standard deviation, interquartile range…
- Probability distribution: Gaussian, Uniform, Exponential…
- Correlation/Dependence: between pairs of features, with the dependent feature…
- Data viz: tables, charts, boxplots, scatter plots, histograms, …

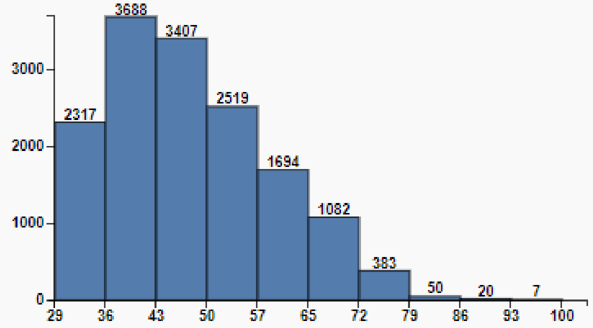
Data Exploration

Data Explorer View

Column	Exclude Column	Minimum	Maximum	Mean	Standard Deviation	Variance	Skewness	Kurtosis	Overall Sum	No. zeros	No. missings
CustomerKey		11000	27336	17559.847	5576.039	31092215.201	0.333	-1.566	266330201	0	0
WebActivity		0	5	0.999	1.520	2.310	1.395	0.687	15159	9159	0
SentimentRating		0	5	1.851	1.620	2.624	0.482	-0.958	28073	4173	0
EstimatedYearlyIncome		10000	170000	57718.072	32091.910	1029890707.928	0.796	0.617	875410000	0	0
NumberOfContracts		0	4	1.465	1.145	1.311	0.430	-0.457	22227	3711	0
Age		29	100	48.203	11.300	127.694	0.571	-0.182	731101	0	0

No. NaN	0
No. +∞	0
No. -∞	0

Histogram



Reset Apply Close

Data Exploration - Contingency Tables

Frequency Percent	F	M	Total
Negative	1.585	1.537	3.122
	10,4503%	10,1338%	20,5842%
Positive	941	1.019	1.960
	6,2043%	6,7185%	12,9228%
Slightly Negative	1.501	1.522	3.023
	9,8965%	10,0349%	19,9314%
Slightly Positive	861	829	1.690
	5,6768%	5,4658%	11,1426%
Very Negative	2.054	2.119	4.173
	13,5426%	13,9711%	27,5137%
Very Positive	639	560	1.199
	4,2131%	3,6922%	7,9053%
Total	7.581	7.586	15.167
	49,9835%	50,0165%	100%

- [x] Frequency
- [ ] Expected
- [ ] Deviation
- [x] Percent
- [ ] Row Percent
- [ ] Column Percent
- [ ] Cell Chi-Square

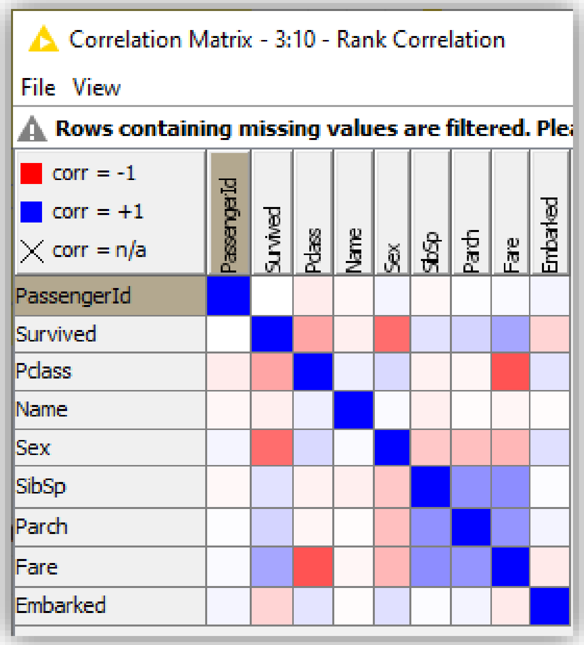
Max rows: 10

Max columns: 10

Statistics for Table of Sentiment Analysis by Gender

Statistic	DF	Value	Prob
Chi-Square	5	10,8099	0,0553

Data Exploration - Correlation Matrix



Correlation measure - 3:10 - Rank Correlation

File Hilite Navigation View

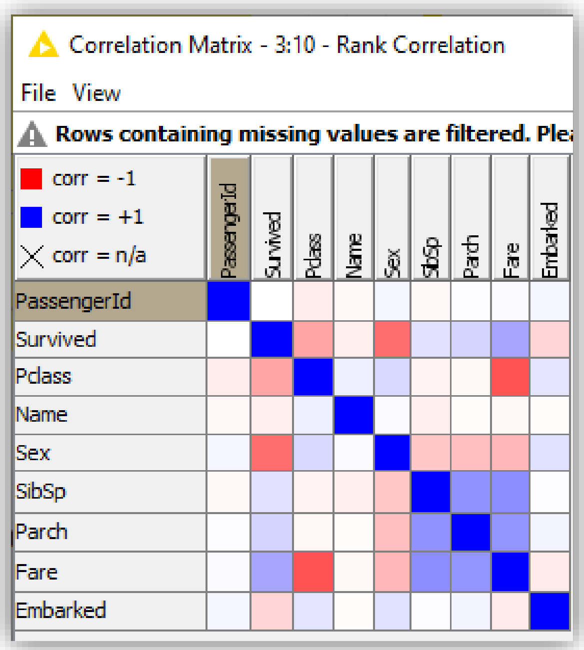
Table "Correlation values" - Rows: 9 | Spec - Columns: 9 | Properties | Flow Variables

Row ID	D Passeng...	D Survived	D Pclass	D Name	D Sex	D SibSp	D Parch	D Fare	D Embarked
Passeng...	1.0	-0.00174741...	-0.07274348...	-0.03142687...	0.0404574...	-0.02578774...	0.009305237...	0.019408214...	0.0380052514...
Survived	-0.00174741...	1.0	-0.35175083...	-0.06396644...	-0.571791...	0.113309900...	0.169963720...	0.350965386...	-0.1699515717...
Pclass	-0.07274348...	-0.35175083...	1.0	0.063095975...	0.1499334...	-0.05215363...	-0.035163461...	-0.67404431...	0.1039440255...
Name	-0.03142687...	-0.06396644...	0.06309597...	1.0	0.0211633...	-0.06164769...	-0.012894871...	-0.03634128...	-0.0135577924...
Sex	0.040457449...	-0.57179163...	0.14993345...	0.021163349...	1.0	-0.21708710...	-0.250155569...	-0.28053568...	0.1228843568...
SibSp	-0.02578774...	0.11330990...	-0.05215363...	-0.06164769...	-0.217087...	1.0	0.432451332...	0.447081227...	0.0122413820...
Parch	0.009305237...	0.16996372...	-0.03516346...	-0.01289487...	-0.250155...	0.432451332...	1.0	0.416985332...	0.0417986920...
Fare	0.019408214...	0.35096538...	-0.67404431...	-0.03634128...	-0.280535...	0.447081227...	0.416985332...	1.0	-0.0820274778...
Embarked	0.038005251...	-0.16995157...	0.10394402...	-0.01355779...	0.1228843...	0.012241382...	0.041798692...	-0.08202747...	1.0

Data Exploration - Correlation Matrix

- Do we want to keep highly-correlated features?
- Both positive and negatively correlated ones?
- What about the correlation between the dependent and the independent features?
- …

What are those?



Data Exploration - Features

Input Features/Input Vector (independent variables)

Target/Class/Label (dependent variable)

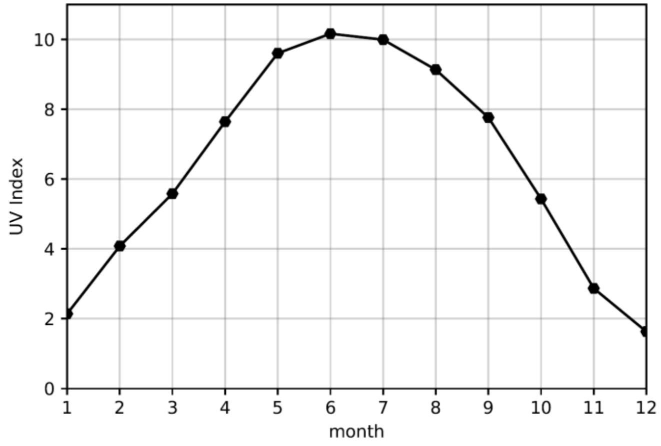
File Table - 3:1 - CSV Reader (Read Wine)

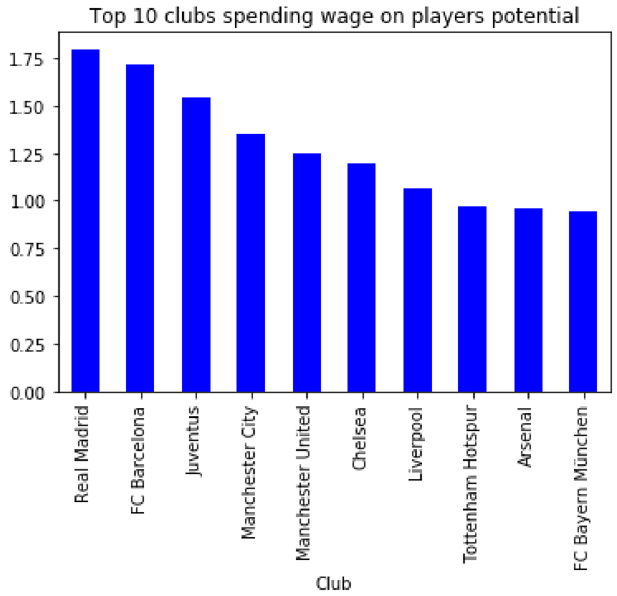
File Hilite Navigation View

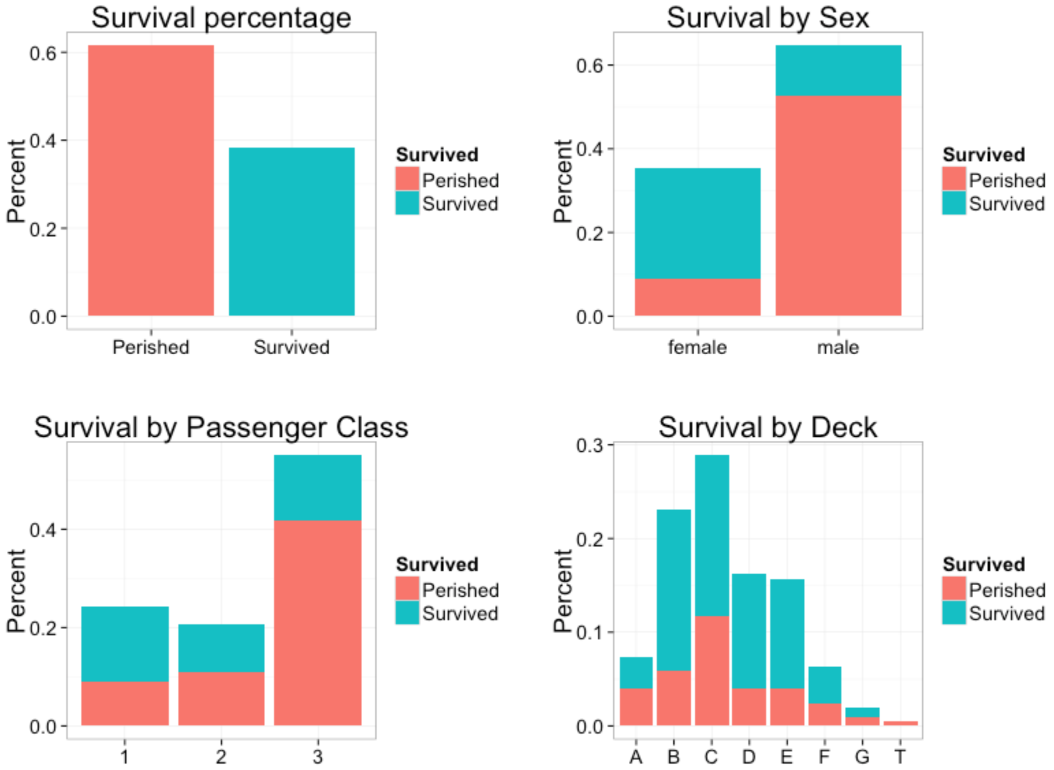
Table "winequality-red.csv" - Rows: 1599 | Spec - Columns: 12 | Properties | Flow Variables

Row ID	D fixed a...	D volatile ...	D citric acid	D residual...	D chlorides	D free sul...	D total su...	D density	D pH	D sulphates	D alcohol	S quality
Row0	7.4	0.7	0	1.9	0.076	11	34	0.998	3.51	0.56	9.4	=5
Row1	7.8	0.88	0	2.6	0.098	25	67	0.997	3.2	0.68	9.8	=5
Row2	7.8	0.76	0.04	2.3	0.092	15	54	0.997	3.26	0.65	9.8	=5
Row3	11.2	0.28	0.56	1.9	0.075	17	60	0.998	3.16	0.58	9.8	=6
Row4	7.4	0.7	0	1.9	0.076	11	34	0.998	3.51	0.56	9.4	=5
Row5	7.4	0.66	0	1.8	0.075	13	40	0.998	3.51	0.56	9.4	=5
Row6	7.9	0.6	0.06	1.6	0.069	15	59	0.996	3.3	0.46	9.4	=5
Row7	7.3	0.65	0	1.2	0.065	15	21	0.995	3.39	0.47	10	=7
Row8	7.8	0.58	0.02	2	0.073	9	18	0.997	3.36	0.57	9.5	=7
Row9	7.5	0.5	0.36	6.1	0.071	17	102	0.998	3.35	0.8	10.5	=5
Row10	6.7	0.58	0.08	1.8	0.097	15	65	0.996	3.28	0.54	9.2	=5
Row11	7.5	0.5	0.36	6.1	0.071	17	102	0.998	3.35	0.8	10.5	=5
Row12	5.6	0.615	0	1.6	0.089	16	59	0.994	3.58	0.52	9.9	=5
Row13	7.8	0.61	0.29	1.6	0.114	9	29	0.997	3.26	1.56	9.1	=5
Row14	8.9	0.62	0.18	3.8	0.176	52	145	0.999	3.16	0.88	9.2	=5
Row15	8.9	0.62	0.19	3.9	0.17	51	148	0.999	3.17	0.93	9.2	=5
Row16	8.5	0.28	0.56	1.8	0.092	35	103	0.997	3.3	0.75	10.5	=7
Row17	8.1	0.56	0.28	1.7	0.368	16	56	0.997	3.11	1.28	9.3	=5
Row18	7.4	0.59	0.08	4.4	0.086	6	29	0.997	3.38	0.5	9	=4
Row19	7.9	0.32	0.51	1.8	0.341	17	56	0.997	3.04	1.08	9.2	=6
Row20	8.9	0.22	0.48	1.8	0.077	29	60	0.997	3.39	0.53	9.4	=6
Row21	7.6	0.39	0.31	2.3	0.082	23	71	0.998	3.52	0.65	9.7	=5
Row22	7.9	0.43	0.21	1.6	0.106	10	37	0.997	3.17	0.91	9.5	=5
Row23	8.5	0.49	0.11	2.3	0.084	9	67	0.997	3.17	0.53	9.4	=5
Row24	6.9	0.4	0.14	2.4	0.085	21	40	0.997	3.43	0.63	9.7	=6

Data Viz. <- Often Neglected







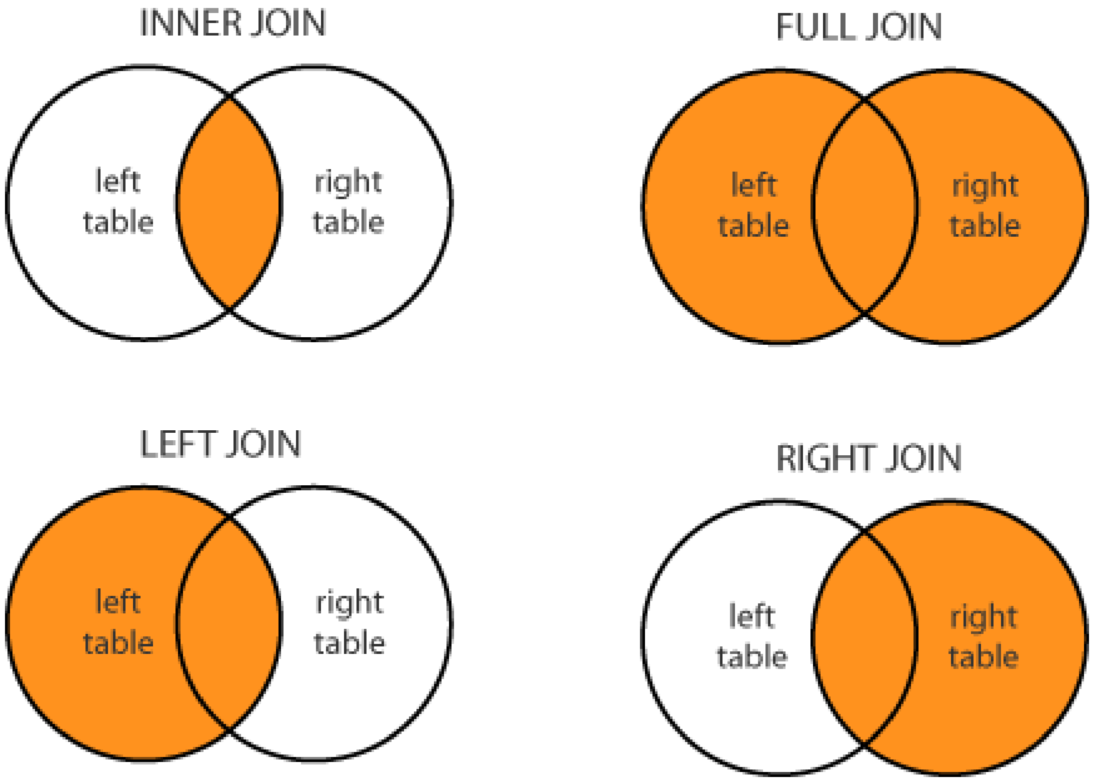
Data Preparation - Basic Preparation

A set of basic data preparation techniques can be used:

- Union/intersection of columns;
- Concatenation;
- Sorters;
- Filters (column, row, nominal, rule-based, …);
- Basic aggregations (counts, unique, mean/sum, …);
- Sampling.

Data Preparation - Basic Preparation

A Join is an operation that combines data from different tables



Aggregation

- Combining two or more attributes (or objects) into a single attribute (or object);
- Purpose:
  - Data reduction - reduce the number of attributes or objects;
  - Change of scale;
    - Cities aggregated into regions, states, countries, etc.
    - Days aggregated into weeks, months, or years
  - More "stable" data - aggregated data tends to have less variability;

Table 2.4. Data set containing information about customer purchases.

Transaction ID	Item	Store Location	Date	Price	...
⋮	⋮	⋮	⋮	⋮	
101123	Watch	Chicago	09/06/04	$25.99	...
101123	Battery	Chicago	09/06/04	$5.99	...
101124	Shoes	Minneapolis	09/06/04	$75.00	...
⋮	⋮	⋮	⋮	⋮	

Source: Introduction to Data Mining, Pang Ning Tan, Michael Steinbach, Anuj Karpatne, Vipin Kumar, ISBN 9780133128901, 2018.

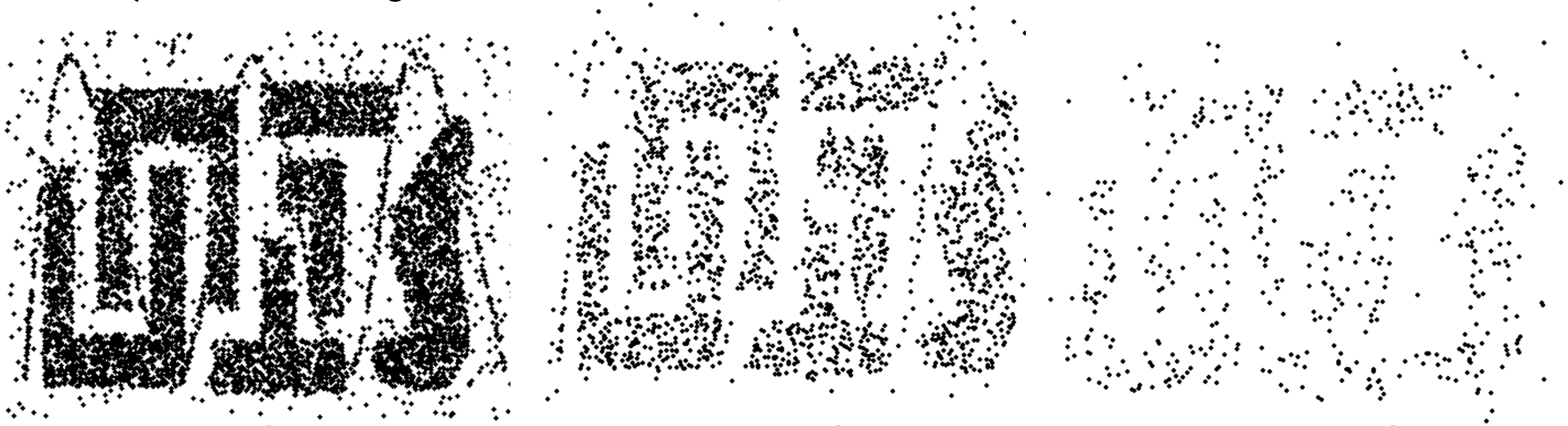
Sampling

- Sampling is one of the main technique employed for data reduction;
  - It is often used for both the preliminary investigation of the data and the final data analysis.
- Statisticians often sample because obtaining the entire set of data of interest is too expensive or time consuming;
- Sampling is typically used in ML because processing the entire set of data of interest is too expensive or time consuming.

Source: Introduction to Data Mining, Pang Ning Tan, Michael Steinbach, Anuj Karpatne, Vipin Kumar, ISBN 9780133128901, 2018.

Sampling

- Key principle for effective sampling:
  - Using a sample will work almost as well as using the entire data set, if the sample is representative;
  - A sample is representative if it has approximately the same properties (of interest) as the original set of data;



8000 points **2000 Points** **500 Points**

Source: Introduction to Data Mining, Pang Ning Tan, Michael Steinbach, Anuj Karpatne, Vipin Kumar, ISBN 9780133128901, 2018.

Types of Sampling

- Simple Random Sampling:
  - There is an equal probability of selecting any particular item;
  - Sampling without replacement;
    - As each item is selected, it is removed from the population.
  - Sampling with replacement:
    - Objects are not removed from the population as they are selected for the sample;
    - In sampling with replacement, the same object can be picked up more than once.
- Stratified sampling:
  - Split the data into several partitions; then draw random samples from each partition.

Source: Introduction to Data Mining, Pang Ning Tan, Michael Steinbach, Anuj Karpatne, Vipin Kumar, ISBN 9780133128901, 2018.

Data Preparation - Advanced Preparation

How?

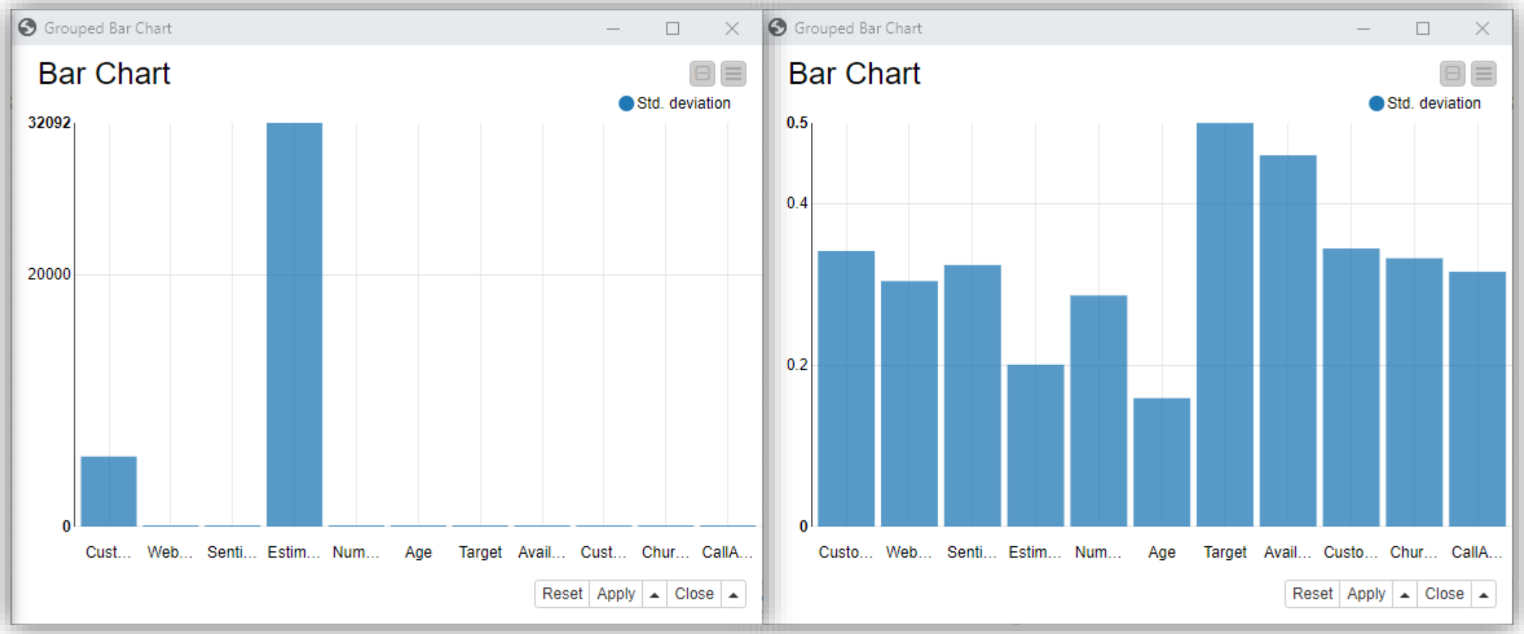
- Feature scaling
- Outlier detection
- Feature selection
- Missing Values treatment
- Nominal value discretization
- Binning
- Feature Engineering

Data Preparation - Feature Scaling

1. Normalizing the range of the independent features

   Rationale:

   Many classifiers use distance metrics (ex.: Euclidean distance) and, if one feature has a broad range of values, the distance will be governed by this particular feature. Hence, the range should be normalized so that each feature may contribute proportionately to the final distance.



Data Preparation - Feature Scaling

1. Normalizing the range of the independent features

   \- Normalization: Rescaling data so that all values fall within the range of 0 and 1, for example.

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Data Preparation - Feature Scaling

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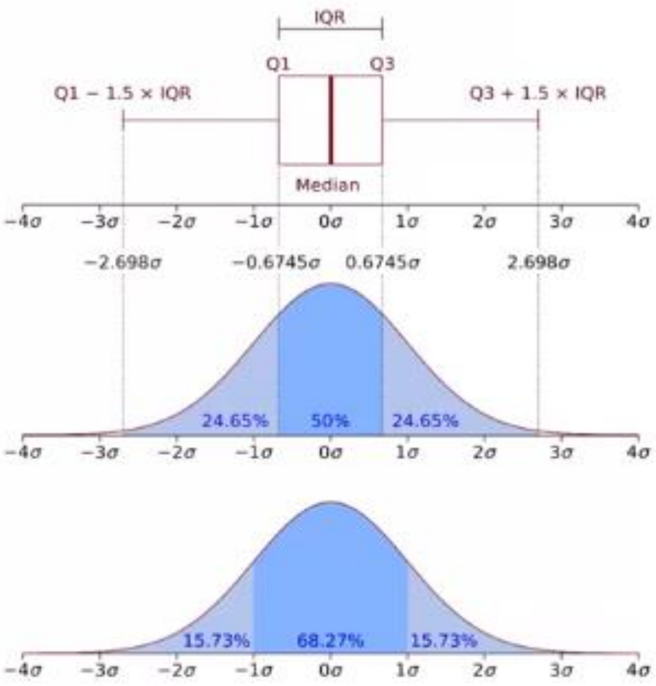
   - Standardization (or Z-score Normalization): Rescaling the distribution of values so that the mean of observed values is 0 and the standard deviation is 1. Assumes observations fit a Gaussian distribution with a well-behaved mean and standard deviation, which may not always be the case.

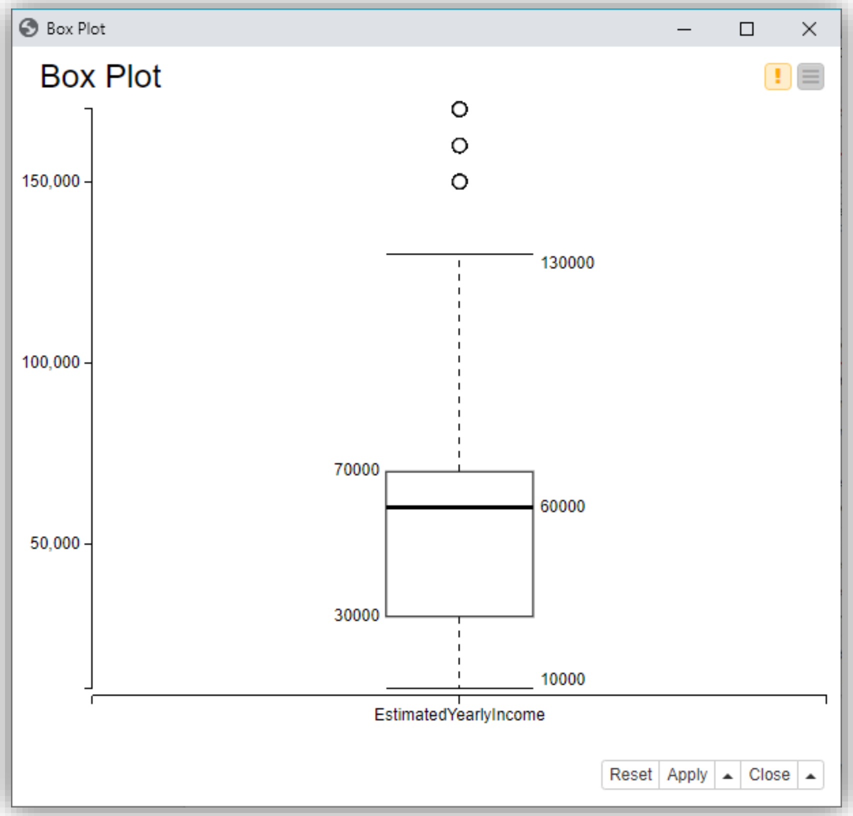
$$z = \frac{x_i - \mu}{\sigma}$$

Data Preparation - Outlier Detection

2. Outlier Detection:

   - Statistical-based strategy: Z-Score, Box Plots, …





Data Preparation - Outlier Detection

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The Outlier Dilemma: Drop or Cap?

To keep the dataset size, we may want to cap outliers instead of dropping them. However, it can affect the distribution of data!

Data Preparation - Feature Selection

3. Feature Selection (or dimensionality reduction):

   Rationale: which features should we use to create a predictive model? Select a sub-set of the most important features to reduce dimensionality.

   The removal of unimportant features:

   - May affect significantly the performance of a model
   - Reduces overfitting (less opportunity to make decisions based on noise)
   - Improves accuracy
   - Helps reducing the complexity of a model (reduces training time)

   What can we remove:

   - Redundant features (duplicate)
   - Irrelevant and unneeded features (non-useful)

   Feature Selection Methods:

   - Filter methods
   - Wrapper methods
   - Embedded methods

Data Preparation - Feature Selection

3. Feature Selection (or dimensionality reduction):

   - Remove a feature if the percentage of missing values is higher than a threshold;

   - Use the chi-square test to measure the degree of dependency between a feature and the target class;

   - Remove feature if low standard deviation;

   - Remove feature if data are highly skewed;

   - Remove features that are highly correlated between each other.

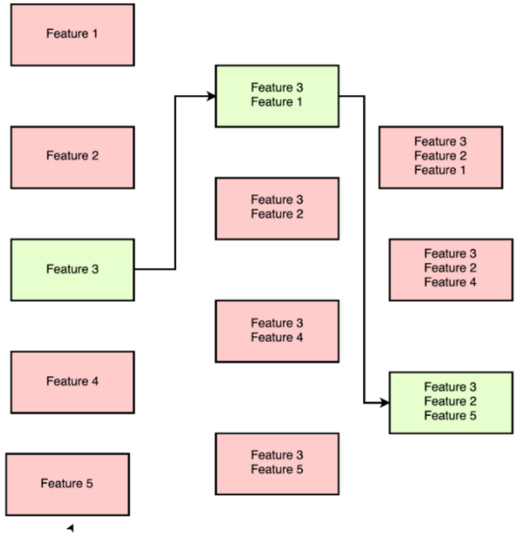
Data Preparation - Feature Selection

3. Feature Selection (or dimensionality reduction):

   - Principal Component Analysis (PCA): a technique to reduce the dimension of the feature space. The goal is to reduce the number of features without losing too much information. A popular application of PCA is for visualizing higher dimensional data.

   - Wrapper Methods: Use a ML algorithm to select the most important features! Select a set of features as a search problem, prepare different combinations, evaluate and compare them! Measure the “usefulness” of features based on the classifier performance

     - *Sequential Forward Selection*



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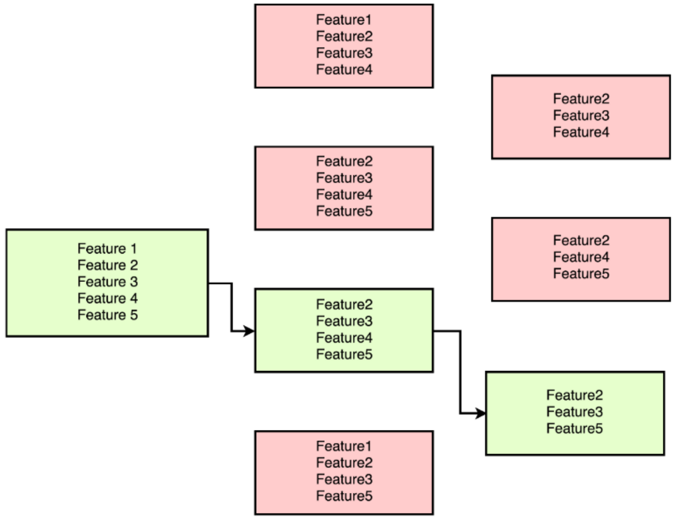
     - *Backward Feature Elimination*



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   - Embedded Methods: Algorithms that already have built-in feature selection methods. Lasso, for example, has their own feature selection methods. For example, if a feature's weight is zero than it has no importance! Regularization - constrain/regularize or shrink the coefficient estimates towards zero!

Data Preparation - Missing Values

4. Missing Values Treatment:

   First analyze each feature in regard to the number and percentage of missing values. Then decide what to do:

   - Remove

   - Mean

   - Interpolation

   - Mask

   - …

Discretization

- Discretization is the process of converting a continuous attribute into an ordinal attribute.
- A potentially infinite number of values are mapped into a small number of categories.

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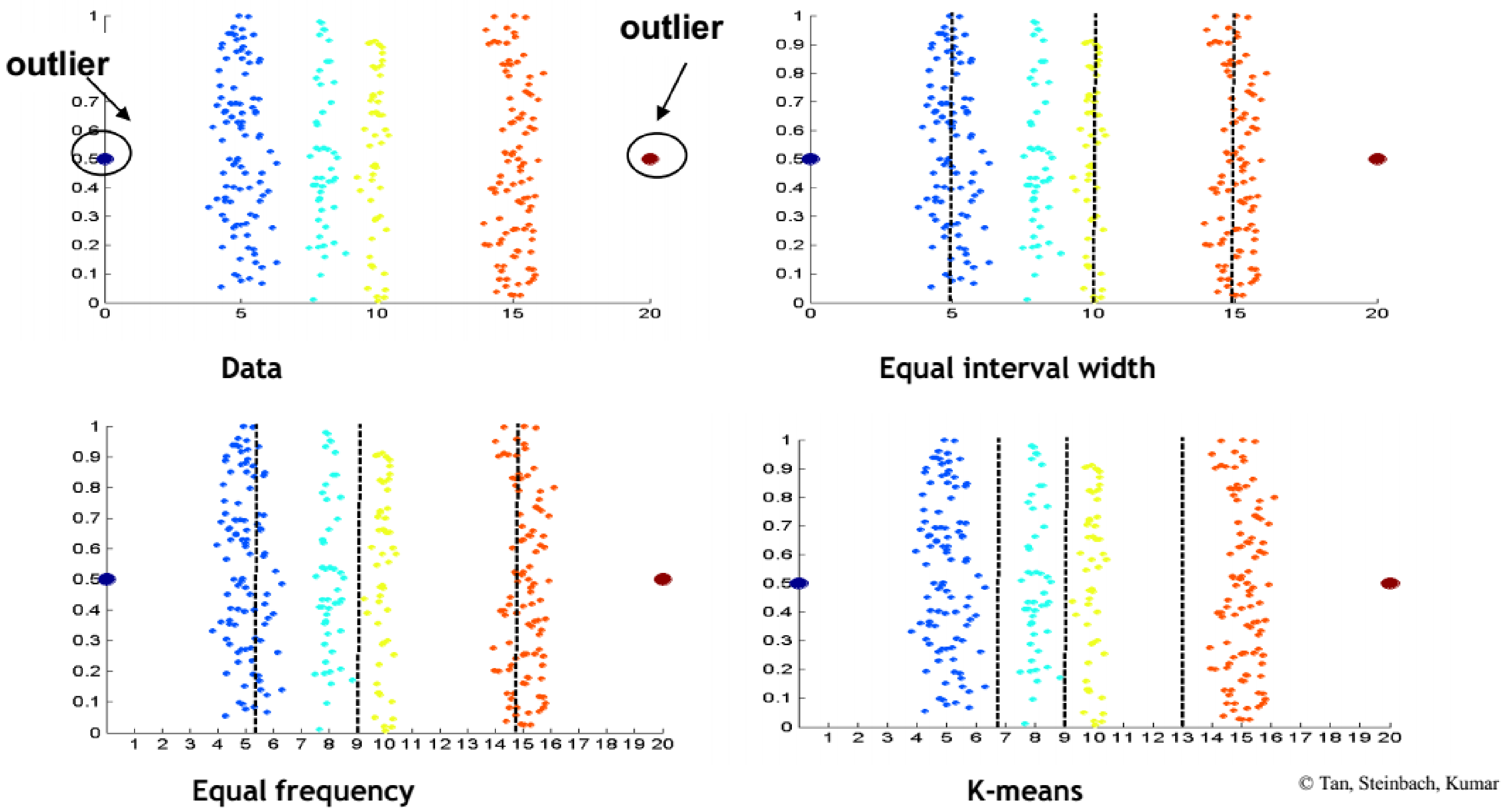
Unsupervised Discretization



Discretization to obtain 4 values

Data consists of four groups of points and two outliers. Data is one-dimensional, but a random y component is added to reduce overlap.

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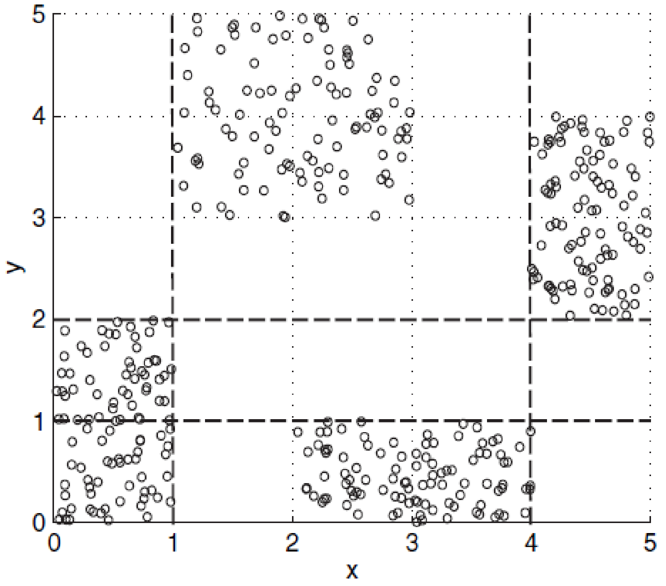
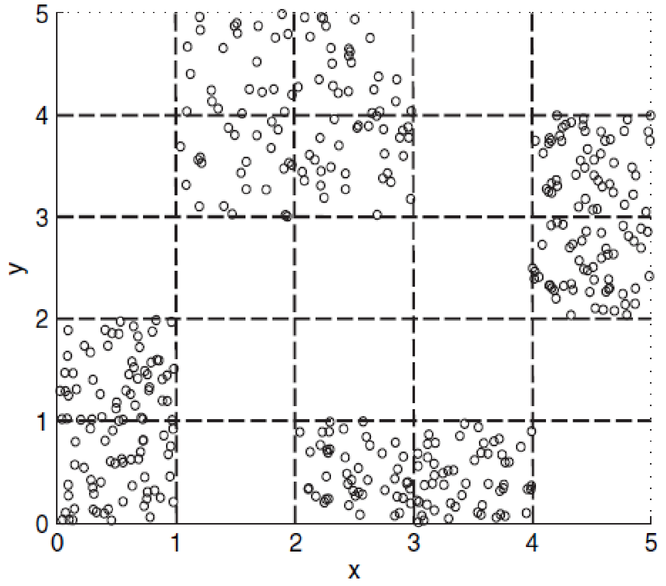
Discretization in Supervised Settings

- Many classification algorithms work best if both the independent and dependent variables have only a few values;
- We give an illustration of the usefulness of discretization using the following example.



(a) Three intervals



(b) Five intervals

Figure 2.14. Discretizing x and y attributes for four groups (classes) of points.

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Data Preparation - Nominal Value Discretization

5. Nominal value discretization:

   Rationale: categorical data often called nominal data, are variables that contain label values rather than numeric ones. Several methods may be applied:

   - One-Hot Encoding

   - Label Encoding

   - Binary Encoding

Data Preparation - Nominal Value Discretization

5. Nominal value discretization:

Movie	Genre
Jumanji	Adventure
American Pie	Comedy
Braveheart	Drama
…	…

Label Encoded

Movie	Genre	Category
Jumanji	Adventure	0
American Pie	Comedy	1
Braveheart	Drama	2
…	…	

Integer values have a natural ordered relationship between each other. ML models may be able to understand such relationships.

One-Hot Encoded

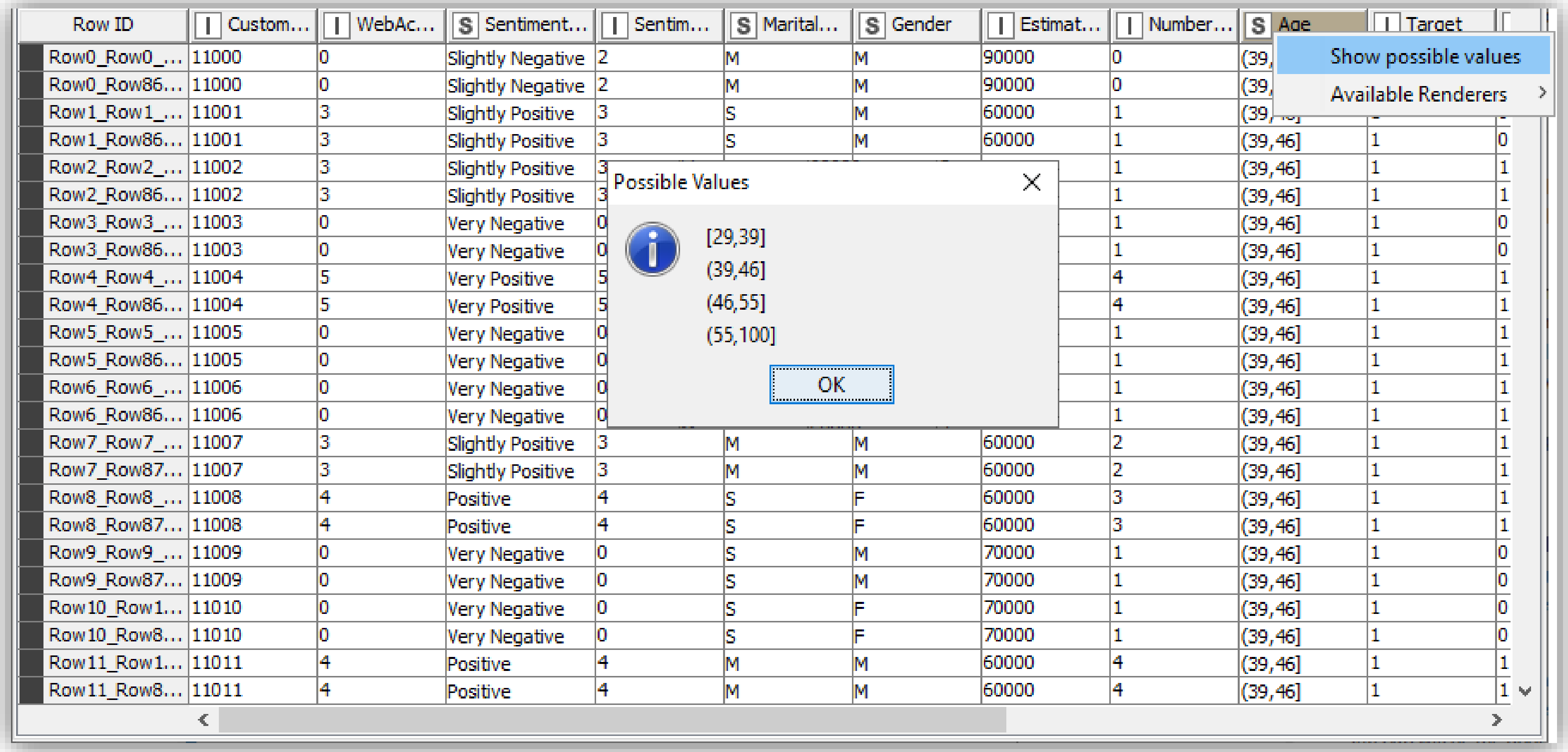
Movie	Adventure	Comedy	Drama
Jumanji	1	0	0
American Pie	0	1	0
Braveheart	0	0	1
…	…		

Categorical features where no such ordinal relationship exists. However, for a huge number of categories…

Data Preparation – Binning/Discretization

6. Binning, i.e., group numeric data into intervals - called bins:

   Rationale: make the model more robust and prevent overfitting. However, it penalizes the model’s performance since every time you bin something, you sacrifice information.



Data Preparation - Feature Engineering

7. Feature Engineering:

   Rationale: The process of creating new features! The goal is to improve the performance of ML models.

   Example: from the creation date of an observation what can we extract?

2021-10-29 16h30

Data Preparation - Feature Engineering

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   Example: from the creation date of an observation what can we extract?

2021-10-29 16h30

We may extract new features such as:

- Year, month and day
- Hour and minutes
- Day of week (Thursday)
- Is Weekend? (No)
- Is Holiday? (No)
- …

References

- Introduction to Data Mining, Pang Ning Tan, Michael Steinbach, Anuj Karpatne, Vipin Kumar, ISBN 9780133128901, 2018;
- Data Preparation for Data Mining, Dorian Pyle, ISBN: 978-1558605299, 1999;
- Data Mining: Concepts and Techniques, Jiawei Han, Micheline Kamber, ISBN: 9780123814791, 2011;
- Data Mining: Descoberta de Conhecimento em BDs, Carla Azevedo, Manuel Filipe Santos, ISBN: 9789727225095, 2005.

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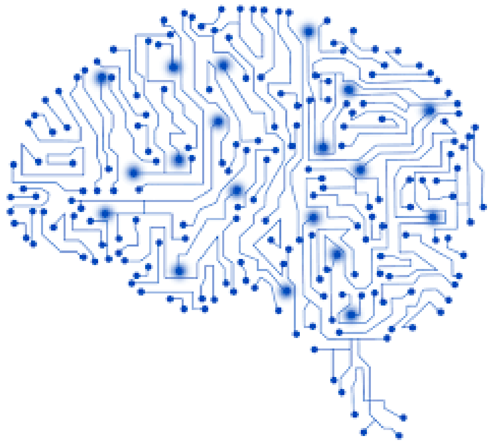

Dados e Aprendizagem Automática

Data Exploration and Preparation

DAA @ MEI/1º ano – 1º Semestre