

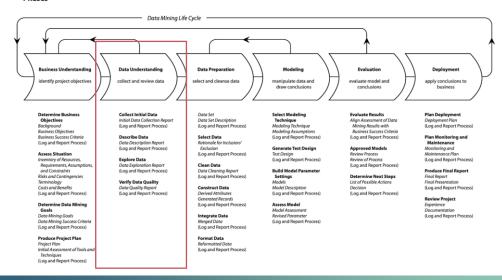
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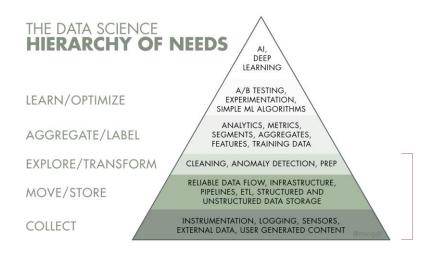
## Today's agenda

#### **Phases**



Data Understanding | Introduction

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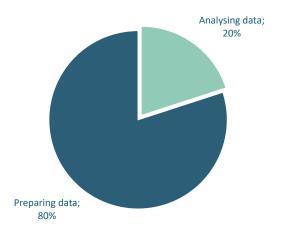
Whatever the goal, whatever type of analysis:

always start with a thorough description and understanding of the data

https://hackernoon.com/the-ai-hierarchy-of-needs-18f111fcc007

Data Understanding | Introduction

# Just to manage expectations: what do data scientists actually do?



Data Understanding | Introduction

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### The smallest data science team

- > If possible, try not to work on your own but at least with one buddy
- > Make a distinction between data engineering and data science activities
  - · Helps you to structure your workflow and pipeline
  - Separation of concerns
- > More specialists roles are possible as your team grows
  - Data Consultant
  - Data visualization (front-end apps)
  - DevOps
  - ...

https://www.datacamp.com/community/blog/data-scientist-vs-data-engineer

DataCamp

Learn Data Science By Doing DATA DATA Scientist Conduct research to answer and maintain architectures (such industry and business questions processing systems) Leverage large volumes of data Ensure architecture will support sources to answer that business the requirements of the business Discover opportunities for data programs, machine learning and statistical methods to acquisition prepare data for use in predictive Develop data set processes for and prescriptive modeling data modeling, mining Explore and examine data to **find** hidden patterns and production tools (e.g. scripting languages) to marry systems together Automate work through the use Recommend ways to **improve data** reliability, efficiency and quality Tell stories to key stakeholders

Data Understanding | Introduction

# Agenda

section	topic	
Data Engineering (very short introduction)	Data types	
	Modern data architectures	
	Data modeling	
Data Understanding	Collect data	
	Describe data	
	Explore data	
	Verify data quality	

Data Understanding | Introduction

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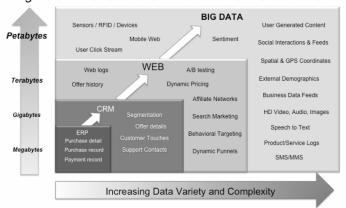
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# **Data Engineering**

A very short introduction

# Evolution of enterprise data

#### Big Data = Transactions + Interactions + Observations



https://www.researchgate.net/figure/Big-Data-Transactions-with-Interactions-and-Observations-Source\_fig3\_243963821

Data Engineering

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# How does a computer store data?

- > Structured data: databases, data model
- > <u>Semi-structured data</u>: json, XML, relationships with <u>graph database</u>
  - 'John is a friend of Mary'
- > <u>Unstructured data</u>: audio files, images, video

Data Engineering 10

# Steven's topology of measurement (1946)

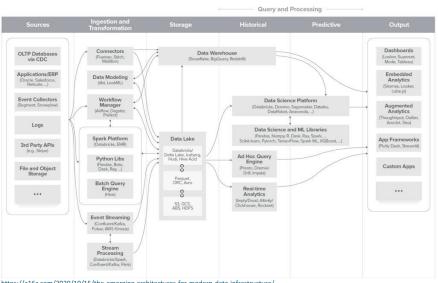
scale	measure property	math operations	advanced operations	central tendency
nominal	classification, membership	=, ≠	grouping	mode
<u>ordinal</u>	comparison, level	>, <	sorting	median
interval	difference, affinity	+, -	<u>yardstick</u>	mean, deviation
ratio	magnitude, amount	x, /	<u>ratio</u>	geometric mean, variation

https://en.wikipedia.org/wiki/Level\_of\_measurement

Data Engineering

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# The main components of a modern data infrastructure



https://a16z.com/2020/10/15/the-emerging-architectures-for-modern-data-infrastructure/

Data Engineering

# From conventional ETL to modern data pipelines

conventional ETL (Extract-Transform-Load) <sup>[1]</sup>	modern data pipelines <sup>[2]</sup>
processing of (semi-)structured data	processing of all kinds of data (incl. unstructured)
works with updates and transformations to save storage	follows principal of immutable data with more copies
more simple, linear process flows executed on central data warehouse	more complex, distributed process flows ( <u>directed acyclic graph</u> ) run on various machines
focuses on creating data marts and dashboard	many different use-cases, including machine learning, streaming processing

https://en.wikipedia.org/wiki/Extract, transform, load https://en.wikipedia.org/wiki/Directed\_acyclic\_graph#Data\_processing\_networks

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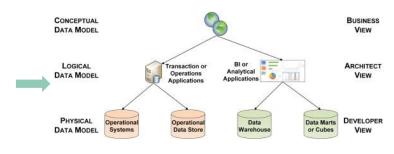
Data Engineering

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### Three levels of data models

# A data model is (Wikipedia):

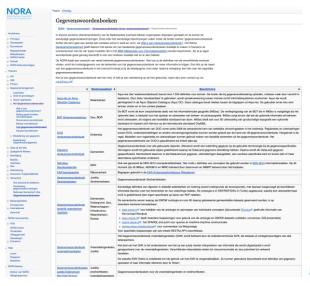
An abstract model that organizes elements of data and standardizes how they relate to one another and to the properties of realworld entities.



https://www.sciencedirect.com/topics/computer-science/logical-data-model

Data Engineering | Data modelling

# Conceptual models and semantic standards



- > Standardized definition of information elements (informatiebouwstenen)
- > Over <u>30 standards</u> currently in use in the Netherlands

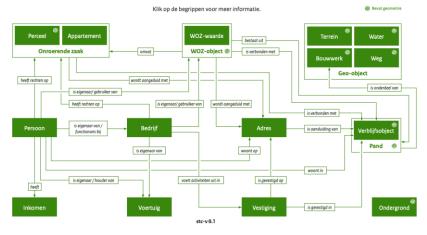
https://www.noraonline.nl/wiki/NORA online

Data Engineering | Data modelling

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# Example: conceptual data model Dutch national registries

# Stelselplaat gegevens 2020



https://www.stelselcatalogus.nl/stelselplaat

Data Engineering | Data modelling

# Three different logical data model types

#### > third normal form

- used for processing transactions
- · optimized for fast inserts and updates

#### > data vault schema:

- · used in data vaults
- optimized for flexibility for integrating different sources

#### > star schema:

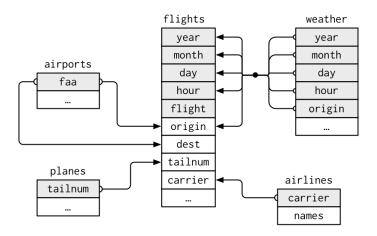
- · used in data marts
- · optimize of fast querying and online analytical processing (OLAP)

Data Engineering | Data modelling

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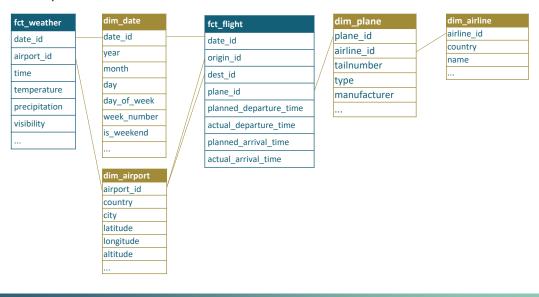
# Example: original data in third normal form



https://r4ds.had.co.nz/relational-data.html

Data Engineering | Data modelling

# Example: data in star schema



Data Engineering | Data modelling

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# **Data Understanding**

Collecting, describing, exploring and verifying your data

# Evolution of enterprise data

Data Understanding 21

# Why bother with data understanding?

- > It checks the feasibility of a project
- > It contributes to refinement of the project scope
- > It provides explicit input for next steps in your project, namely:
  - How to clean data
  - How to adjust existing variables
  - Where to create new variables
  - · How to approach data modelling

Data Understanding 22

### Insight into the available data

- > Create an overview of the available data
  - available variables
  - number of observations per variable
  - levels within categorical variables
  - descriptives of numeric variables
- > Describe the population
  - How did observations (clients, events, etc) make it into the dataset?
  - What do descriptives say about the population?
- > Create an overview of data domains that are relevant for your problem

Data Understanding 23

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### Insight into data quality and usability

- > Explore quality:
  - number of missings per input variable
  - number of missings in the outcome variable
  - occurrence of impossible values or combination of values
  - occurrence of outliers
- > Explore usability
  - Are data available at the intended moment of prediction or classification?
  - How difficult is it to collect this information in practice?
  - How much variation is there in each variable?
  - How much additional variation is there in each variable?

## Confirming or rejecting your project goal

- > Given data availability and data quality, is the project still feasible?
- > Given the descriptions of your outcome variable, is the problem prevalent or pressing enough?

Data Understanding

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# Further refining the outcome Y

- > What choices need to be made in case the outcome Y needs to be defined based on the data?
  - What counts as early dropout?
  - What should be considered a treatment success?
  - What cut-off to choose when defining a satisfied vs unsatisfied customer?
- > How do different definitions of Y impact the balance in the outcome?
- > Has the user been carefully consulted in defining Y?

## Further scoping your project

- > Are there outlying X-values which are better left out-of-scope?
- > Is the problem perhaps more relevant in a subpopulation?
- > Has the user been carefully consulted in scoping the project?

Data Understanding

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## Input for data preparation and cleaning

- > Which variables to exclude as they would not be available at the moment of prediction or classification?
- > Where and how to impute missing values?
- > How to correct infeasible (combinations of) values?
- > Which variables to exclude for having little to no variation?
- > Which variables to exclude for being highly collinear with other variables?
- > Which variables to exclude for containing information that would be too difficult to collect in practice?

# Feature engineering and model considerations

- > Which input variables do and do not have an individual relation with Y?
- > In what (possibly non-linear) way are input variables related to Y?
- > What combination of input variables are related to Y?
- > Which input variables seem to be most strongly related to Y?
  - when is this information available?
  - what does this mean for when the model can be applied?