

07.05.2025

Zühlke & Bader

Data Mining SS25

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Agenda

- About Data
- Data Analysis:
 - IDA & EDA
- Data Visualization
- Additional Resources



About Data

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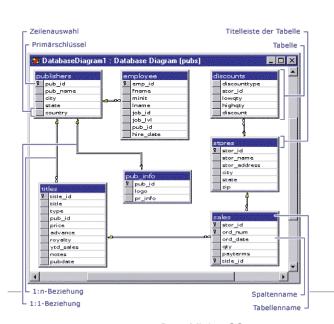
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How Data exists

File (e.g. TXT, CSV, Excel, XML)

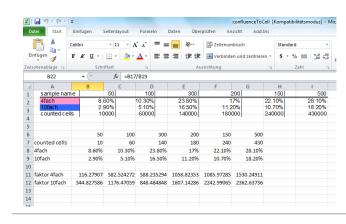
Database (e.g. Access, Oracle, RDF)

Tweets









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Types of data sets

Record

- Data Matrix
- Document Data
- Transaction Data

Graph

- World Wide Web
- Molecular Structures

Ordered

- Spatial Data
- Temporal Data
- Sequential Data
- Genetic Sequence Data

Record Data

Data that consists of a collection of records, each of which consists of a fixed set of attributes Relational Databases

Tid	Refund	Marital Status	Taxable Income	Cheat
1	Yes	Single	125K	No
2	No	Married	100K	No
3	No	Single	70K	No
4	Yes	Married	120K	No
5	No	Divorced	95K	Yes
6	No	Married	60K	No
7	Yes	Divorced	220K	No
8	No	Single	85K	Yes
9	No	Married	75K	No
10	No	Single	90K	Yes

Data Matrix

If data objects have the same fixed set of numeric attributes, then the data objects can be thought of as points in a multi-dimensional space, where each dimension represents a distinct attribute

Such data set can be represented by a m x n matrix, where there are m rows, one for each object, and n columns, one for each attribute

Projection of x Load	Projection of y load	Distance	Load	Thickness
10.23	5.27	15.22	2.7	1.2
12.65	6.25	16.22	2.2	1.1

Document Data: Document Term Matrix

Each document becomes a `term' vector,

- each term is a component (attribute) of the vector,
- the value of each component is the number of times the corresponding term occurs in the document.

	team	coach	pla y	ball	score	game	w <u>i</u>	lost	timeout	season
Document 1	3	0	5	0	2	6	0	2	0	2
Document 2	0	7	0	2	1	0	0	3	0	0
Document 3	0	1	0	0	1	2	2	0	3	0

Transaction Data

A special type of record data, where

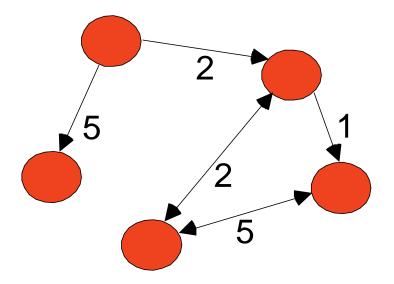
- Each record (transaction) involves a set of items.
- For example, consider a grocery store.
 - The set of products purchased by a customer during one shopping trip constitute a transaction, while the individual products that were purchased are the items.

TID	Items
1	Bread, Coke, Milk
2	Beer, Bread
3	Beer, Coke, Diaper, Milk
4	Beer, Bread, Diaper, Milk
5	Coke, Diaper, Milk

Graph Data

Examples: Generic graph and HTML Links

Usefull for calculating the page rank of a document



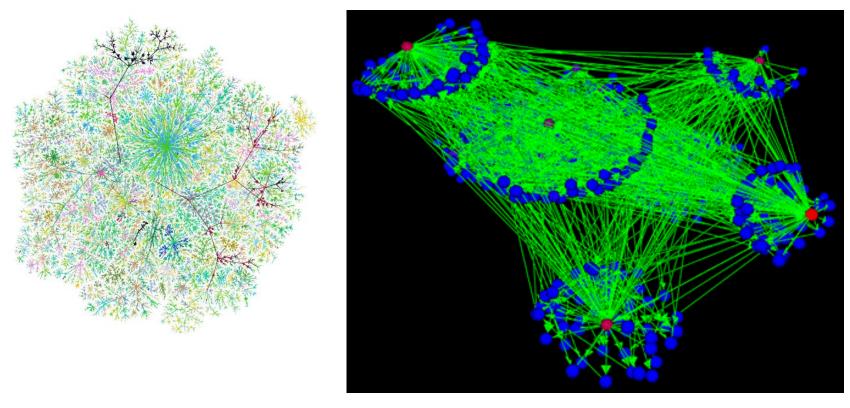
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Graph Partitioning

Parallel Solution of Sparse Linear System of Equations

N-Body Computation and Dense Linear System Solvers

Internet-Graphs: Server which are connected



http://www.maths.dur.ac.uk/users/andrew.wade/research/web.gif

http://www.netdimes.org/new/?q=node/17

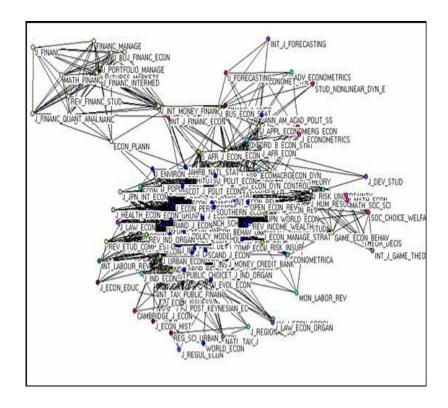
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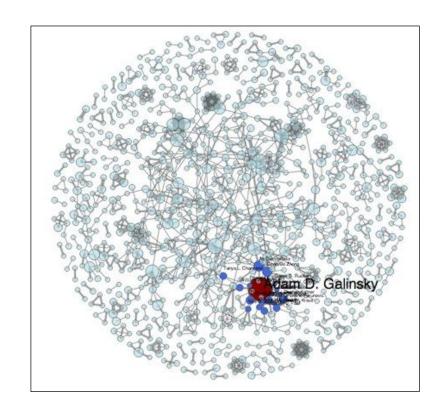
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Citation-Graphs





http://www.netdimes.org/new/?q=node/17

http://www.talyarkoni.org/blog/tag/social-graph/

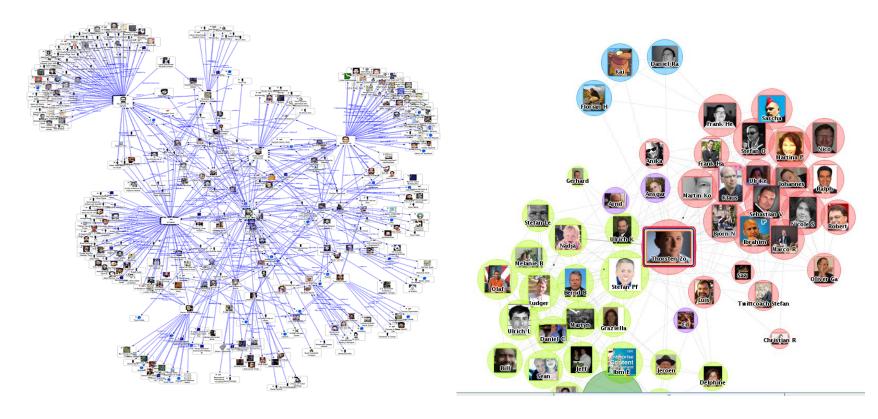
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Friendship-Graphs in Social Networks



http://www.fmsasg.com/SocialNetworkAnalysis/

http://www.cyber-junk.de/wp-content/uploads/2010/05/touchgraph.png

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What data do we use for modelling? => Record data

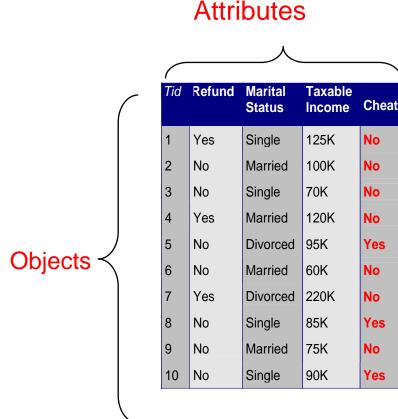
Collection of data objects and their attributes

An attribute is a property or characteristic of an object

- Examples: eye color of a person, temperature, etc.
- Attribute is also known as variable, field, characteristic or feature

A collection of attributes describes an object

 An Object is also known as record, point, case, sample, entity or instance



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Attribute Values

Attribute values are numbers or symbols assigned to an attribute. Distinction between attributes and attribute values:

- Same attribute can be mapped to different attribute values
 - Example: height can be measured in feet or meters
- Different attributes can be mapped to the same set of values
 - Example: Attribute values for ID and age are integers
- But properties of attribute values can be different
 - ID has no limit but age has a maximum and minimum value

Data Types / Types of attributes

Three main data types

- Nominal: values are equal or not, but nothing more can be said
- Ordinal: values have an order
- Numeric: one can do calculations with the values

Algorithms depend on the correct data type

Convert nominal values with an order into ordinal (or numbers)

■ Weight: under, normal, over, very_over → 1,2,3,4

Convert numbers where math does not make sense into nominal

■ ID: 11 → "11"

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Technology

Arts Sciences

Properties of Attribute Values

The type of an attribute depends on which of the following methods can be applied:

- Distinctness: $= \neq$
- Order: < >
- Addition: + -
- Multiplication: * /
- Nominal attribute: distinctness (colors: red, blue, yellow, ... / gender: male, female, other)
- Ordinal attribute: distinctness & order (school grades: A, B, C / satisfaction: low, medium, high)
- Interval attribute: distinctness, order & addition (temperature in °C or °F / calendar years)
- Ratio attribute: all four methods (Income: 0\$, 2000\$ /weight / height / time duration / age)

Other Categorization: Discrete & Continuous Attributes

Discrete Attribute

- Has only a finite or countable infinite set of values
 - Examples: zip codes, counts or the set of words in a collection of documents
- Often represented as integer variables.
- Note: binary attributes are a special case of discrete attributes

Continuous Attribute

- Has real numbers as attribute values
 - Examples: temperature, height, or weight.
- Practically, real values can only be measured and represented using a finite number of digits.
- Continuous attributes are typically represented as floating-point variables.

1. Excercise about different types of attribute values

Which operations are allowed?

Attribut Type	Mathem. Operation (two values)	Aggregation (many values)
nominal		
ordinal		
interval		
ratio		

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1. Excercise about different types of attribute values

Which operations are allowed?

Attribut Type		Aggregation (many values)
nominal	= ≠	Mode, count
ordinal	all from nominal & <>	Median, count
interval	all from ordinal & +, -	Mean, sum
ratio	all from intervall & *, /	Mean, sum, division

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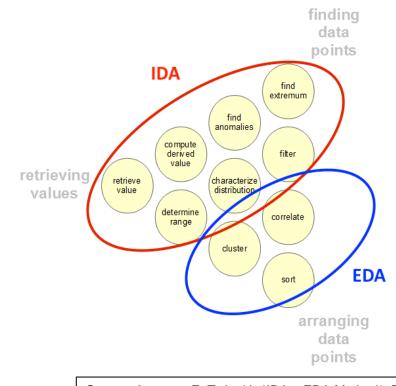
Initial Data Analysis (IDA) vs. Exploratory Data Analysis (EDA)

IDA

- Uncover underlying structure of the dataset.
- Detect outliers and anomalies.
- Test any necessary underlying assumptions.
- Treatment of problems (typically through transformations or imputations)

EDA

- Maximize insight into a data set.
- Understand and rank features by importance.
- Evaluate trade-offs between model simplicity and performance, and identify optimal parameter settings to enhance statistical methods



Source: Avornyo, E. T. (n.d.). *IDA – EDA Method*. Retrieved from https://etav.github.io/articles/ida eda method.html

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Initial Data Analysis (IDA) / Structure of the dataset

Understand underlying data structure

Goal: Understand the content, structure, origin and quality of the data.

- 1. Check the Quality of the Data (Important this happens first)
- Overview of variables: Types (categorical, numerical, etc.), units, meaning.
- Descriptive Summary Statistics (numerically): mean, median, standard deviation, size of the data set (number of features & observations)
- 1.2 Check the Quality of Data Collection Method
- Check metadata, data description, data collection methods. (Do we have any reason to believe the collection process could lead to systematic errors within the data?)

Initial Data Analysis (IDA) / Structure of the dataset

Checking structure: df.shape

Checking data types: df.info()

Checking first & last rows: df.head() & df.tail()

Checking unque values: df.nunique().sort_values()

Checking data quality:

Missing values: df.isnull().sum().sort_values(ascending=False)

Latest year for features [

	2019	2020	2021	2022	2023	2024	2025	2026	2027
Indicator									
Business freedom index (0-100)	182	181	181	175	179	175	0	0	0
Capital investment as percent of GDP	165	163	162	154	128	0	0	0	0
Economic decline index 0 (low) - 10 (high)	175	175	172	176	176	174	0	0	0
Economic freedom overall index (0-100)	177	176	176	175	174	174	0	0	0
Economic globalization index (0-100)	182	181	181	181	0	0	0	0	0
Economic growth: the rate of change of real GDP	190	190	190	190	184	0	0	0	0
Gross Domestic Product billions of U.S. dollars	191	191	191	191	184	0	0	0	0
Industry value added billion USD	187	185	184	181	167	0	0	0	0
Literacy rate	40	32	48	54	5	0	0	0	0
Manufacturing value added billion USD	176	175	172	166	152	0	0	0	0
Population growth percent	196	196	196	195	196	0	0	0	0
Population size in millions	196	196	196	196	196	0	0	0	0
Trade freedom index (0-100)	178	177	177	173	174	175	0	0	0

<class 'pandas.core.frame.DataFrame'> RangeIndex: 13692 entries, 0 to 13691 Data columns (total 17 columns): Column Non-Null Count Dtype Country 13692 non-null object Code 13692 non-null ContinentCode 11932 non-null object 13692 non-null Year int64 Industry value added billion USD 8324 non-null float64 Manufacturing value added billion USD float64 7498 non-null Population size in millions 12514 non-null float64 Capital investment as percent of GDP 8264 non-null float64 Economic growth: the rate of change of real GDP float64 10427 non-null Economic decline index 0 (low) - 10 (high) 3148 non-null float64 Economic freedom overall index (0-100) 4941 non-null float64 Gross Domestic Product billions of U.S. dollars 10734 non-null float64 12 Population growth percent float64 12316 non-null 13 Business freedom index (0-100) 4984 non-null float64 Trade freedom index (0-100) 4928 non-null float64 15 Economic globalization index (0-100) 9064 non-null float64 16 Literacy rate 1044 non-null float64 dtypes: float64(13), int64(1), object(3) memory usage: 1.8+ MB

> Technology Arts Sciences

TH Köln

Initial Data Analysis (IDA) / Structure of the dataset

Basic statistics: df.describe(include='all').T

	count	unique	top	freq	mean	std	min	25%	50%	75%	max
Country	13692	202	Lithuania	69	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Code	13692	202	LTU	69	NaN	NaN	NaN	NaN	NaN	NaN	NaN
ContinentCode	11932	5	AF	3653	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Year	13692.0	NaN	NaN	NaN	1993.928498	19.815637	1960.0	1977.0	1994.0	2011.0	2028.0
Industry value added billion USD	8324.0	NaN	NaN	NaN	60.273512	300.015825	0.0	0.47	2.94	23.185	7032.49
Manufacturing value added billion USD	7498.0	NaN	NaN	NaN	39.128145	210.326726	0.0	0.21	1.44	12.35	4909.02
Population size in millions	12514.0	NaN	NaN	NaN	27.664585	110.160467	0.01	1.0525	5.06	16.49	1428.63
Capital investment as percent of GDP	8264.0	NaN	NaN	NaN	23.147631	8.659905	-15.92	17.965	22.55	27.46	76.78
Economic growth: the rate of change of real GDP	10427.0	NaN	NaN	NaN	9637.170829	983697.553267	-64.05	1.27	3.83	6.31	100448000.0
Economic decline index 0 (low) - 10 (high)	3148.0	NaN	NaN	NaN	5.681226	1.963554	0.7	4.3	5.8	7.1	10.0
Economic freedom overall index (0-100)	4941.0	NaN	NaN	NaN	59.665857	11.681306	1.0	53.0	60.0	67.0	91.0
Gross Domestic Product billions of U.S. dollars	10734.0	NaN	NaN	NaN	197.469521	1078.606597	0.0	1.6125	8.785	56.0025	27720.71
Population growth percent	12316.0	NaN	NaN	NaN	1.731267	1.669597	-27.72	0.71	1.705	2.64	19.36
Business freedom index (0-100)	4984.0	NaN	NaN	NaN	63.899679	15.919347	5.0	55.0	65.0	74.0	100.0
Trade freedom index (0-100)	4928.0	NaN	NaN	NaN	69.99513	14.293197	13.0	62.0	72.0	80.0	95.0
Economic globalization index (0-100)	9064.0	NaN	NaN	NaN	50.264654	17.006363	11.12	37.6075	49.12	62.0	95.29
Literacy rate	1044.0	NaN	NaN	NaN	79.986705	21.092663	5.4	69.0	90.0	96.0	100.0

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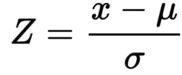
Initial Data Analysis (IDA) / Detect outliers and anomalies

Detect outliers:

- **Z-Score** (The **Z-score** indicates how many **standard deviations** a value is from the **mean**):
 - Assumption: normal distribution
 - Values with |Z| > 3 (or another threshold value) are considered outliers.

Interquartile range (IQR):

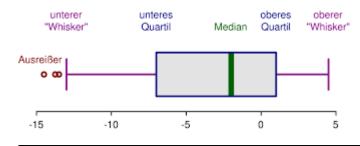
- IQR is the range of the middle 50% of the data:
 - Q1 = 25th percentile (lower quartile)
 - Q3 = 75th percentile (upper quartile)
 - IQR=Q3-Q1
- Outliers are outside the range:
 - Lower limit: Q1-1.5×IQR
 - Upper limit: Q3+1.5×IQR



x = data point

 $\mu = mean$

 σ = standard deviation



Source: RobSeb - Eigenes Werk, "Elements of a

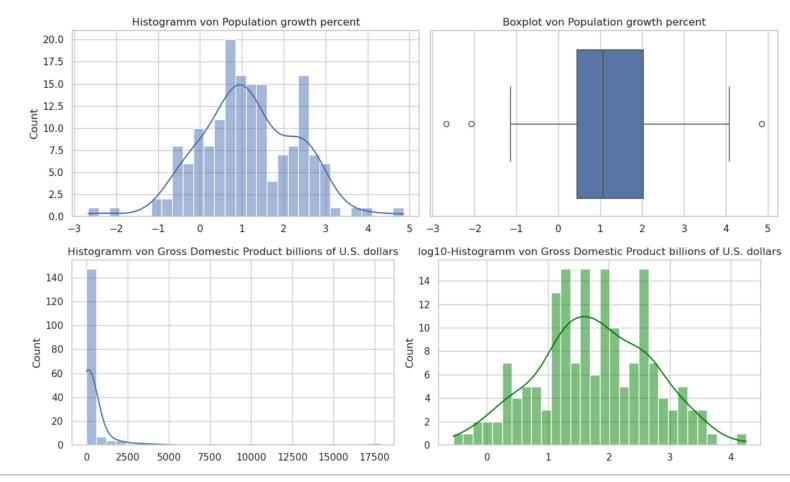
boxplot", Wikipedia

Initial Data Analysis (IDA) / Detect outliers and anomalies

Visually: histograms / boxplots

Check the normality of the dataset

Visually: histograms



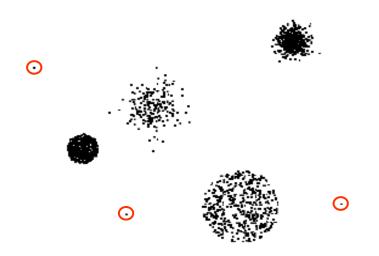
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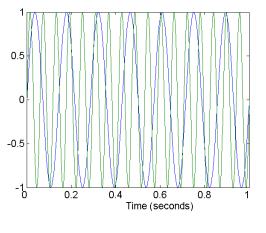
Initial Data Analysis (IDA) / Detect outliers and anomalies

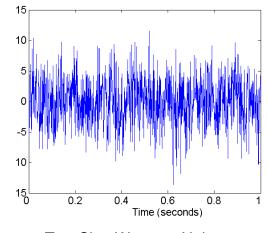
Outliers are data objects with characteristics that are considerably different than most of the other data objects in the data set



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





Two Sine Waves

Two Sine Waves + Noise

Exploratory Data Analysis (EDA)

Exploratory data analysis techniques are designed to for open-minded exploration and not guided by a research question. EDA should not be thought of as an exhaustive set of steps to be strictly followed but rather a mindset or philosophy the analyst brings with her to guide her exploration.

The analyst uses EDA techniques to "tease out" the underlying structure of the data and manipulate it in ways that will reveal otherwise hidden patterns, relationships and features. EDA techniques are primarily graphical because humans have innate pattern recognition abilities which we utilize to synthesize complex conclusions from visual cues. [1]

[1] Völkl, T. (n.d.). Initial Data Analysis (IDA) & Exploratory Data Analysis (EDA) – Method. etav.github.io. Retrieved April 30, 2025, from https://etav.github.io/articles/ida_eda_method.html

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Exploratory Data Analysis (EDA) / Univariate vs. Bivariate / Multivariate Analysis

	Univariate Analysis	Bivariate / Multivariate Analysis
Purpose	Examine single variables individually and understand their distribution	Analyze relationships between two or more variables
Typical Questions	What is the distribution? Are there outliers?	Are variables correlated? Are there patterns or associations?
Common Tools	HistogramsBoxplots	Scatter PlotsPair PlotsCorrelation Heatmaps
Usefulness	Assess transformations or effects of imputations	Detect relationships, multicollinearity, or confounding variables (relevant for modeling)
Python Tools	seaborn.histplot(), matplotlib.pyplot.hist()	seaborn.scatterplot(), seaborn.pairplot(), seaborn.heatmap()

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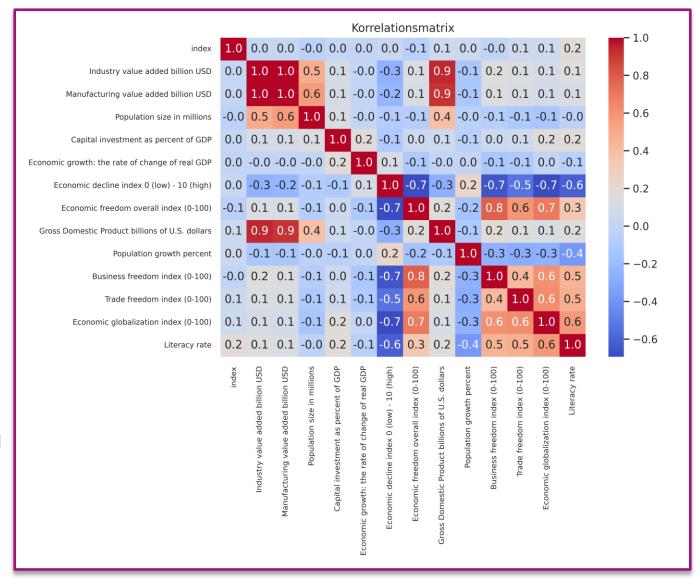
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Exploratory Data Analysis (EDA)

Correlation heatmap

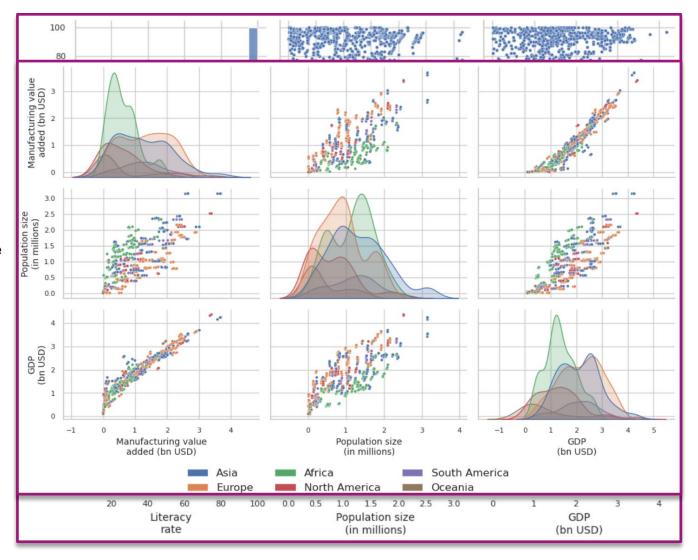
- Identify strong relationships: Easily spot variables with high positive or negative correlation.
- Detect multicollinearity: Helps to identify redundant features that may affect models.
- Simplify feature selection: Supports decisions on which variables to keep or drop.
- Get a quick overview: Offers a compact visual summary of all pairwise correlations in the dataset.



Exploratory Data Analysis (EDA)

Pairplot

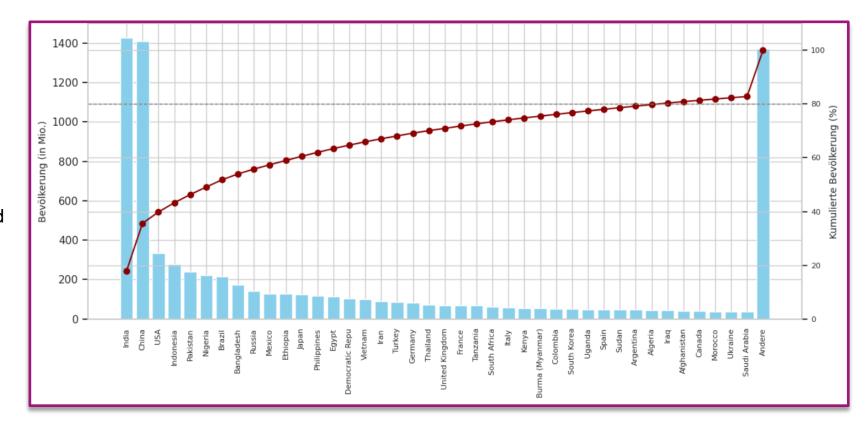
- Recognize correlations: Visualize linear and non-linear relationships between variables.
- See distributions: Individual distributions of each variable (e.g. skewness, outliers, multi-peakedness).
- Scatter & cluster: Indications of natural groups or separability in scatterplots.
- Make class differences visible: With hue, differences between categories can be visualized.



Exploratory Data Analysis (EDA)

Paretoplot

- Shows top contributors clearly by sorting values.
- Reveals 80/20 patterns (Pareto principle).
- Helps prioritize efforts and focus areas.
- Improves clarity with descending bars and cumulative line.



Exploratory Data Analysis (EDA)

Visualization overview: <u>Link</u>

What do you want to show?

Here you can find a list of charts categorised by their data visualization functions or by what you want a chart to communicate to an audience. While the allocation of each chart into specific functions isn't a perfect system, it still works as a useful guide for selecting chart based on your analysis or communication needs.



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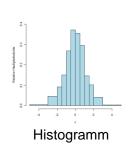
Data Visualization in the CRISP-DM

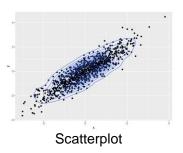
Data Understanding

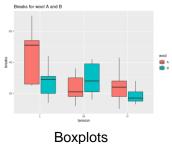
Use Cases:

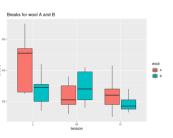
- Overview of the data structure (e.g. distributions, correlations, gaps)
- Recognize anomalies (outliers, incorrect entries) (IDA)
- Forming initial hypotheses through exploratory data analysis (EDA)

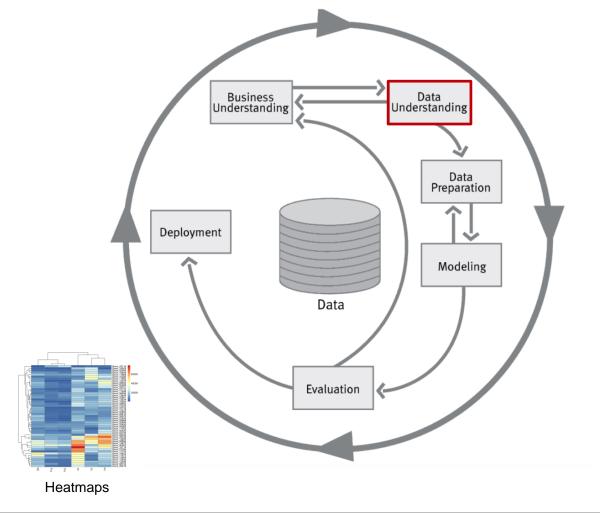
Typical visualization methods:











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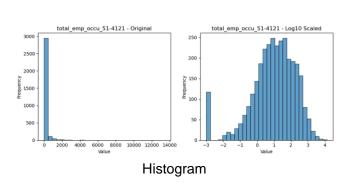
Data Visualization in the CRISP-DM

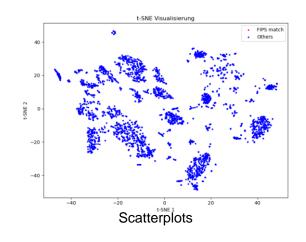
Data Preparation

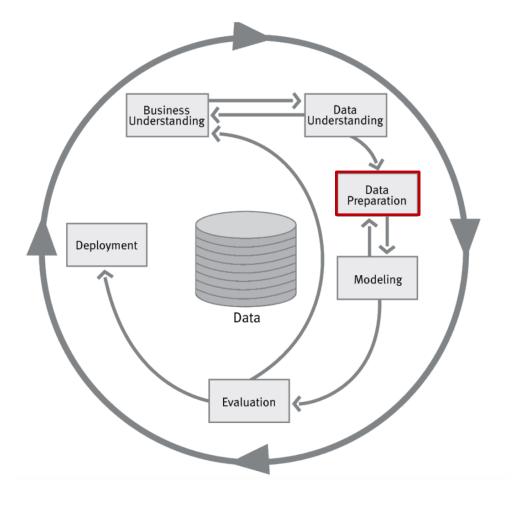
Use Cases:

- Visual control of transformations:
 - Before and after comparisons
 - Ensure that scaling, coding, feature engineering, etc. have been carried out correctly
 - Cluster or dimension reductions can be evaluated visually (e.g. PCA, t-SNE, ...)

Typical visualization methods:







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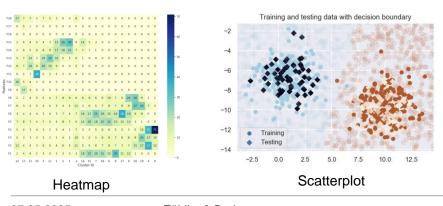
Data Visualization in the CRISP-DM

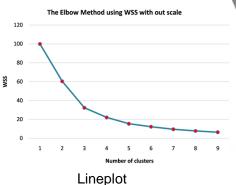
Modeling

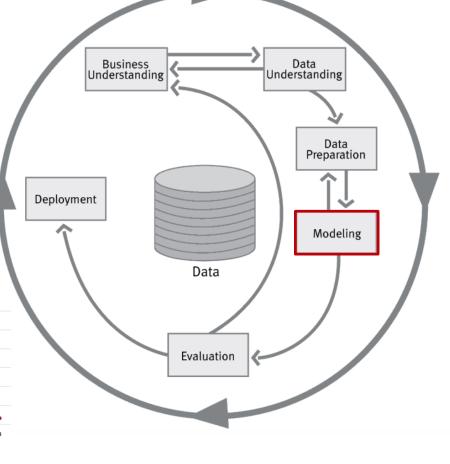
Use Cases:

- Feature imports (e.g. with random forest)
- Model behavior in the scatter plot
- Visualization of decision boundaries
- Hyperparameter tuning can be supported by heat maps or line plots

Typical visualization methods:







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Data Visualization in the CRISP-DM

Modeling

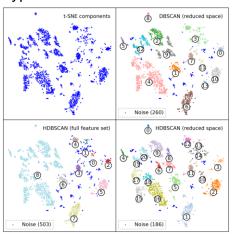
Use Cases:

Visualization of specific model-dependent metrics

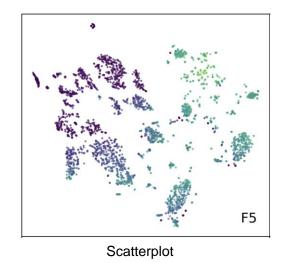
Comparison of several models (e.g. DBSCAN vs. K-Means vs. HDBSCAN)

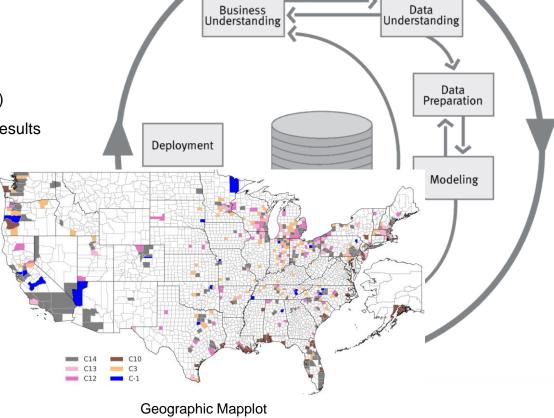
Visual Interactive Evaluation: Domain experts can validate visual clusters/results

Typical visualization methods:



Scatterplot





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Data Visualization in the CRISP-DM

Deployment

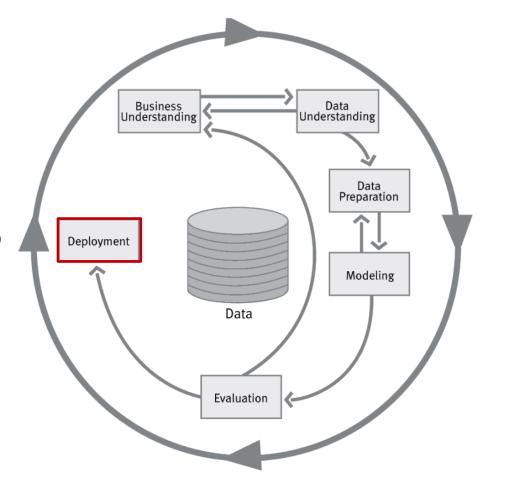
Use Cases:

- Visualization for stakeholders or monitoring:
 - Dashboards for presenting results (e.g. in Power BI, Tableau, Streamlit)
 - Visualization of KPIs
 - Regular monitoring of model performance (drift detection, performance over time)

Typical visualization methods:







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Additional Resources

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Additional Resources

Inspiring Examples:

- PBS Digital Studios. The Art of Data Visualization | Off Book_ [video]. YouTube, 2012-11-28 [accessed 2025-04-24]. Available at: [https://www.youtube.com/watch?v=AdSZJzb-aX8]
- Ribecca, Severino. The Data Visualisation Catalogue [online]. 2014 [accessed 2025-04-24]. Available at: [https://datavizcatalogue.com]

Literature:

- KNAFLIC, Cole Nussbaumer. Storytelling with data: A data visualization guide for business professionals. John Wiley & Sons, 2015. (Link)
- Few, Stephen. Information Dashboard Design: Displaying Data for At-a-Glance Monitoring. 2nd ed. Burlingame: Analytics Press, 2013. (Link)
- Bolten, Randall. Painting with Numbers: Presenting Financials and Other Numbers So People Will Understand You. Hoboken: Wiley, 2012. (Link)
- Wexler, Steve; Shaffer, Jeffrey; Cotgreave, Andy. The Big Book of Dashboards: Visualizing Your Data Using Real-World Business Scenarios.
 Hoboken: Wiley, 2017. (<u>Link</u>)

Podcasts:

- Data Stories (Link)
- Storytelling with data podcast (<u>Link</u>)
- Data Viz Today (<u>Link</u>)

