

Introduction to Data Science

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Contents

1 Basics of data science	2
1.1 Data science pipeline	2
1.2 Types of data	4
1.3 Supervised and unsupervised learning	5
1.4 Data science process	7
1.5 Challenges	10
2 Data visualization and exploration	12
2.1 Data extraction	12
2.2 Characterizing individual features	15
2.3 Data quality	17
2.4 Showing relations among features	17
2.5 Preparing for analysis	17
2.6 Good and poor visualizations	17

Introduction

Let's first introduce the general term of data science. It is a new and important discipline that can be viewed as:

- An amalgamation of classical disciplines such as statistics, data mining, databases, and distributed systems,
- With additional new challenges constantly emerging and making the field highly dynamic and appealing.

The problems grow in terms of size ("Big data") and complexity of the questions to be answered. But the basic job can be summarized as:

- Input: data \Rightarrow Processed by data scientist (with tools) \Rightarrow Output: value
- Where the skills of a data scientist are the combination of open mind, human interest, analytical skills, creativity, business-benefiting weighting, ...
- Or in other terms as can be seen in 0.1

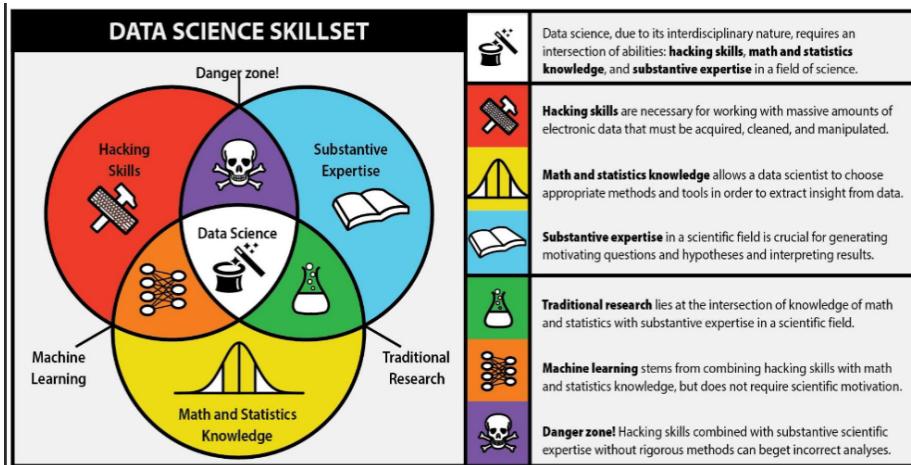


Figure 0.1: Skillset of a data scientist

With the growing importance of data and digitalization, organizations are looking for data scientists, maybe outnumbering computer scientists in the future. Important is the ability to handle data in any form, so basically the need for an all-around skilled "data wizard". This importance can be further highlighted when looking at the tech-development over the past 20 to 30 years. While the hardware got tremendously cheaper, faster, and more compact (20 times faster for MIP = mixed integer programs), also software has progressed in terms of speed (50 times faster for MIP). Interesting to look at is also the aspect of automation.

Dimensions of data science are:

- The different types of data (structured or unstructured, text, images, events, ...)
- The different types of tasks (supervised or unsupervised, ...)
- Human versus machine (Who does what?)
- Algorithm versus visualization (What is needed?)
- Flexibility versus usability
- Scalability versus quality (exact versus heuristics)

- Responsibility versus utility (accuracy and precision versus fairness, privacy, transparency, ...)

Besides raw data science, interesting to look at is also the connection to process science. The interplay between process and data science (PADS) leads to the term process mining. Imagine the connection as shown in 0.2.

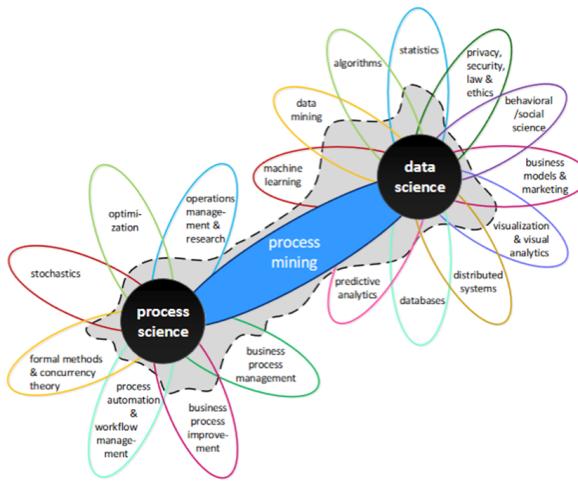


Figure 0.2: Interplay between process science and data science

As the final part of the introduction, we will now see the general covered topics in this course:

- Basic data exploration and visualization
- Decision trees, regression, support vector machines
- Neural networks, evaluation of supervised learning problems, clustering
- Frequent items sets, association rules, sequence mining, process mining, text mining
- Data preprocessing, data quality and binning, visual analytics and information visualization
- Responsible data science
- Big data technologies

1 Basics of data science

1.1 Data science pipeline

First, we are going to look at how data is processed in terms of the **data science pipeline** as it can be seen in 1.1.

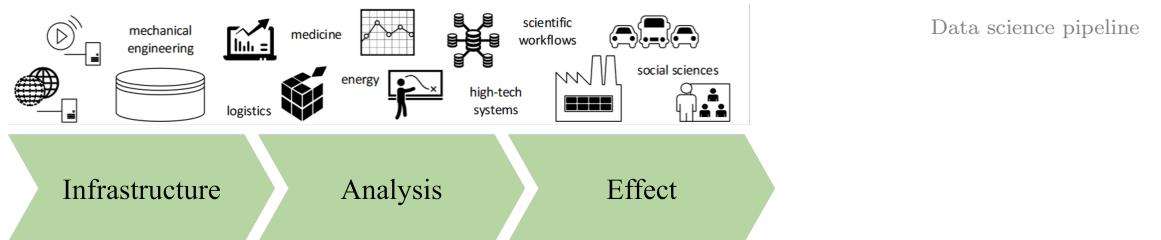


Figure 1.1: Pipeline of data science

Let's look at the individual components. The first step to pay attention to when wanting to handle data is the **infrastructure** with the keywords "**volume and velocity**". The main challenge is making things scalable and instant (responsiveness). Important terms are for example:

- Instrumentation
- Big data infrastructures, distributed systems
- Data engineering (databases and data management)
- Programming
- Security

Next, we have the step of the actual **analysis** concerned with **extracting knowledge** from data. The core challenge can be put as providing answers to known and unknown unknowns. Important terms are for example:

- Statistics, algorithms
- Data and process mining
- Machine learning, artificial intelligence
- Operations research
- Visualization

Finally, we also need to be concerned with the **effect** of our results on people, organizations, and society. The main challenge of this pipeline step is to do **responsibly** perform data handling. Important terms are for example:

- Ethics and privacy, and IT law
- Human-technology interaction
- Operations management
- Business models, entrepreneurship

This course will look into all the steps of the pipeline, but the main focus lies on the data analysis.

Four generic data science questions

Important to answering all these questions is to keep attention to all three pipeline steps, so not only what analysis we need to perform to answer them, but also how we collect our input (data) and how to deal with our output (result).

Nonetheless, here are the four generic data science questions, with variety in terms of difficulty and predicting the future:

1. **What** happened?
2. **Why** did it happen?
3. What will happen in the **future**?
4. What is the **best** that can happen?

1.2 Types of data

Now that we know that we have some kind of data as our input, we need to take a look at what this data can look like. Generally speaking, there are two types:

Structured data
Unstructured data

For **structured data** we have a further subdivision into structured data types. The data types depicted in 1.2 will be described in detail.

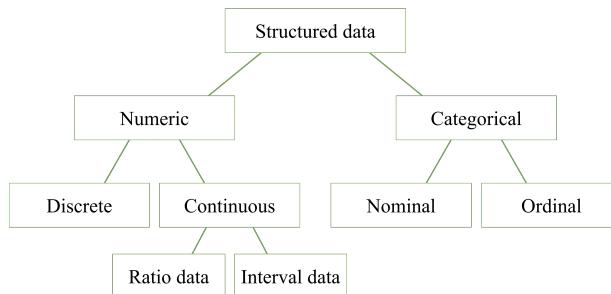


Figure 1.2: Overview structured data types

- Categorical data
Nominal data
Ordinal data
Numerical data
Discrete data
Continuous data
Interval data
- **Categorical** data can be stored and identified based on names or labels given to them and is also known as "qualitative" data. Matching can be applied, where data is grouped based on similarities.
 - Concretely, **nominal** data or naming data has a label and its characteristic similar to a noun and doesn't imply an order. (Example: name, color=red, country=NL)
 - **Ordinal** data on the other hand is ranked, ordered, or used on a rating scale. This means, you can count and order ordinal data but are not able to measure it. (Example: risk=medium, score=good)
 - In contrast to categorical data, we also have **numerical** data referring to data in the form of numbers instead of another language or descriptive form. It is also known as "quantitative" data. Important is the ability to be statistically and arithmetically calculated (allowing for $+, -, >, =, \dots$).
 - One subtype of numerical data is **discrete** data representing countable items, that are collected in a list (finite or infinite). (Example: number of items=5, age=18)
 - Then, there's also **continuous** data in the form of intervals or ranges. The data represents measurements with their intervals falling on a number line (so counting isn't involved).
 - Continuous data can now be further distinguished. One subtype is **interval** data where the data can be measured only along a scale at equal distances from each other, so only addition and subtraction operations are allowed. There is no true zero (and hence no $\cdot, /$). (Example: data=11-11-2018, temp=18.5°C)

- And finally, we have **ratio** data describing measurement with a defined (true) zero point. (Example: `dropout=33%`, `speed=128.34km/h`) Ratio data

For **unstructured data**, we just take the raw data and interpret it as a stream of bits. This goes for text, audio, images, signals, and videos exactly the same. Examples can be seen in 1.3.

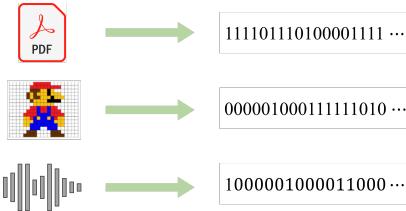


Figure 1.3: Input for unstructured data

Data can now be stored and ordered together by putting it into **tables**. Concretely, columns represent different features (can be different kinds of data types) whereas rows describe data instances (also known as individuals, entities, cases, objects, or records). Examples can be seen in 1.4.

feature							
Order id	Product	Price	Date	From	To	Message	Image
32424	718 Cayman	66.000	21-10-2018	Sue	Peter	“How are you?”	😊
34535	911 Carrera	102.000	22-10-2018	Peter	Sue	“Very good!”	😎
43555	911 Turbo	154.000	24-10-2018	Peter	Mary	“Let’s go out.”	💃
...

Ordinal
Nominal
Ratio data
Interval data
Nominal
Unstructured

Figure 1.4: Table data with data types

Features can now be raw or derived (e.g. `max`, `min`, `average`, `rank`, `bin`, `...`). An important aspect is time, as it cannot decrease and we usually want to predict the future based on the past.

An important distinction to be made when it comes to tabular data is whether the items are labeled or not.

- In case of labelled data we have **descriptive features** and a **target feature**.
 - The descriptive features are also known as predictor variables or independent variables.
 - Alternative names for target features are response variable, dependent variable, or also label.Labelled data
Descriptive features
Target feature
- Unlabelled data on the other hand doesn’t have a selected target feature. Unlabelled data

1.3 Supervised and unsupervised learning

Derived from the different kinds of tabular data, we have two fundamental learning paradigms. Exemplary input data and possible results for both paradigms can be seen

in 1.5.

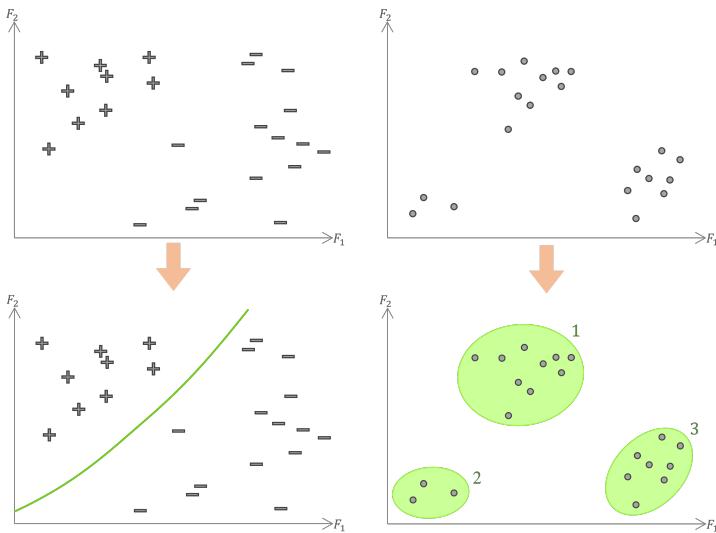


Figure 1.5: Comparing supervised (left) and unsupervised (right) learning

Supervised learning In the case of labeled data, we can apply **supervised learning**. The goal is to find a "rule" in terms of descriptive features explaining the target feature as well as possible. Examples include:

- Hospital environments where:
 - The target variable can be **recover** (yes or no), and
 - The descriptive variables can be **age**, **gender**, **smoking**, ...
- University environments where:
 - The target variable can be **drops out** (yes or no), and
 - The descriptive variables can be **mentor**, **prior education**, ...
- Production environments where:
 - The target variable can be **order is delivered in time** (yes or no), and
 - The descriptive variables can be **product**, **agent**, ...

Unsupervised learning In contrast to labeled data, we can also have instances without target labels, where we can only apply techniques of **unsupervised learning**. The goal is to find clusters or patterns.

- | | |
|----------------|--|
| Cluster | • Clusters are homogeneous sets of instances. Examples include finding similar groups of patients, students, customers, orders, cars, companies, and so on. |
| Pattern | • Patterns on the other hand reveal hidden structures in the data, so basically the unknown unknowns. Rules of some form can be found in many environments and can for example look like this: <ul style="list-style-type: none"> – Customers who buy bread and butter typically pay by phone. – Patients who drink and smoke typically pay the hospital bill earlier than others. – Products produced by team A on Monday tend to be returned more frequently by customers. |

Interesting to regard is process discovery as a form of unsupervised learning in the way that a process model is just a very sophisticated rule. Important to mention, that this

task can get very complex very quickly.

Terminology

Important to see for all of data science: many different names are used to refer to the key disciplines contributing to data science.

- This includes statistics, data analytics, data mining, machine learning, artificial intelligence, predictive analytics, process mining, generative AI, etc.
- Since frequently the same name is used for different concepts (names describe heavily overlapping areas), they really need to be put in context and interpreted accordingly.

The point can be highlighted when looking at scoping machine learning. Here are examples of confusions:

- Sometimes "machine learning" is used as a synonym for "deep neural networks" and sometimes they cover the entire spectrum of learning techniques.
- Neural networks can be used as classifiers. But this doesn't imply that numerous classification techniques developed in data mining are part of machine learning in the narrow sense.

How confusing specifically the arrangement of terms around machine learning is and how fluent and unclear the actual terms are, is depicted in 1.6.

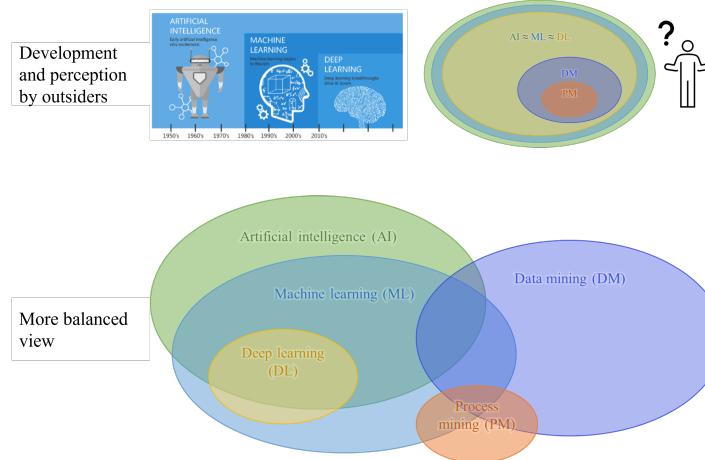


Figure 1.6: Terms around machine learning

1.4 Data science process

There are many different lifecycle models to describe phases in a data science project. This section will give a quick overview of some important ones.

We'll start with **CRISP-DM** which stands for "Cross-industry standard process for data mining". It was developed in the late 1990s by different involved companies (SPSS, Teradata, Daimler AG, NCR Corporation, Ohra). The process consists of multiple steps playing together as visualized in 1.7

CRISP-DM

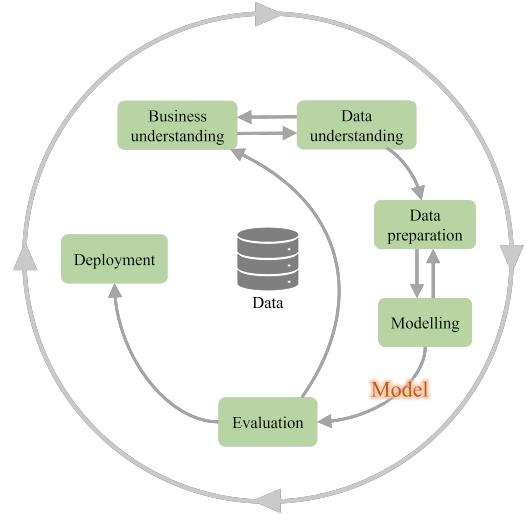


Figure 1.7: CRISP-DM process

Business understanding

- Determine business objective
- Situation assessment

- Background, business objective, business success criteria
- Inventory of resources, requirements, assumptions, constraints, risks, contingencies, terminology, costs, benefits

- Determine data mining goal
- Produce project plan

- Data mining goals, data mining success criteria
- Project plan, initial assessment of tools and techniques

Data understanding

- Collect initial data
- Describe and explore data
- Verify data quality

- Initial data collection report
- Data description, exploration report
- Data quality report

Data preparation

- Starting point: data set
- Select data
- Clean data
- Construct data
- Integrate and format data

- Data set, data set description
- Rationale for inclusion and exclusion
- Data cleaning report
- Derived attributes, generated records
- Merged/reformatted data

Modeling¹

- Select modeling technique
- Generate test design
- Build model
- Assess model

- Modeling technique, modeling assumptions
- Test design
- Parameter settings, models, model description
- Model assessment, revised parameter settings

Evaluation

- Evaluate results
- Review process
- Determine next steps

- Assessment of data mining results w.r.t. business success criteria, approved models
- Review of process
- List of possible actions settings

Deployment

- Plan deployment
- Plan monitoring and maintenance

- Deployment plan
- Monitoring and maintenance plan

¹The term "modeling" can be misleading, meant is the selection and assumptions (human) or automated learning by a tool or algorithm

Produce final report
Review project

Final report and final presentation
Experience documentation

Next, we have the **KDD** (Knowledge Discovery in Databases) process as shown in 1.8. Another process model also developed by SAS institute is called **SEMMA** consisting of the phases Sample, Explore, Modify, Model, and Assess.

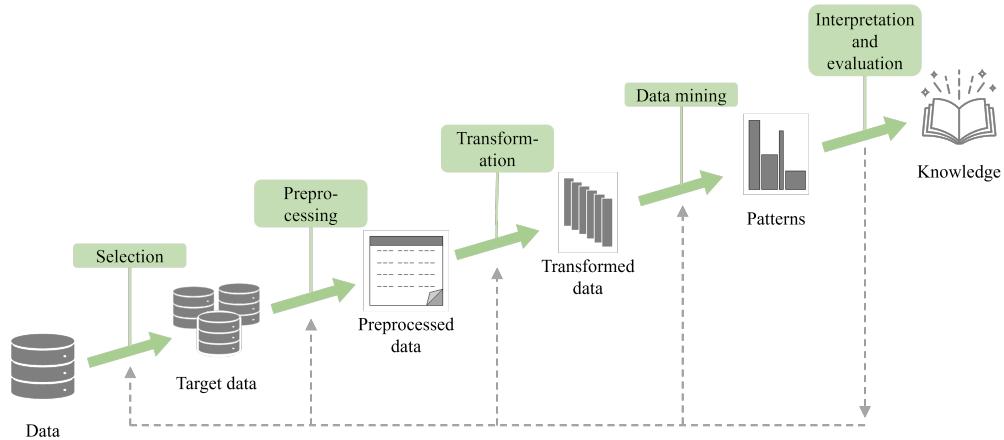


Figure 1.8: KDD process

The next process model is specifically developed for **L* lifecycle model** with multiple stages as shown in 1.9.

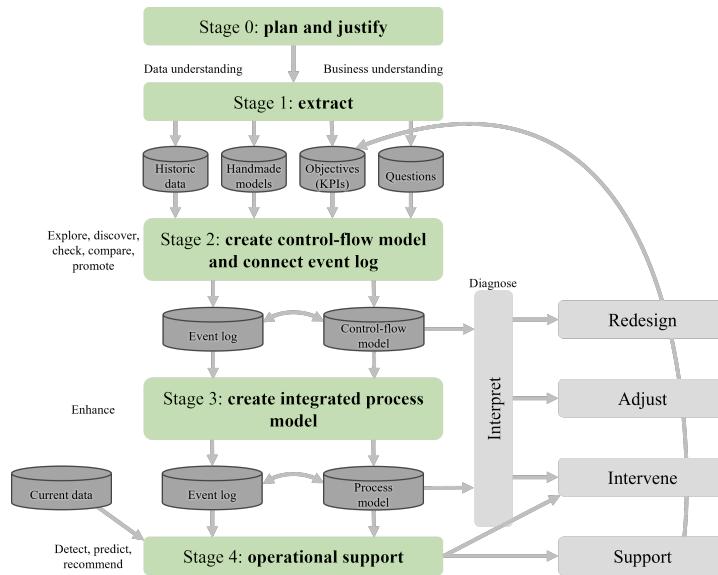


Figure 1.9: L* lifecycle model

Furthermore, we have two methodologies the process model can be related to. Important to implement and solidify are improvements in both.

- PDCA
- **PDCA** stands for Plan-Do-Check-Act and is a never-ending cycle with exactly these steps.
- DMAIC
- The other one **DMAIC** stands for Define-Measure-Analyze-Improve-Control, with the following subtasks:
 - Define: launch team, establish charter, plan project, gather VOC/VOB, plan for change
 - Measure: document process, collect baseline data, narrow project focus
 - Analyze: analyze data, identify root causes, identify and remove waste
 - Improve: generate, evaluate, and optimize solutions, pilot, plan and implement
 - Control: control the process, validate project benefits

Finally, we have two processes with the same components, but different ordering of the steps as can be seen in 1.10. The short terms for the processes are **ETL** (extract, transform, load) and **ELT** (extract, load, transform).

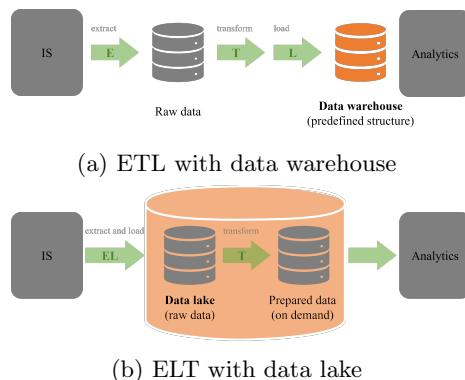


Figure 1.10: Processes with extraction, transform, and load steps

As a final note on which steps are usually the most time-expensive: there is a so-called "80/20 rule" stating:

- 80% of a data scientist's time is spent on finding, cleaning, preprocessing, and organizing data. This leaves only 20% to actually perform an analysis.
- On the other hand, we have 20% effort determining 80% of the final result.

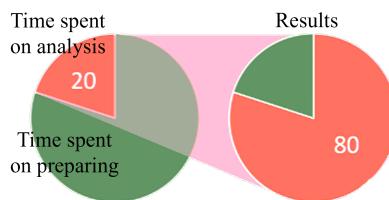


Figure 1.11: 80-20 rule

1.5 Challenges

To finalize the overview and basics of data science, let's look at the typical challenges.

First, we have the challenge of **finding data**. There may be hundreds or thousands of tables, for example in the case of SAP the numbers can easily go up to **800'000**. But,

different entities differ in their relevance, meaning some are less relevant than others.

The next challenge is the **transformation of data**, meaning reorganization of data, filtering, extraction of relevant features, and so on. Not only for transformations, but also in general other challenges are **dealing with big data and streaming data**. The challenge of big data evolved over the last few decades, meaning typical stochastic methods try to solve the problem of saying something about entities given only a small amount of samples, whereas now we have a very high load of data, and need to solve the problem of dealing with these large amounts in a correct way. Also for streaming data, new approaches need to be thought of. Additionally, we also need to **deal with a concept shift**.

Another huge challenge is ensuring **data quality**. This goes especially, since our provided data may be incomplete, invalid, inconsistent, imprecise, and/or outdated. Consider for example timestamps. They might be incomplete (event is missing), invalid (e.g. 14-14-2018), inconsistent (14-07-2018 in contrast to 7-14-2018), or imprecise (only regard part of available data: 2018-09-21T13:00:10).

A very typical problem is **overfitting and underfitting** as it can be seen 1.12.

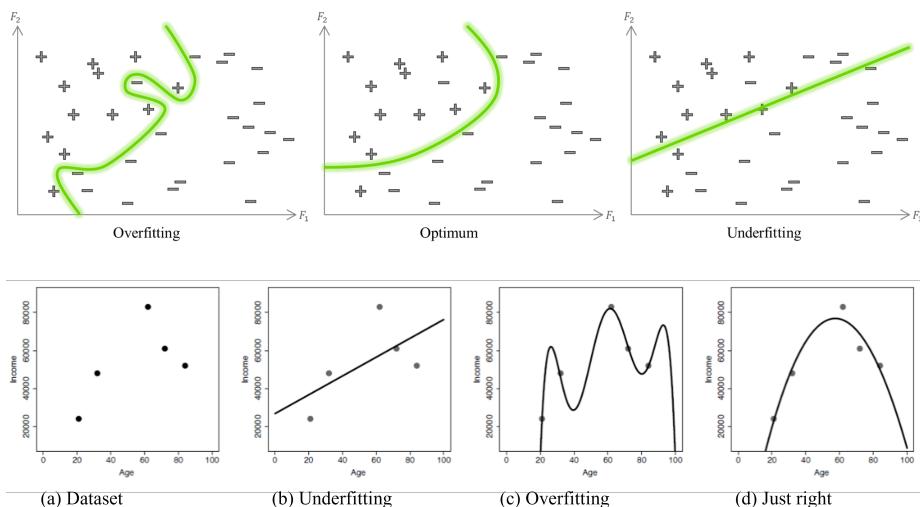


Figure 1.12: Over- and underfitting visualized

The next challenge is the distinction of **correlation and causation**, explicitly that correlation does not imply causation. Consider this example:

- Sunburn and ice cream have a strong correlation. When only these two features are considered, one might derive that either ice cream causes sunburn, or the other way around.
- We know of course, that this is not correct and instead an additional factor causes both phenomena: if the sun is shining, it's warm and people eat ice cream, and also sun directly causes sunburn.

Besides the accuracy of our results, we also need to look into whether our results are valuable. Concretely, **results** should be **made actionable**. This means, that analysis results should be relevant, specific, timely, novel, and clear. Our goal is to go from "data" to "insight" and finally "action". Consider these examples:

- Warning about a traffic jam should come before entering said traffic jam.

Responsible data science

- That it's currently raining is not too helpful information. Preferably is a notice ahead of time.

The last, but very important challenge is **responsible data science** (RDS) . This includes ensuring of:

- **Fairness**, meaning data science should exclude prejudice (How to avoid unfair conclusions even if they are true?)
- **Accuracy**, so data science without guesswork (How to answer questions with a guaranteed level of accuracy?)
- **Confidentiality** (How to answer questions without revealing secrets?)
- **Transparency** (How to clarify answers such that they become indisputable?)

2 Data visualization and exploration

2.1 Data extraction

Generally, we have a bunch of different data sources, with a multitude of different standards, features, and also information that can be extracted. The general problem is depicted in 2.1.

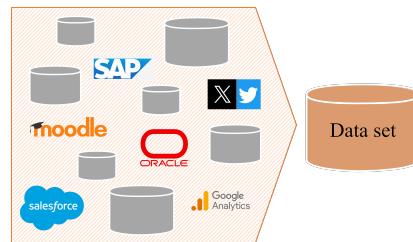


Figure 2.1: Data extraction from different sources

The different datatypes were already analyzed in the previous chapter, but still 2.2 shows a quick recap. Important to mention, that any unstructured data is considered a bit stream.

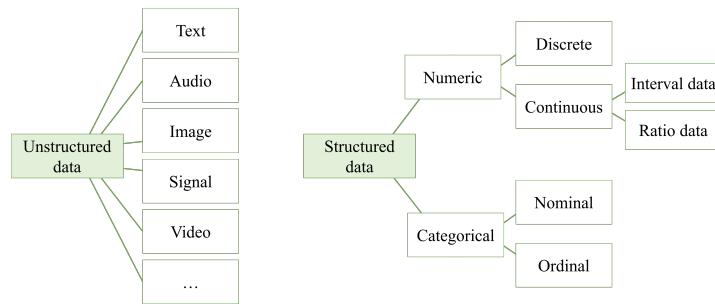


Figure 2.2: Recap: overview types of data

Important when wanting to obtain any object is of course the feature extraction. The data described by features are usually captured in a tabular form, with rows as the

instances and columns as the features. There exist some special features:

- **Time** usually always plays a role in data observation, which is why it is usually one of the recorded features.
- Then there are also the **target features**, in contrast to the descriptive features. The concept was introduced in the last section as part of supervised learning.

Importance of visualization

We now looked at how we can represent our data in a very machine-friendly represented way. The following subsection shows, why visualization of data has any importance, even though tabular data already captures the features nicely.

It is important as a human to explore your data before applying mathematical operations to see, which techniques make sense to apply to the provided data. As an extreme example, we will take a look at **Anscombe's quartet** created by Francis Anscombe in 1973.

- You can see the raw data of all four datasets in the table in 2.3. Since the format isn't human-friendly to read, you might not see any significant differences in the data.
- Now consider applying the evaluation depicted below the data table. As you can see: all of the properties that are evaluated are exactly the same for all datasets.
- BUT, if you visualize the datasets, e.g. as simple scatter plots, you see, how drastically they vary. These show the importance of first exploring your data, to then have a better evaluation foundation for the applied techniques.

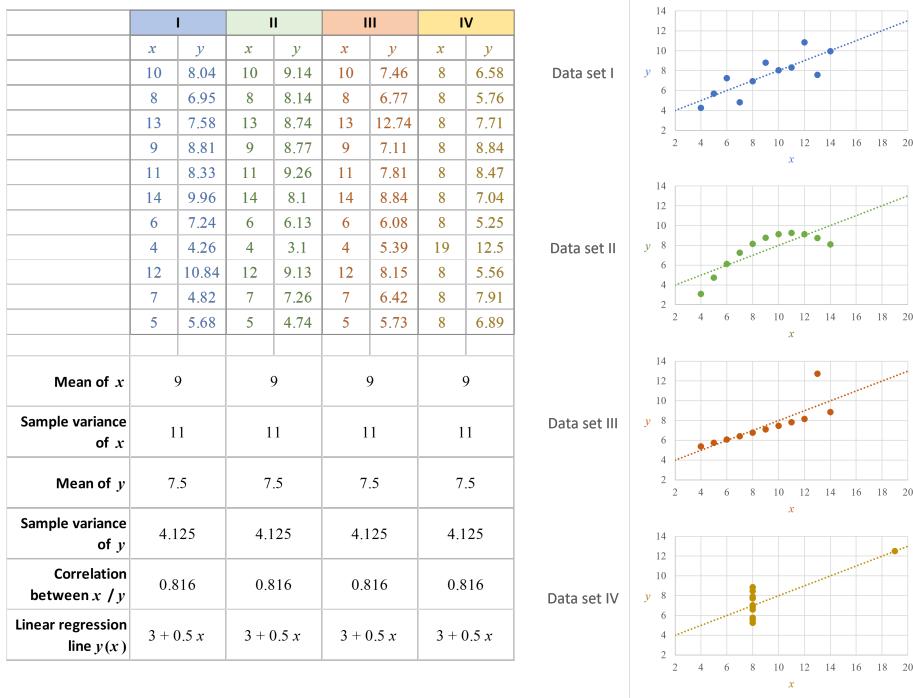


Figure 2.3: Anscombes quartet

The next example highlighting the importance of visualization and especially of a fitting and well-thought-out visualization is the diagram as shown in 2.4. The chart shows the following aspects, which are quite a lot, while still keeping a good overview:

- The number of men in Napoleon's 1812 Russian campaign army,
- Their movements (direction),
- The temperature encountered on the return path,
- All given a specific geographic point.

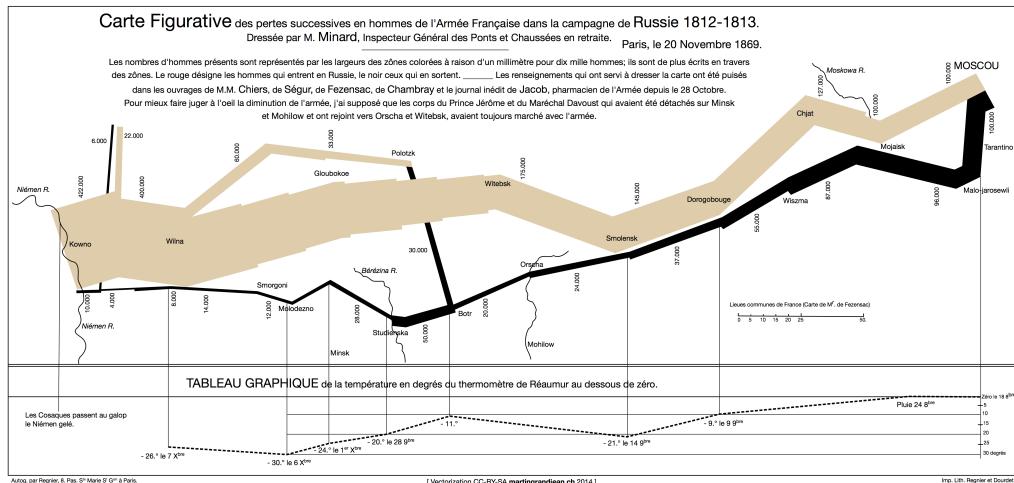


Figure 2.4: Multi-feature visualization (Napoleon's army)

As a final example: when we have given different event data, it often helps to plot this in some way as can be seen in 2.5. With the visualization, some sort of trend, similarities, certain batching areas, etc. can be directly seen.

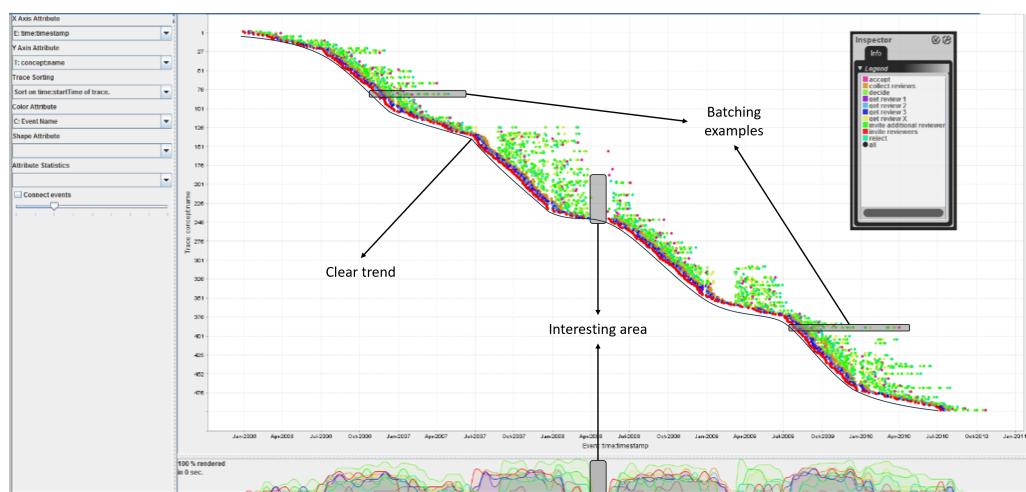


Figure 2.5: Visualization of event data

2.2 Characterizing individual features

As a first step of actual data exploration, we are now going to look at which information we can get from a single data feature. In terms of tabular data: we're going to focus on a single column.

What kind of data we can derive from the feature, depends of course on the data type. Generally deriving features from other ones is of course done best when dealing with structured data. Here, we have two types from which we can derive different properties.

From **continuous features**, we can derive

count : Number of instances having this feature

% miss : Percentage of missing information (how many instances don't have this feature)

card : Number of unique values (cardinality)

min : Minimal value over all instances

1st qrt : 25th percentile (largest value of the quarter of instances having the lowest values)

mean : Average value over all instances

median : Middle value of all instances

3rd qrt : 75th percentile (smallest value of the quarter of instances having the highest values)

max : Maximal value over all instances

std. dev : Standard deviation over all instances

Properties from investigating individual **continuous** feature

From **categorical features**, we can derive ²

count : Number of instances having this feature

% miss : Percentage of missing information (how many instances don't have this feature)

card : Number of unique values (cardinality)

mode : Most common value

mode frequ : Frequency of the mode

mode % : Percentage of the mode

2nd mode : Second most common value

2nd mode frequ : Frequency for the second mode

2nd mode % : Percentage of the second mode

Properties from investigating individual **categorical** feature

To get a better idea of how to get these properties for all of the features, we will look at an example. Consider a table containing information about insurance claims fraud. The dataset contains 500 instances (claims) and a bunch of different features such as type, claim amount, etc. Now first, determine the data type of each feature, and then

²obvious: **min**, **max**, **mean**, etc. can't be computed

create one table for the numerical and one for the categorical features and fill it with the according information. The original data and the resulting feature-describing tables can be found in 2.6.

ID	TYPE	INC.	MARITAL STATUS	NUM CLMNTS.	INJURY TYPE	HOSPITAL STAY	CLAIM AMNT.	TOTAL CLAIMED	NUM CLAIMS	NUM SOFT TISS.	% SOFT TISS.	CLAIM AMT RCVD.	FRAUD FLAG			
1	CI	0		2	Soft Tissue	No	1,625	3250	2	2	1.0	0	1			
2	CI	0		2	Back	Yes	15,028	60,112	1	0	0	15,028	0			
3	CI	54,613	Married	1	Broken Limb	No	-99,999	0	0	0	0	572	0			
4	CI	0		4	Broken Limb	Yes	5,097	11,661	1	1	1.0	7,864	0			
5	CI	0		4	Soft Tissue	No	8869	0	0	0	0	0	1			
6	CI	0		1	Broken Limb	Yes	17,480	0	0	0	0	17,480	0			
7	CI	52,567	Single	3	Broken Limb	No	3,017	18,102	2	1	0.5	0	1			
8	CI	0		2	Back	Yes	7463	0	0	0	0	7,463	0			
9	CI	0		1	Soft Tissue	No	2,067	0	0	0	0	2,067	0			
10	CI	42,300	Married	4	Back	No	2,260	0	0	0	0	2,260	0			
...			
300	CI	0		2	Broken Limb	No	2,244	0	0	0	0	2,244	0			
301	CI	0		1	Broken Limb	No	1,627	92,283	3	0	0	1,627	0			
302	CI	0		3	Serious	Yes	270,200	0	0	0	0	270,200	0			
303	CI	0		1	Soft Tissue	No	7,668	92,806	3	0	0	7,668	0			
304	CI	46,365	Married	1	Back	No	3,217	0	0	0	0	1,653	0			
...			
458	CI	48,176	Married	3	Soft Tissue	Yes	4,653	8,203	1	0	0	4,653	0			
459	CI	0		1	Soft Tissue	Yes	881	51,245	3	0	0	0	1			
460	CI	0		3	Back	No	8,688	729,792	56	5	0.08	8,688	0			
461	CI	47,371	Divorced	1	Broken Limb	Yes	3,194	11,668	1	0	0	3,194	0			
462	CI	0		1	Soft Tissue	No	6,821	0	0	0	0	0	1			
...			
491	CI	40,204	Single	1	Back	No	75,748	11,116	1	0	0	0	1			
492	CI	0		1	Broken Limb	No	6,172	6,041	1	0	0	6,172	0			
493	CI	0		1	Soft Tissue	Yes	2,569	20,055	1	0	0	2,569	0			
494	CI	31,951	Married	1	Broken Limb	No	5,227	22,095	1	0	0	5,227	0			
495	CI	0		2	Back	No	3,813	9,882	3	0	0	0	1			
496	CI	0		1	Soft Tissue	No	2,118	0	0	0	0	0	1			
497	CI	29,280	Married	4	Broken Limb	Yes	3,199	0	0	0	0	0	1			
498	CI	0		1	Broken Limb	Yes	32,469	0	0	0	0	16,763	0			
499	CI	46,683	Married	1	Broken Limb	No	179,448	0	0	0	0	179,448	0			
500	CI	0		1	Broken Limb	No	8,259	0	0	0	0	0	1			
Continuous/ numerical features																
Feature	Count	% Miss.	Card.	Min	1 st Quart.	Mean	Median	3 rd Quart.	Max	Std. Dev.						
INCOME	500	0.0	171	0.0	0.0	13,740.0	0.0	33,918.5	71,284.0	20,081.5						
NUM CLAIMANTS	500	0.0	4	1.0	1.0	1.9	2	3.0	4.0	1.0						
CLAIM AMOUNT	500	0.0	493	-99,999	3,322.3	16,373.2	5,663.0	12,245.5	270,200.0	29,426.3						
TOTAL CLAIMED	500	0.0	235	0.0	0.0	9,597.2	0.0	11,282.8	729,792.0	35,655.7						
NUM CLAIMS	500	0.0	7	0.0	0.0	0.8	0.0	1.0	56.0	2.7						
NUM SOFT TISSUE	500	2.0	6	0.0	0.0	0.2	0.0	0.0	5.0	0.6						
% SOFT TISSUE	500	0.0	9	0.0	0.0	0.2	0.0	0.0	2.0	0.4						
AMOUNT RECEIVED	500	0.0	329	0.0	13,051.9	3,253.5	8,191.8	295,303.0	30,547.2							
FRAUD FLAG	500	0.0	2	0.0	0.0	0.3	0.0	1.0	1.0	0.5						
Categorical features																
Feature	Count	% Miss.	Card.	Mode	Mode Freq.	Mode %	2 nd Mode	2 nd Mode Freq.	2 nd Mode %							
INSURANCE TYPE	500	0.0	1	CI	500	100.0										
MARITAL STATUS	500	61.2	4	Married	99	51.0	Single	48	24.7							
INJURY TYPE	500	0.0	4	Broken Limb	177	35.4	Soft Tissue	172	34.4							
HOSPITAL STAY	500	0.0	2	No	354	70.8	Yes	146	29.2							

Figure 2.6: Example for single feature investigation (insurance claim fraud)

To investigate the raw data further, let's visualize it. More specifically, we're going to visualize the distributions of the different features.

- For finite amounts of possible feature classes, simply visualize the distribution as a bar diagram with the different classes as entries on the x-axis. The y-axis can either be the frequency or a percentage.
- For continuous features with continuous variables/ininitely many possible feature values, group items (**binning**) and then visualize the resulting histogram.

Binning

2.3 Data quality

2.4 Showing relations among features

2.5 Preparing for analysis

2.6 Good and poor visualizations