Tag 2: Einführung in Data Science – Prüfungsfragen

Frage 1: Die drei Säulen von Data Science
Welche drei Disziplinen bilden die Grundpfeiler von Data Science?
A) Mathematik, Physik, Chemie B) Domänenexpertise, Statistik/Mathematik, Informatik ✓ C) Big Data, Cloud Computing, Machine Learning D) Programmierung, Datenbanken, Visualisierung
Antwort: B

Frage 2: Big Data Charakteristiken
Welche der folgenden gehört NICHT zu den "5 V's" von Big Data?
A) Volume B) Velocity C) Verification ✓ D) Variety
Antwort: C (Die 5 V's sind: Volume, Velocity, Variety, Veracity, Value)

Frage 3: AI-Hierarchie
Welche Aussage zur Hierarchie von künstlicher Intelligenz ist korrekt?
A) Machine Learning ist ein Teilbereich von Deep Learning B) Deep Learning ist ein Teilbereich von Machine Learning ✓ C) AI und Machine Learning sind identisch D) GenAI umfasst alle anderen AI-Bereiche
Antwort: B (AI → Machine Learning → Deep Learning → LLM/GenAI)

Frage 4: Anwendungsfälle von Data Science
Welcher der folgenden ist KEIN typischer Anwendungsfall von Data Science in der Produktion?
A) Predictive Maintenance (vorausschauende Wartung) B) Qualitätskontrolle durch Bilderkennung C) Manuelle Rechnungsprüfung ✓ D) Vorhersage der Produktqualität
Antwort: C

Frage 5: Datenvisualisierung
Welche visuelle Eigenschaft eignet sich am BESTEN für die Darstellung quantitativer Variablen?
A) Form B) Farbe (Hue) C) Länge ✓ D) Gruppierung
Antwort: C (Länge ist sehr gut für quantitative Variablen geeignet)

Frage 6: Korrelation vs. Kausalität
Was ist der wichtigste Unterschied zwischen Korrelation und Kausalität?
A) Korrelation ist stärker als Kausalität B) Kausalität impliziert immer Korrelation, aber Korrelation impliziert nicht notwendigerweise Kausalität ✓ C) Es gibt keinen Unterschied D) Kausalität kann nur bei Big Data nachgewiesen werden
Antwort: B

Frage 7: Datenquellen
Welche der folgenden ist eine typische Open-Source Datenquelle?
A) Interne Unternehmensdatenbank B) Kaggle ✓ C) Proprietäre Cloud-Marketplaces D) Kundentransaktionsdaten
Antwort: B (Weitere Beispiele: WHO, Our World in Data, UC Irvine ML Repository)

Frage 8: Diagrammtypen
Welcher Diagrammtyp eignet sich am besten zur Darstellung der Verteilung von Werten und zur Identifikation von Ausreißern?
A) Liniendiagramm B) Kreisdiagramm C) Boxplot ✓ D) Heatmap
Antwort: C

Frage 9: Risiken von Data Science
Welches der folgenden ist ein wichtiges Risiko bei der Anwendung von Data Science?
A) Zu geringe Datenmengen B) Datenschutzverletzungen und Manipulation ✓ C) Mangel an Visualisierungstools D) Fehlende Internetverbindung
Antwort: B (Weitere Risiken: fehlerhafte Modellierung, Überwachung, Manipulation

Tag 4: Datenaufbereitung & Feature Engineering – Prüfungsfragen

Frage 1: Wissenstreppe nach Prof. Klaus North
In welcher Reihenfolge sind die Stufen der Wissenstreppe korrekt angeordnet?
A) Information → Daten → Wissen → Fähigkeiten B) Daten → Information → Wissen → Fähigkeiten ✓ C) Wissen → Daten → Information → Fähigkeiten D) Daten → Wissen → Information → Fähigkeiten
Antwort: B

Frage 2: Dimensionale Datenstrukturen
Was sind "Fakten" in einer dimensionalen Datenstruktur?
A) Beschreibende, qualitative Attribute B) Hierarchische Strukturen C) Quantitative Kennzahlen, die durch Aggregationsfunktionen berechnet werden können ✓ D) Kategoriale Variablen
Antwort: C (Fakten sind numerische Attribute wie sum(turnover), count(employee-number))

Frage 3: Datenoperationen
Was beschreibt die Operation "Roll-Up"?
A) Disaggregation von Daten B) Selektion von Tupeln nach Bedingungen C) Aggregation von Daten entlang einer dimensionalen Hierarchie von spezifisch zu allgemein ✓ D) Projektion auf bestimmte Dimensionen
Antwort: C

Frage 4: Zeitaufwand in Data Science
Wie viel Prozent ihrer Zeit verbringen Data Scientists typischerweise mit Datenaufbereitung ("Janitor Work")?
A) 10-20% B) 25-35% C) 45-80% ✓ D) 90-95%
Antwort: C

Frage 5: Fehlende Daten – Typen
Was bedeutet MCAR (Missing Completely at Random)?
A) Die Wahrscheinlichkeit, dass ein Datenpunkt fehlt, hängt von den beobachteten Daten ab B) Die Wahrscheinlichkeit, dass ein Datenpunkt fehlt, ist für alle Fälle gleich ✓ C) Die Wahrscheinlichkeit hängt vom fehlenden Wert selbst ab D) Daten fehlen systematisch in bestimmten Kategorien
Antwort: B

Frage 6: Ausreißer-Erkennung
Welche Methode wird zur Erkennung von Ausreißern verwendet?
A) One-Hot Encoding B) Min-Max Normalisierung C) IQR (Interquartile Range) ✓ D) Cross-Validation
Antwort: C (Weitere Methoden: Z-Score, Isolation Forest)

Frage 7: Normalisierung
Was ist das Ergebnis der Min-Max Normalisierung?
A) Daten werden auf Mittelwert 0 und Standardabweichung 1 skaliert B) Daten werden auf den Bereich [0, 1] skaliert ✓ C) Kategoriale Variablen werden in numerische umgewandelt D) Ausreißer werden entfernt
Antwort: B

Frage 8: One-Hot Encoding
Wofür wird One-Hot Encoding verwendet?
A) Zur Normalisierung numerischer Daten B) Zur Kodierung kategorialer Variablen in numerische Vektoren ✓ C) Zur Erkennung von Ausreißern D) Zur Aggregation von Daten
Antwort: B

Frage 9: Strukturierte vs. unstrukturierte Daten
Welche Aussage über strukturierte Daten ist korrekt?
A) Sie haben keine vordefinierten Datentypen B) Sie werden in Data Lakes gespeichert C) Sie sind in Zeilen und Spalten organisiert und können in relationale Datenbanken gespeichert werden ✓ D) Sie umfassen hauptsächlich Bilder, Videos und Audio
Antwort: C

Tag 6: Einführung in maschinelles Lernen – Prüfungsfragen

Frage 1: Machine Learning Paradigmen
Welche Art von Machine Learning verwendet gelabelte Trainingsdaten?
A) Unsupervised Learning B) Supervised Learning ✓ C) Reinforcement Learning D) Semi-Supervised Learning
Antwort: B

Frage 2: Klassifikation vs. Regression
Was ist der Hauptunterschied zwischen Klassifikation und Regression?
A) Klassifikation verwendet mehr Daten als Regression B) Klassifikation ordnet Eingaben vordefinierten Klassen zu, während Regression kontinuierliche Werte vorhersagt ✓ C) Regression ist schneller als Klassifikation D) Es gibt keinen Unterschied
Antwort: B

Frage 3: Unsupervised Learning
Welcher Algorithmus gehört zum Unsupervised Learning?
A) K-Nearest Neighbors (KNN) B) Support Vector Machine (SVM) C) K-Means Clustering ✓ D) Decision Tree Classification
Antwort: C

Frage 4: Train-Test Split
Warum ist ein Train-Test Split wichtig?
A) Um mehr Daten zu generieren B) Um die Modellleistung auf ungesehenen Daten zu evaluieren ✓ C) Um die Trainingszeit zu verkürzen D) Um Overfitting zu erzeugen
Antwort: B

Frage 5: Neuronale Netze – Struktur
Welche Schichten gehören zu einem neuronalen Netz?
A) Nur Input Layer und Output Layer B) Input Layer, Hidden Layer(s), Output Layer ✓ C) Nur Hidden Layers D) Training Layer, Testing Layer, Validation Layer
Antwort: B

Frage 6: Aktivierungsfunktionen
Welche Aktivierungsfunktion gibt Werte zwischen 0 und 1 aus und wird häufig für binäre Klassifikation verwendet?
A) Tanh B) ReLU C) Sigmoid ✓ D) Linear
Antwort: C

Frage 7: Hyperparameter
Was ist ein Hyperparameter?
A) Ein Parameter, der während des Trainings automatisch gelernt wird B) Ein Parameter, der vor dem Training festgelegt wird und die Modellperformance beeinflusst ✓ C) Ein Gewicht in einem neuronalen Netz D) Eine Aktivierungsfunktion
Antwort: B (Beispiele: Learning Rate, Batch Size, Epochs, Anzahl Hidden Layers)

Frage 8: Reinforcement Learning
Was ist das Ziel von Reinforcement Learning?
A) Daten in Cluster zu gruppieren B) Die kumulative Belohnung über die Zeit zu maximieren ✓ C) Fehlende Werte zu imputieren D) Kategoriale Variablen zu kodieren
Antwort: B

Frage 9: Batch Size
Was beschreibt der Hyperparameter "Batch Size"?
A) Die Anzahl der Epochen im Training B) Die Größe einer Dateneinheit, nach der das Modell angepasst wird ✓ C) Die Lernrate des Modells D) Die Anzahl der Hidden Layers
Antwort: B

Introduction to Data Science by W&S

Tag 8: Modellbewertung – Abschlussfragen

Frage 1: Overfitting vs. Underfitting
Was charakterisiert Overfitting?
A) Das Modell ist zu einfach und passt nicht gut zu den Trainingsdaten B) Das Modell ist zu flexibel und "memoriert" die Trainingsdaten (High Variance) ✓ C) Das Modell hat einen hohen Bias D) Das Modell generalisiert zu gut
Antwort: B

Frage 2: Confusion Matrix
In einer Confusion Matrix, was bedeutet "False Positive" (Type 1 Error)?
A) Das Modell sagt negativ voraus, aber die wahre Klasse ist positiv B) Das Modell sagt positiv voraus, aber die wahre Klasse ist negativ ✓ C) Das Modell sagt korrekt positiv voraus D) Das Modell sagt korrekt negativ voraus
Antwort: B

Frage 3: Precision vs. Recall
Was misst "Precision"?
A) Von allen realen positiven Fällen, wie viele hat das System korrekt erkannt B) Von allen Vorhersagen des Systems als positiv, wie viele waren tatsächlich positiv ✓ C) Die Gesamtgenauigkeit des Modells D) Die Anzahl der True Negatives
Antwort: B
Formel: Precision = TP / (TP + FP)

Frage 4: Regressionsmetriken
Welche Metrik gibt die durchschnittliche absolute Abweichung zwischen vorhergesagten und tatsächlichen Werten an?
A) R^2 (R-Squared) B) MSE (Mean Squared Error) C) MAE (Mean Absolute Error) ✓ D) RMSE (Root Mean Squared Error)
Antwort: C

Frage 5: EU AI Act – Risikokategorien
Welche Risikokategorie im EU AI Act hat die strengsten Anforderungen?
A) Minimal Risk B) Limited Risk C) High Risk ✓ D) Medium Risk
Antwort: C (Unacceptable Risk ist verboten; High Risk hat die strengsten Anforderungen für erlaubte Systeme)

Frage 6: EU AI Act – Strafen
Was ist die maximale Strafe bei Verstößen gegen den EU AI Act?
A) €1 Million B) €10 Million oder 2% des Jahresumsatzes C) €35 Million oder 7% des globalen Jahresumsatzes ✓ D) €50 Million oder 10% des Jahresumsatzes
Antwort: C

Frage 7: Trustworthy AI
Welches der folgenden gehört NICHT zu den Prinzipien von Trustworthy AI?
A) Explainability (Erklärbarkeit) B) Fairness C) Profitability (Profitabilität) ✓ D) Privacy (Datenschutz)
Antwort: C (Trustworthy AI: Explainability, Fairness, Privacy, Robustness, Accountability, Security)

Frage 8: ROC/AUC Curve
Wofür wird die ROC/AUC Kurve verwendet?
A) Zur Normalisierung von Daten B) Zur Bewertung der Performance von Klassifikationsmodellen ✓ C) Zur Feature-Selektion D) Zur Imputation fehlender Werte
Antwort: B

Frage 9: Explainable AI (XAI)
Warum ist Explainable AI wichtig?
A) Nur um gesetzliche Anforderungen zu erfüllen B) Um sicherzustellen, dass Modelle nicht nur "was" vorhersagen, sondern auch "wie" sie zu Entscheidungen kommen, was Robustheit und Vertrauen erhöht ✓ C) Um die Trainingszeit zu verkürzen D) Um mehr Daten zu sammeln
Antwort: B

Day 2: Introduction to Data Science

Samuel Schlenker

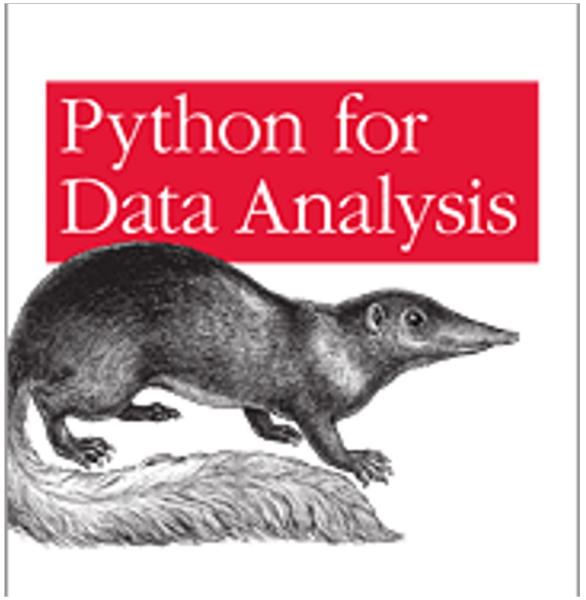
04.11.2025, WWI 2025F

Students should ...

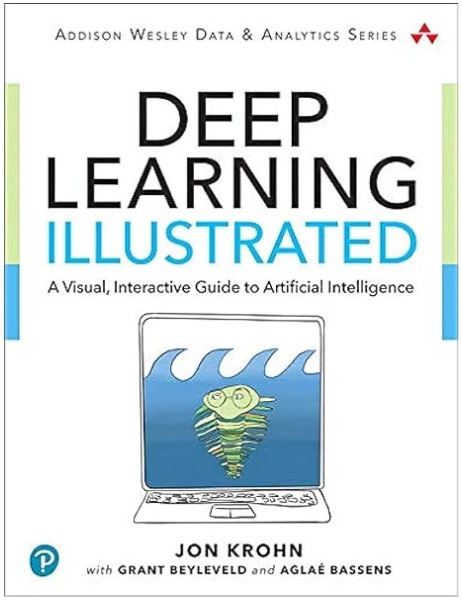
- Understand the fundamental definition and scope of data science as an interdisciplinary field
- Identify the three pillars of data science: domain expertise, statistics/mathematics, and computer science
- Recognize real-world applications of data science across industries (quality control, predictive maintenance, fraud detection, autonomous driving)
- Distinguish between AI, Machine Learning, Deep Learning, and Generative AI
- Understand the characteristics of Big Data (Volume, Velocity, Variety, Veracity, Value)
- Identify different data sources (open-source, private, commercial) and their accessibility
- Apply principles of effective data visualization and storytelling
- Recognize poor or misleading visualizations and understand common pitfalls
- Understand different chart types and their appropriate use cases (line charts, bar charts, scatterplots, heatmaps, etc.)
- Recognize the difference between correlation and causation
- Identify opportunities and risks associated with data science applications

Recommended Reading

Data Science from Scratch, by Joel Grus. O'Reilly



Python for Data Analysis, 2nd ed by Wes McKinney. O'Reilly

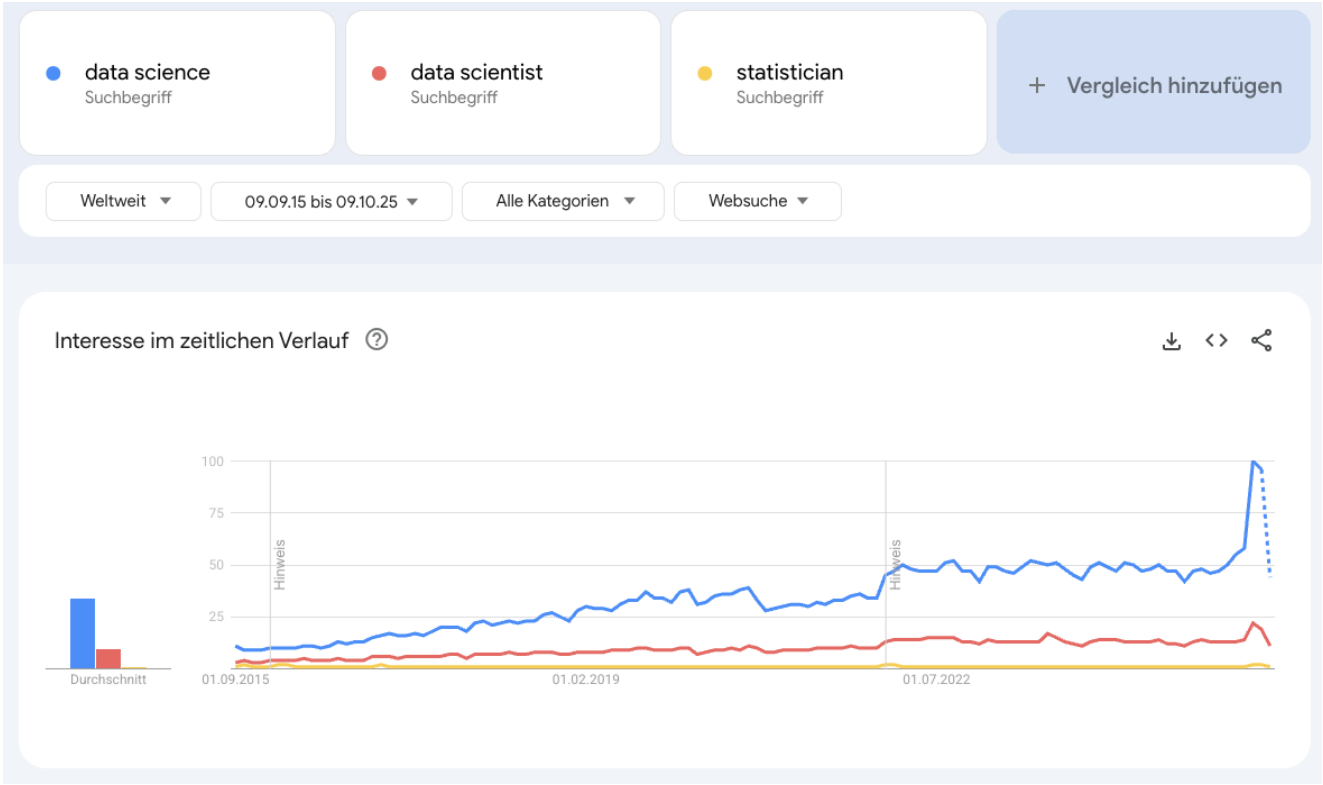


https://www.deeplearningillustrated.com/

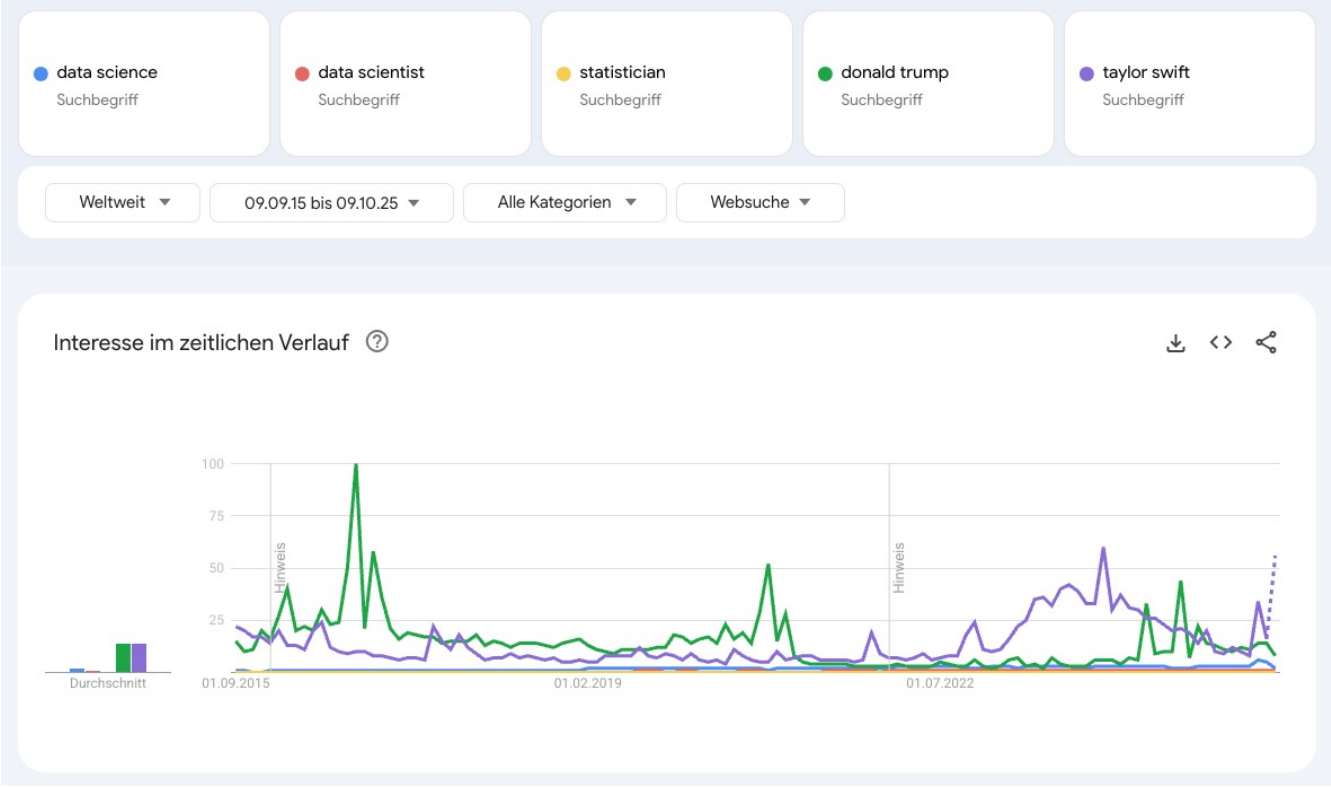
What do you think...

https://www.menti.com/alb5874akgdy

Google Trends



In comparison ...



Facebook knows us better than friends and family

- 2015: Study with 86,220 volunteers
- Collaboration between the University of Cambridge and Stanford University
- Questionnaire with 100 items on the Five Factor Model (FFM) of personality psychology / "Big Five"
- Neuroticism, extraversion, openness to experience, conscientiousness, and agreeableness
- Computer algorithm (linear regression) vs. assessment by individuals
    - From 10 likes: Computer is better than coworkers
    - From 70 likes: Computer is better than friends
    - From 150 likes: Computer is better than family
    - From 300 likes: Computer is better than spouse
- The average Facebook user shares 227 likes

Self-test: https://applymagicsauce.com/demo

As of 2011, the global size of data in healthcare was estimated to be

150 EXABYTES

[161 BILLION GIGABYTES]

Modern cars have close to

100 SENSORS

that monitor items such as fuel level and tire pressure

30 BILLION PIECES OF CONTENT

are shared on Facebook every month

4 BILLION+ HOURS OF VIDEO

are watched on YouTube each month

By 2016, it is projected there will be

18.9 BILLION NETWORK CONNECTIONS

– almost 2.5 connections per person on earth

400 MILLION TWEETS

are sent per day by about 200 million monthly active users

It's estimated that

2.5 QUINTILLION BYTES

[2.3 TRILLION GIGABYTES]

of data are created each day

Most companies in the U.S. have at least

100 TERABYTES

[100,000 GIGABYTES]

of data stored

40 ZETTABYTES

[43 TRILLION GIGABYTES]

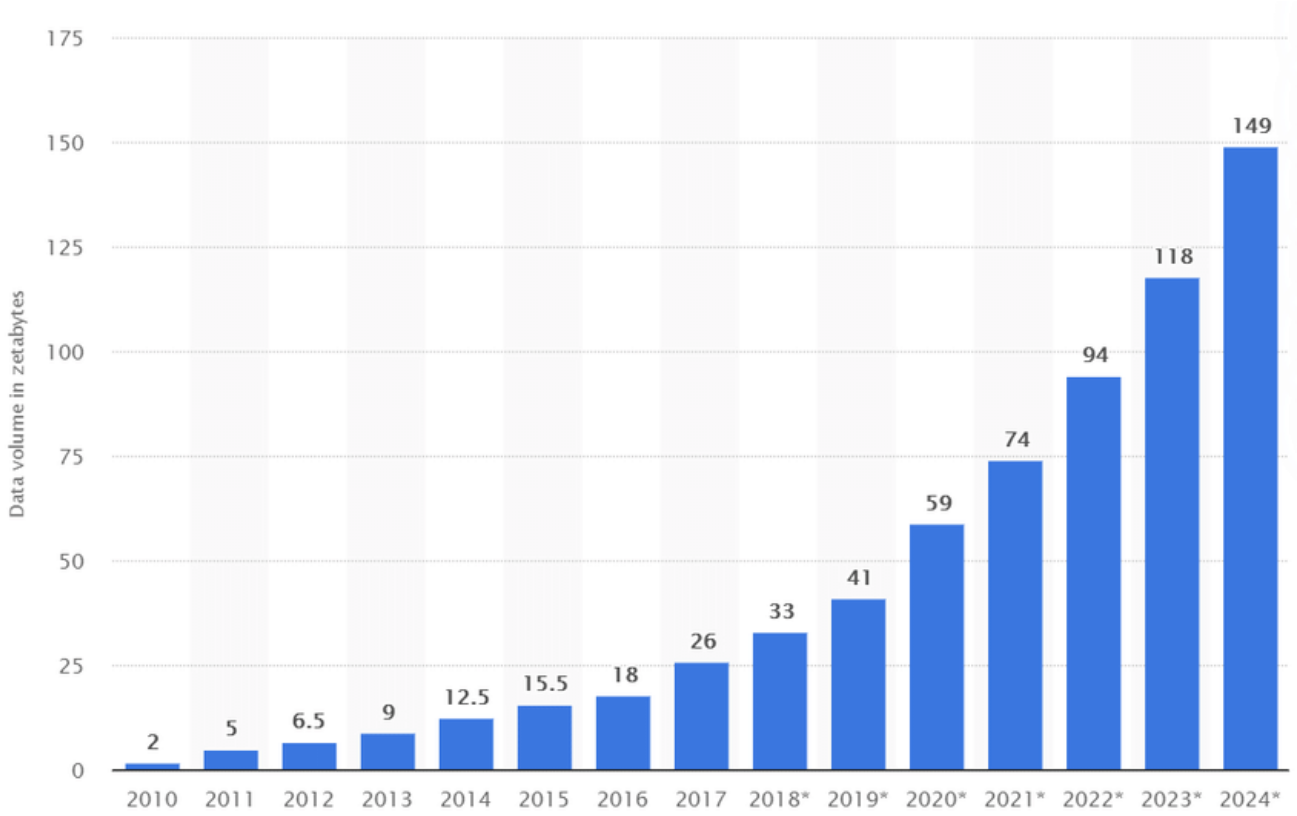
of data will be created by 2020, an increase of 300 times from 2005

The New York Stock Exchange captures

1 TB OF TRADE INFORMATION

during each trading session

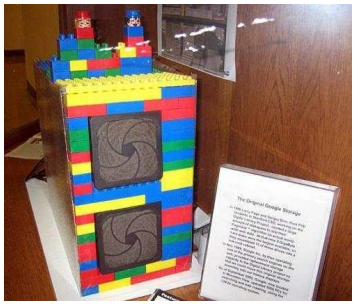
Pure Amount of data



Distributed Computing

This amount of data requires more than one computer.

Google – 1998:



Distributed Computing

This amount of data requires more than one computer.

Google – 2014:


INTRODUCTION TO DATA SCIENCE BY W&S
YOUR TURN!
EXERCISE / QUESTION

Data Science

Needs massive data processing

Distributed computing

Why is this the case?

Data Is Driving Everything

- Modern data acquisition is inexpensive!
    - Smartphones, embedded systems, inexpensive sensors,
    - Medical devices, simulators, ...
- Data storage is inexpensive!
- Parallel (compute cluster) computation is inexpensive
    - The Cloud, clusters of computers, GPUs, tensor processors, ...
- Science only has explanatory and predictive models in a few (mostly physical sciences-related) domains
- ... So: can we use algorithms + data to understand phenomena? Build or augment models? Build detectors? Make diagnoses?

Data Is Driving Everything

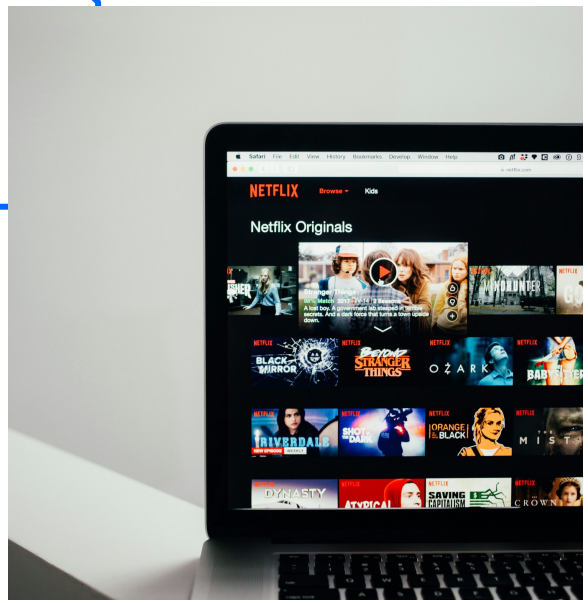
"Big data"
"Data science"
"Data lakes"
"Visual analytics"

"Deep learning"
"Statistical analysis"
"Biomedical informatics"
"Business analytics"

Lots of trends in pursuit of the same goals!
Discovery, models, decision-making, …

Also, new issues -
"Ethical algorithms"
"Reproducibility"

Data Science

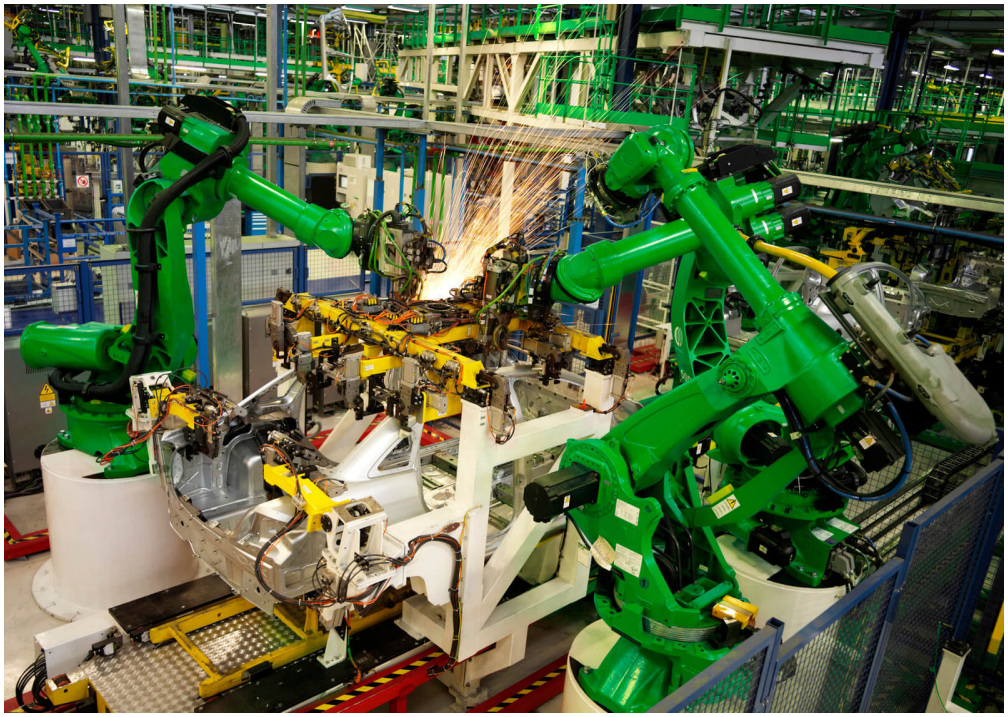


Reccomandation engines

Autonomous driving

Business intelligence

Applications of data science (Use cases)



Quality control:

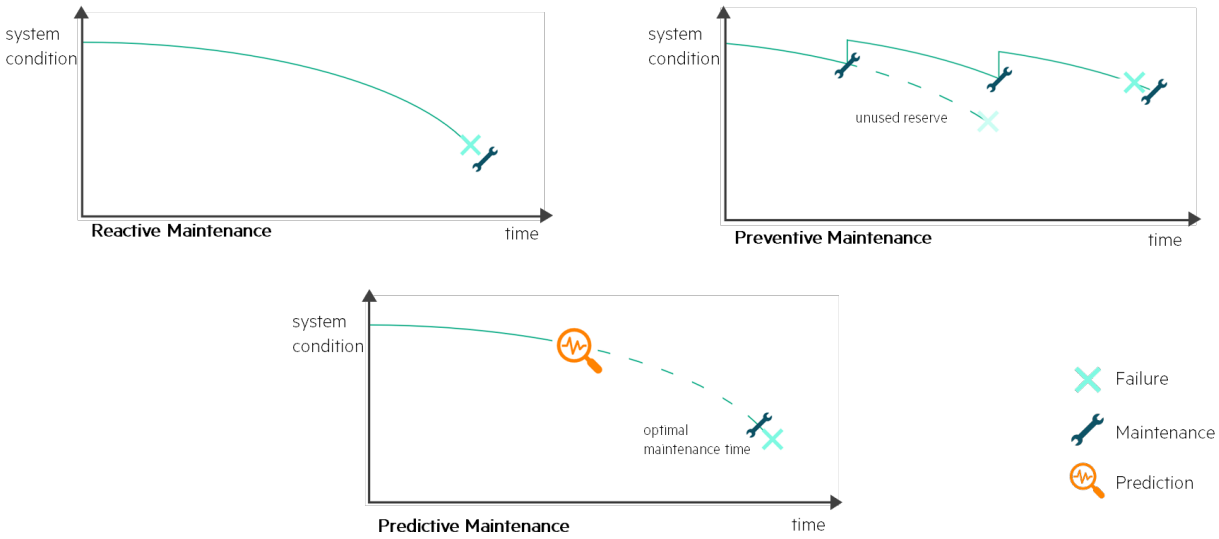
- Quantity: Is there the right number of salami slices on the frozen pizza?
- Correct product: Are the right components installed in the server?
- Quality: Are there scratches in the paintwork on the car door? Is the weld seam flawless?
- Results in: Fewer complaints, Cost reduction, Higher customer satisfaction

Applications of data science (Use cases)

Predictive Quality: Predicting the quality of the product before the production process is complete.

- Early correction of the product, if possible, or discontinuation of production.
- Reduction of waste.
- Energy, water, and material savings by avoiding finishing steps for poor-quality products.
- Cost reduction.

Applications of data science (Use cases)



Predictive Maintenance:

Predicting the failure of a production machine

- Avoiding unplanned production downtime
- Replacing/repairing the component that is about to fail at the best possible time
- Using the production machine or individual parts for as long as possible

Applications of data science (Use cases)

Fraud Detection:

Detection of credit card fraud, for example, through anomaly detection

- Early account blocking
- Loss minimization

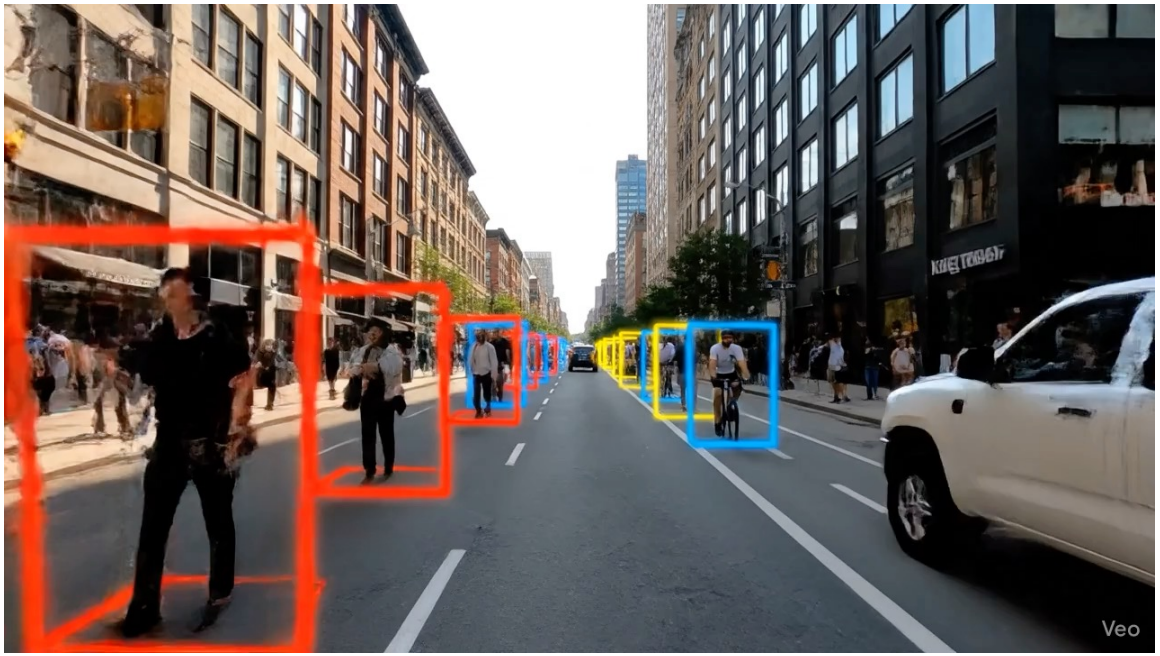
Applications of data science (Use cases)

Personalized recommendations:

For example, shopping cart analysis

- Individualized shopping experience
- Higher customer loyalty
- Higher shopping cart values
- Increased sales

Applications of data science (Use cases)



Autonomous driving:

Detection of pedestrians, their direction of travel, and derivation of the appropriate action

- Traffic sign recognition
- Enables innovation
- Minimization of human error
- Reduction in the number of accidents

Applications by industry

Financial Services

- Fraud Detection
- Risk Assessment
- Algorithmic Trading
- Sentiment Analysis

Healthcare

- Gene Research
- Drug Discovery
- Patient Assistant
- Medical Records

Public Sector

- Urban Planning & Design
- Predictive Policing
- Citizen Engagement
- Document Summarization

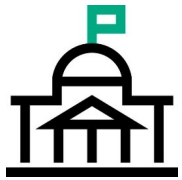
Manufacturing

- QC / Defect Detection
- Supply Chain Optimization
- Predictive Maintenance
- Generative Design

Telecommunications

- Customer Support
- Network Optimization
- Predictive Maintenance
- Fraud Detection

Financial Services & Insurance



Public Sector / Defense

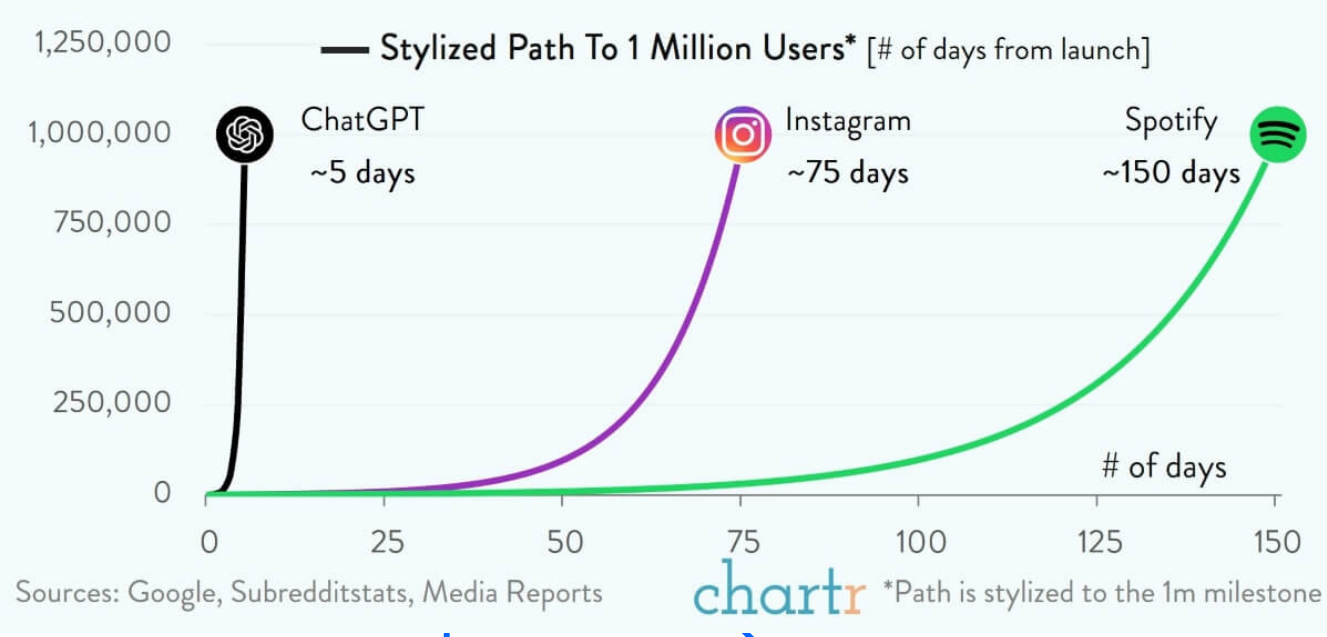
Healthcare / Life Sciences

Autonomous Driving

Manufacturing

AI goes mainstream with ChatGPT

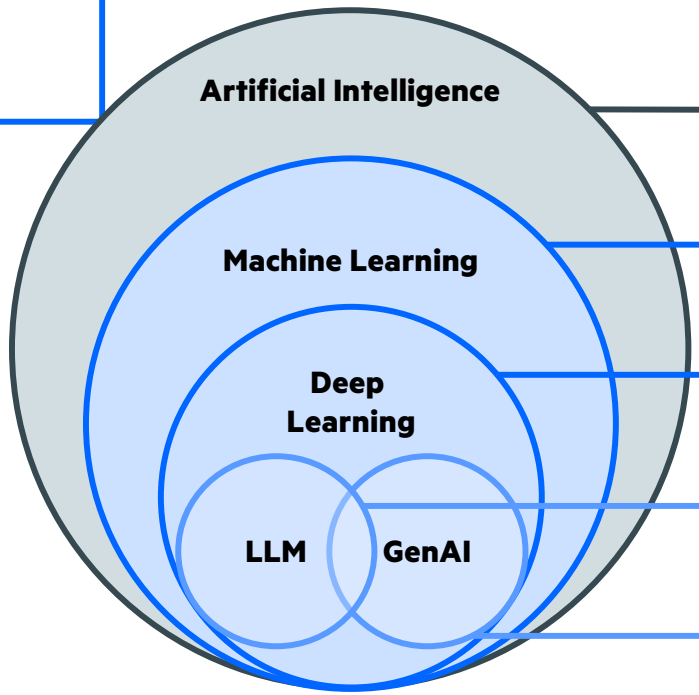
1M users in 5 days



Introduction to Data Science by W&S

But how does AI fit into the picture?

Navigating Artificial Intelligence: Understanding its fundamental building blocks



Artificial Intelligence (AI)
Any technology that enables machines to solve tasks in a way like humans do

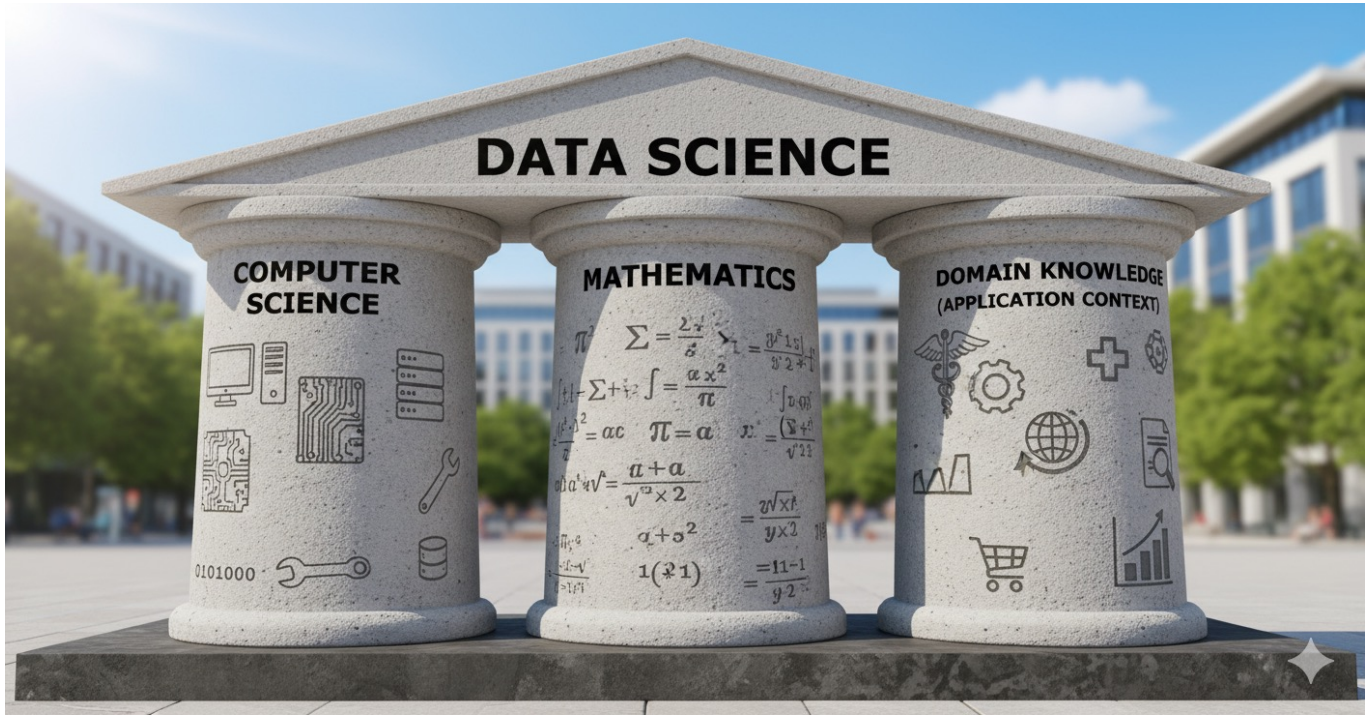
Machine Learning (ML)
Algorithms that allow computers to learn from examples without being explicitly programmed (supervised & unsupervised)

Deep Learning (DL)
Using deep artificial neural networks as models, inspired by the structure and function of the human brain

Large Language Models (LLM)
Models trained on massive datasets to understand and generate human-like text across diverse subjects

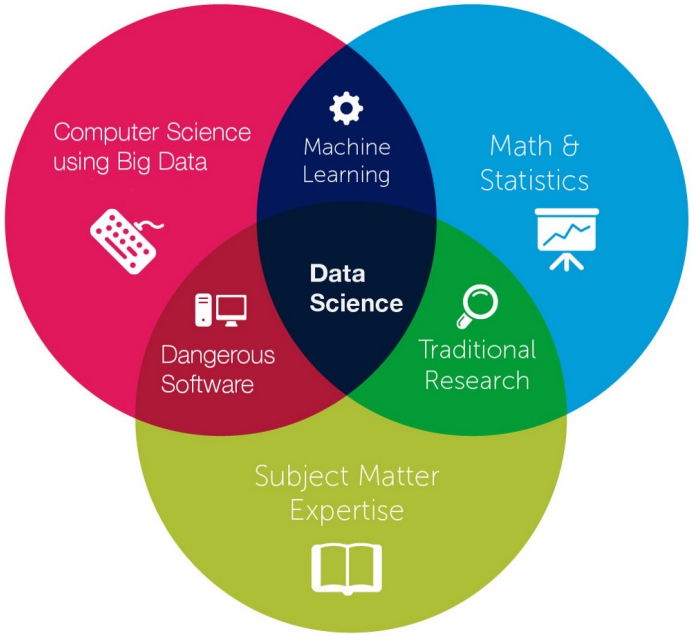
Generative Artificial Intelligence (GenAI)
Refers to technologies that utilize machine learning models to generate human-like text, images, or other content

The three pillars of data science



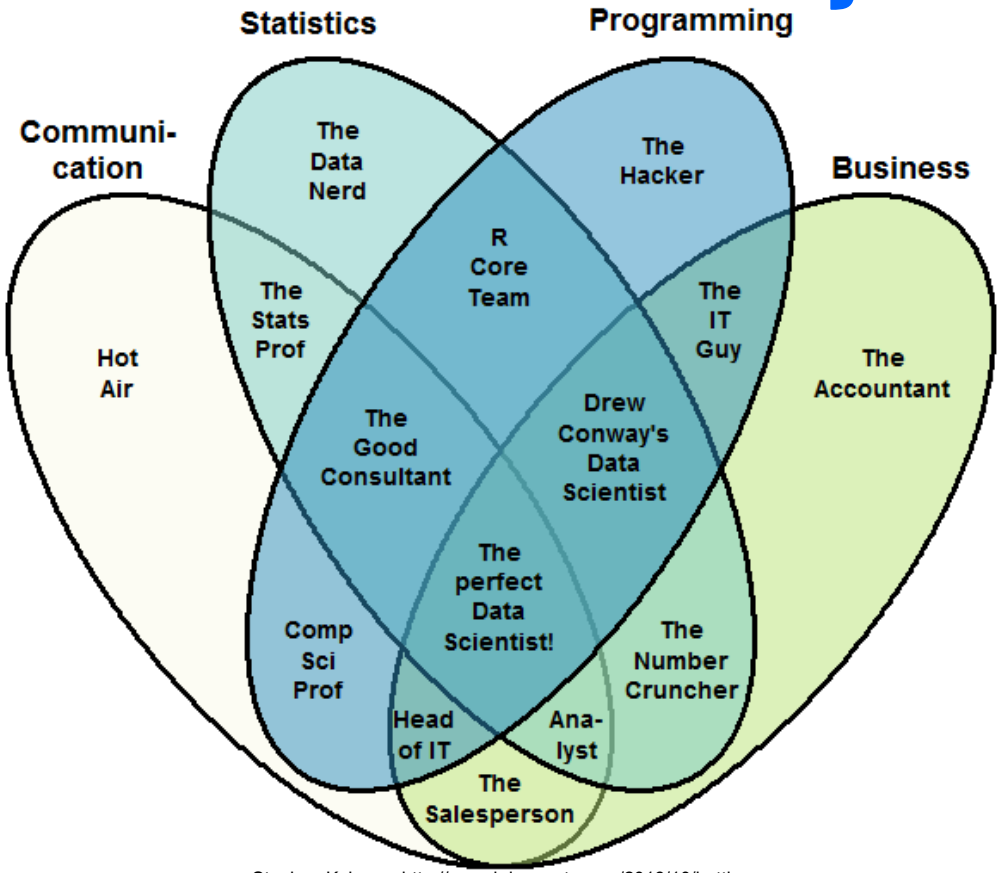
Why so many disciplines?

- Enormous amounts of data → Big Data
  - New algorithms. Must be scalable and efficient
  - New data management technologies and concepts
- High dimensionality of data
  - Data can have thousands of dimensions/attributes
  - High complexity and variability of data
- New, complex fields of application
- Data science is not (only) out-of-the-box, but domain-specific



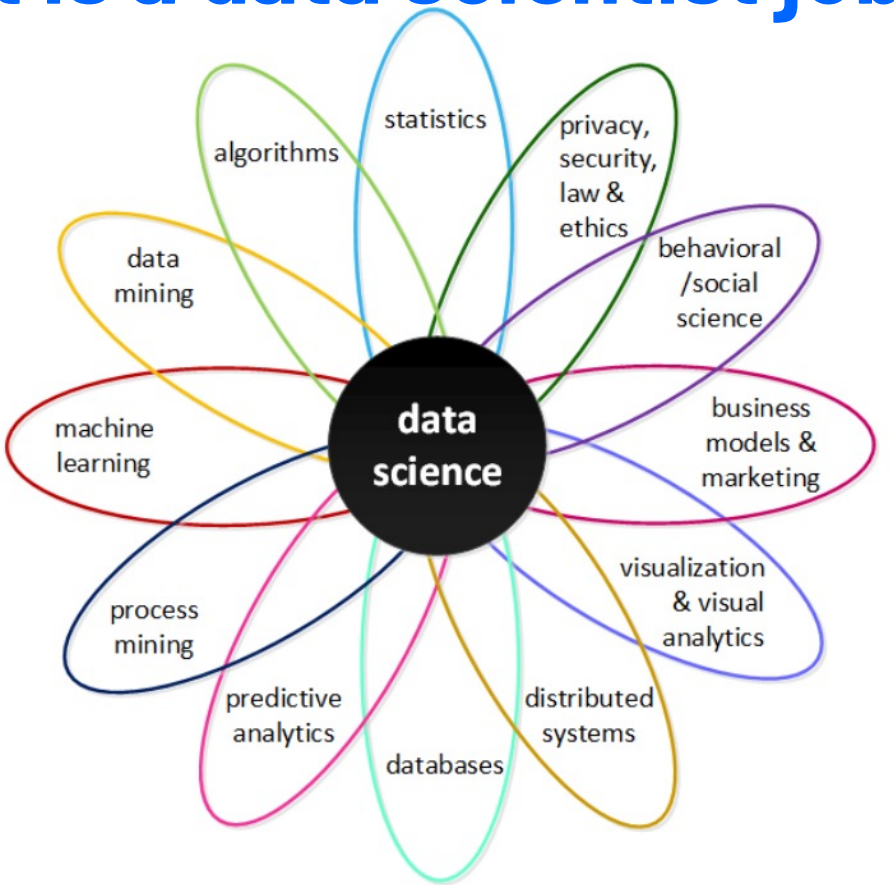
https://miro.medium.com/max/1100/1*aXJWLmf-CYqVTrNiE2pdCw.png

So, what is a data scientist job?



Stephan Kolassa: http://www.kdnuggets.com/2016/10/battle-data-science-venn-diagrams.html/2

So, what is a data scientist job?



https://sda.tech/wp-content/uploads/file-manager/Bonn-SDA-WvdA-2017.pdf

And more concrete ... ?

Data Steward

- Monitoring data quality and integrity
- Responsible for the technical accuracy of data

Tasks:

- Data owner
- Data governance
- Master of data

Data Engineer

- Data supply
- Develop, implement, test, and maintain architecture for data storage

Tasks:

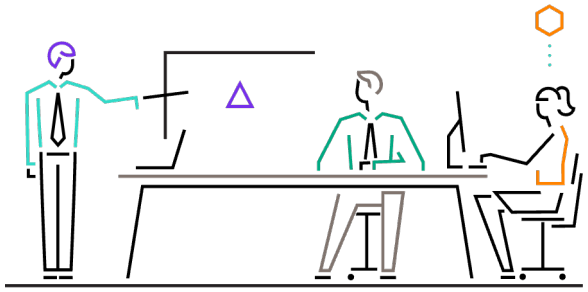
- Data Quality Improvement
- Data Transformation

Data Scientist

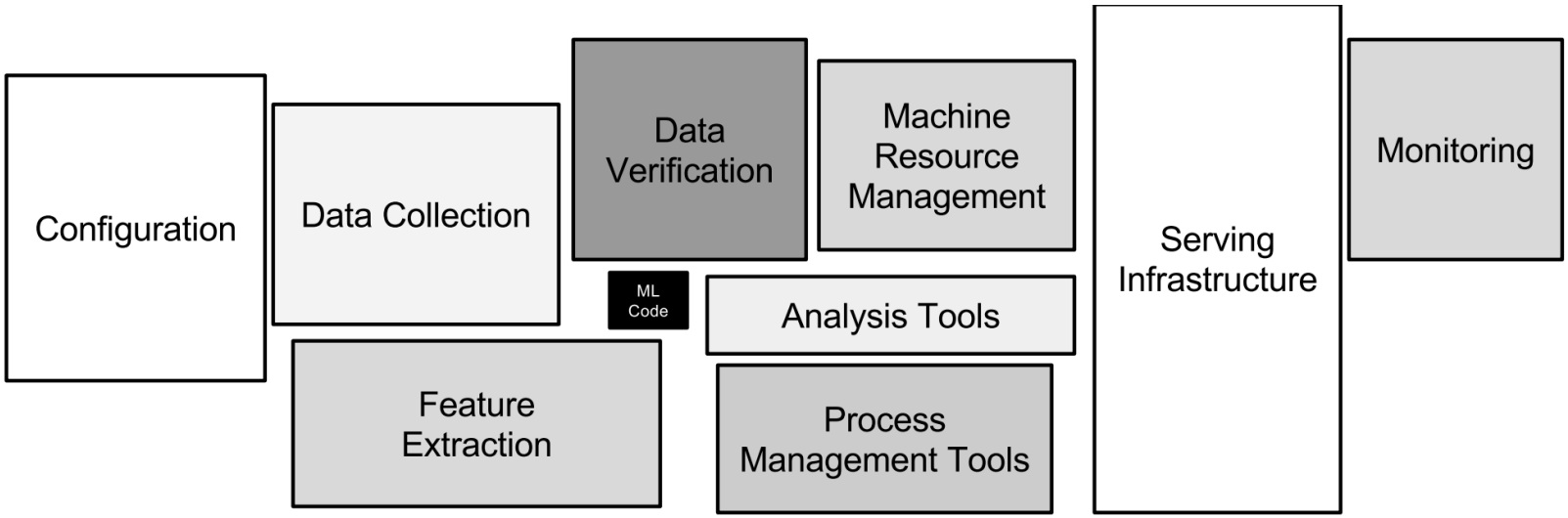
- Provides answers to analytical questions using data

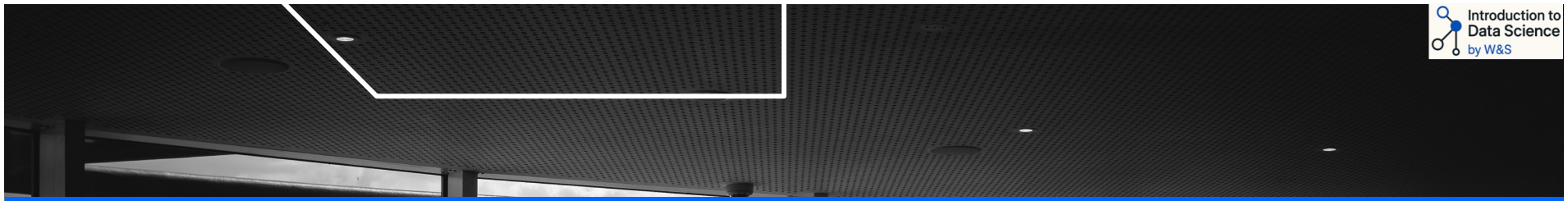
Tasks:

- Data Exploration & Visual Analytics
- Model Deployment & Scoring
- Big Data Handling & Manipulation



https://www.bertelsmann-university.com/fileadmin/Programs/AI_Curriculum/1_FAQ__%C3%9Cbersicht_Data_Curriculum_DE_final.pdf


Configuration
Data Collection
Data Verification
Machine Resource Management
Monitoring
Serving Infrastructure
ML Code
Analysis Tools
Feature Extraction
Process Management Tools



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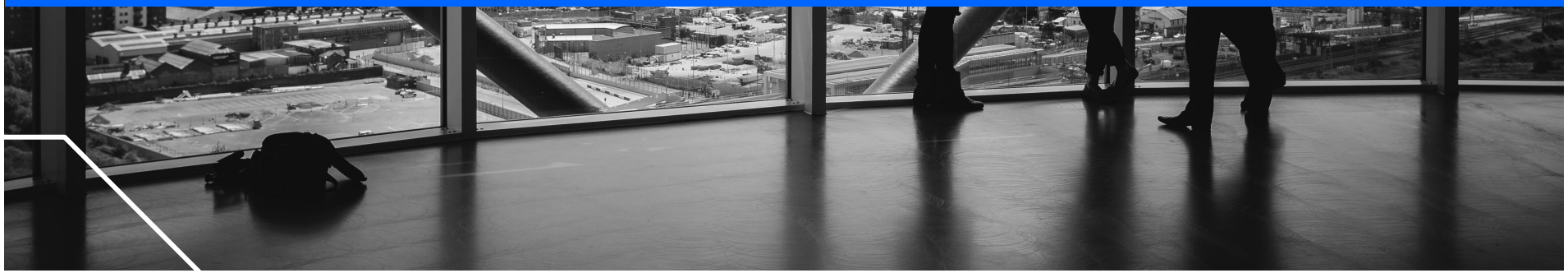
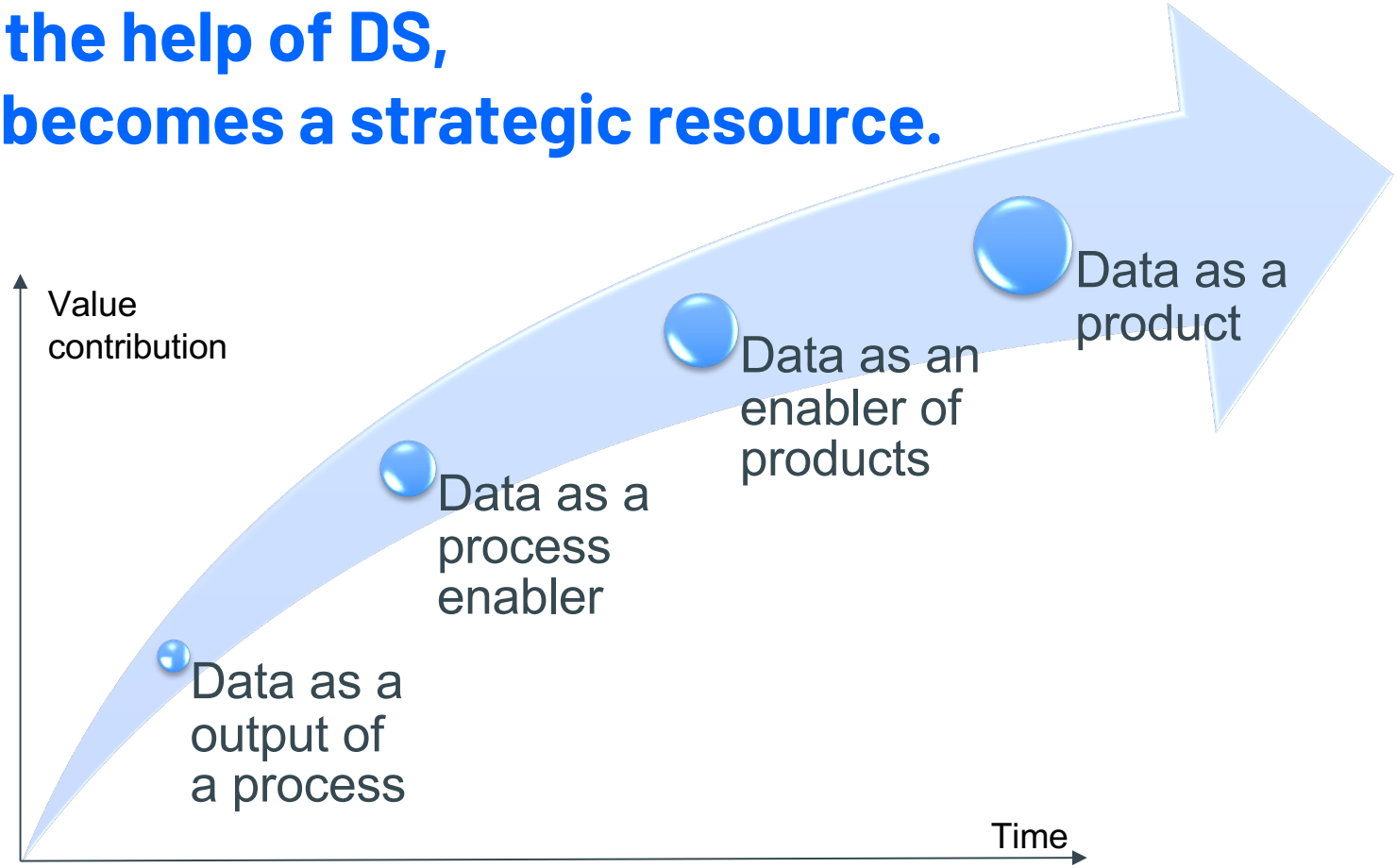
Big Data



With the help of DS, data becomes a strategic resource.



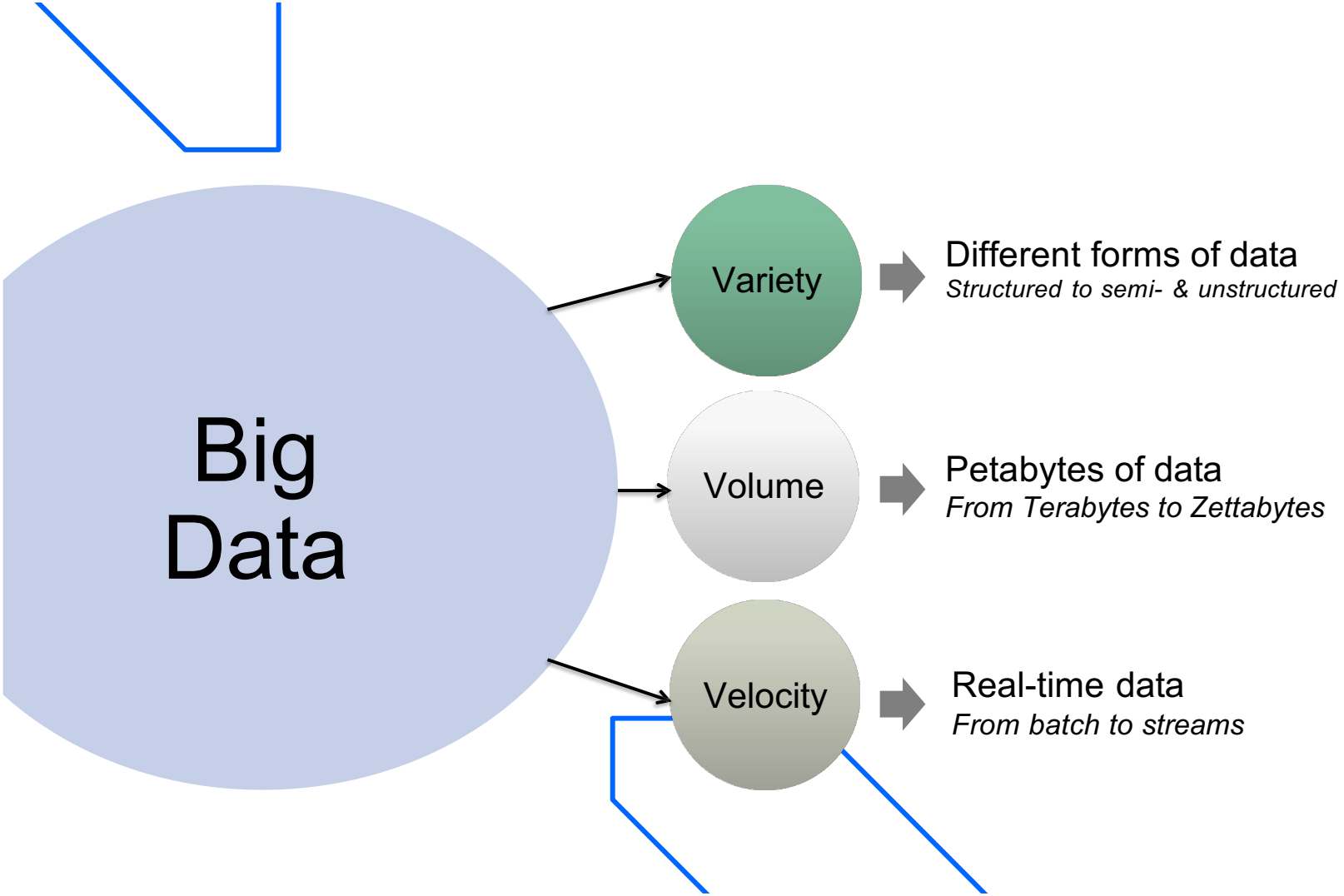
Otto, B.: Industrial Data Space im Überblick, Fraunhofer Institut für Materialfluss und Logistik, Dortmund, 30.10.2015, URL: http://de.slideshare.net/borisotto/berblick- zum-industrial-data-space

Big Data

Refers to datasets whose size is beyond the ability of typical database software tools to capture, store, manage and analyze.

Big does not stand primarily for size, but as an analogy for “overwhelming”

Big can mean “high variety”, “high volume” or “high velocity”


Big Data
Variety
Different forms of data
Structured to semi- & unstructured
Volume
Petabytes of data
From Terabytes to Zettabytes
Velocity
Real-time data
From batch to streams

More Vs

Turning data into knowledge

Variation in meaning in different contexts

Uncertainty of the data

- Not easy to measure
- Depend on context and intended use

Where is the data coming from?

Possible data sources

- Questionnaires, interviews, ...
- Observations & measurements (e.g. in production)
- Analysis of content (documents, web scraping, social media...)

Raw data: Data received or collected

- no variables have been manipulated
- no data removed from the record
- no summary / aggregation

Not prepared
(pre-processed)

Where is the data coming from?

Private data

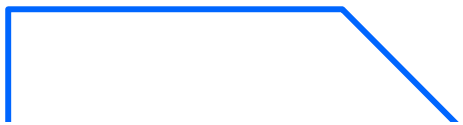
Created by customers
Created during business process execution

Commercial data

Cloud Marketplaces (e.g., AWS Data)
Qlik DataMarket, Statista

Open-source data

Data that is publicly available (check for limits on usage)



Open-Source Data Sources examples

Kaggle
World Health Organization
Our World in Data
Census Bureau (U.S.)
National Oceanic and Atmospheric Administration (U.S.)
UC Irvine Machine Learning Repository
Harvard Dataverse
AWS, Facebook, Google, Microsoft, ...

CAN YOU GET THE DATA OUT OF SILOS?

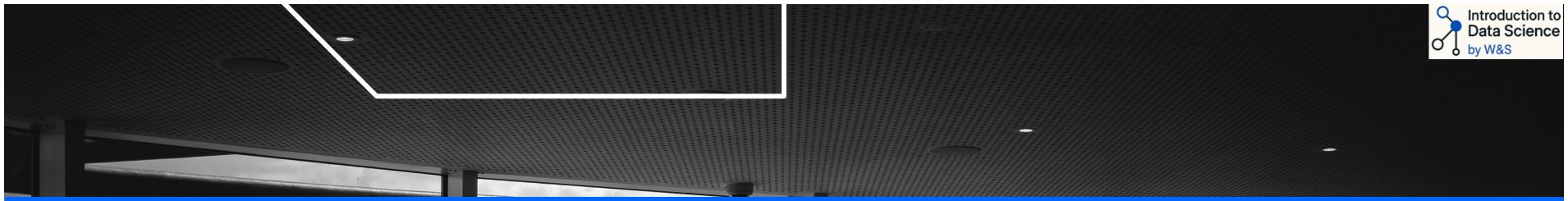
Value ≠ Quality

While value and quality of big data may be correlated, they are conceptually different. For example, one can have high quality data about the names of all the countries in North America, but this list of names may not have much perceived value. In contrast, even relatively incomplete data about the shopping habits of people can be quite valuable to online advertisers.

Xin Luna Dong, Google, 2015

Raw data (including high quality data) itself does not hold any value, unless it is processed in analytical tasks from which humans or downstream applications can derive insight.

Gerhard Weikum, Max Planck Institute for Informatics, 2015



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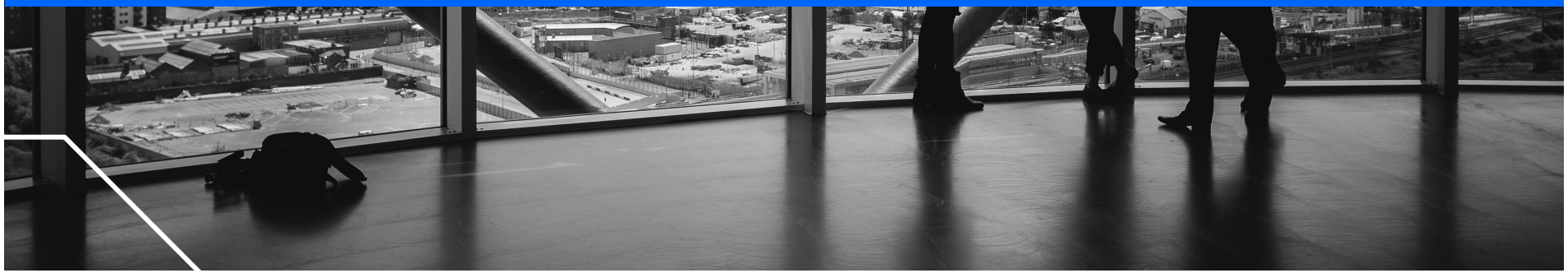
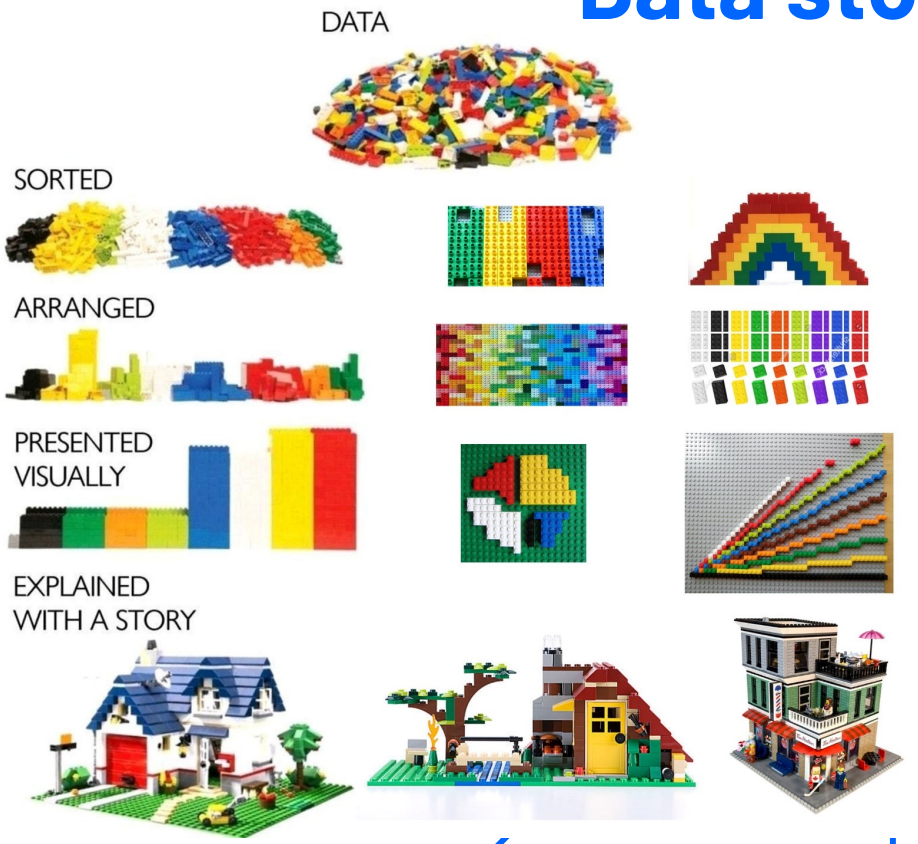
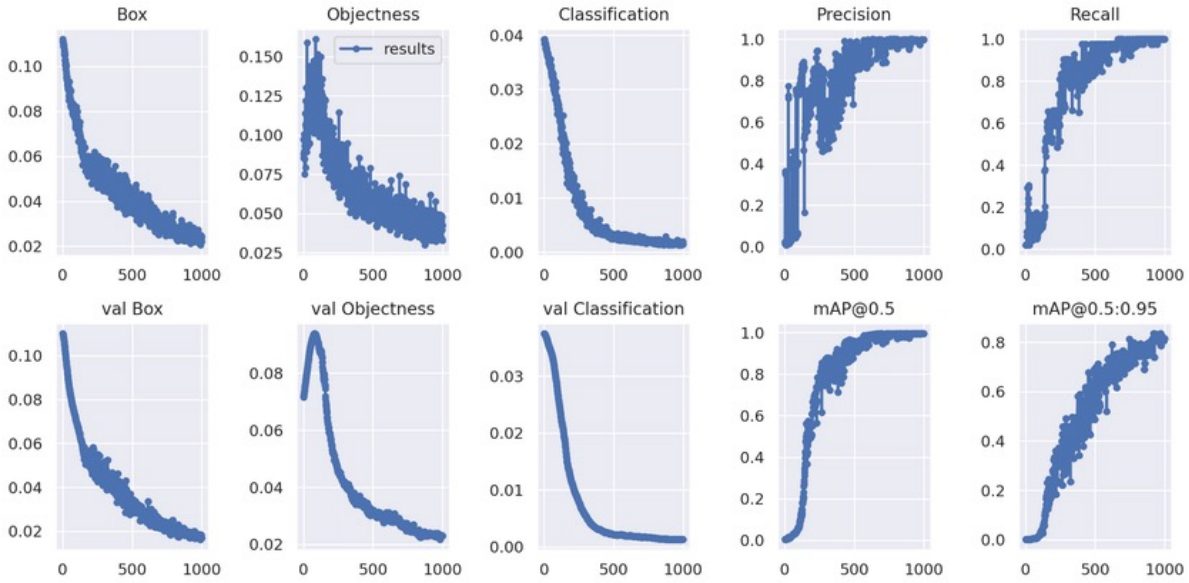
Data Storytelling and Visualization



Data story telling



https://twitter.com/wcastillophd/status/1463600788140396550


Box
Objectness
Classification
Precision
Recall
results
val Box
val Objectness
val Classification
mAP@0.5
mAP@0.5:0.95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Data Science
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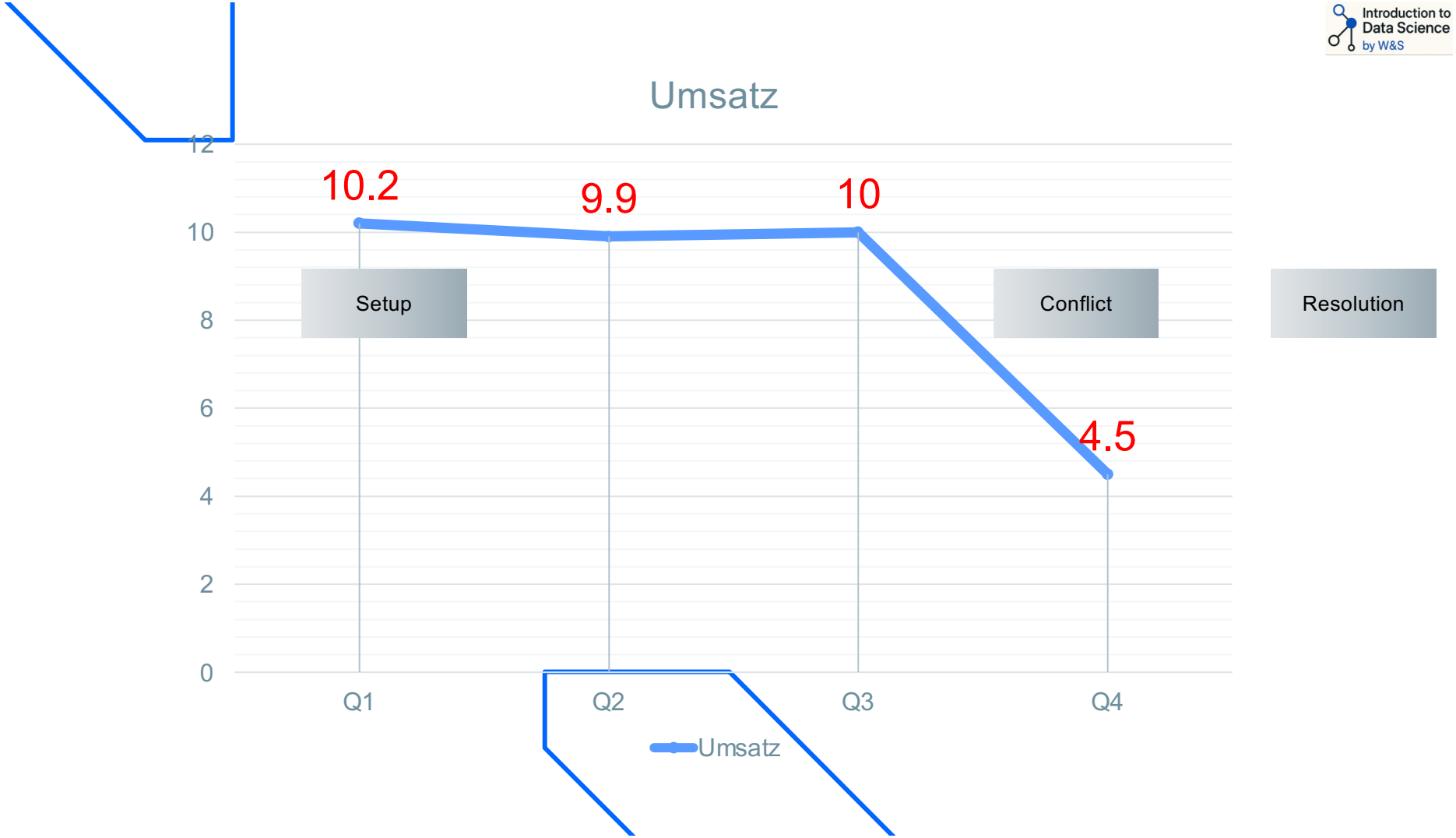
30%
Saved marketing budget

https://upload.wikimedia.org/wikipedia/commons/c/c4/Kiss_Logo.svg

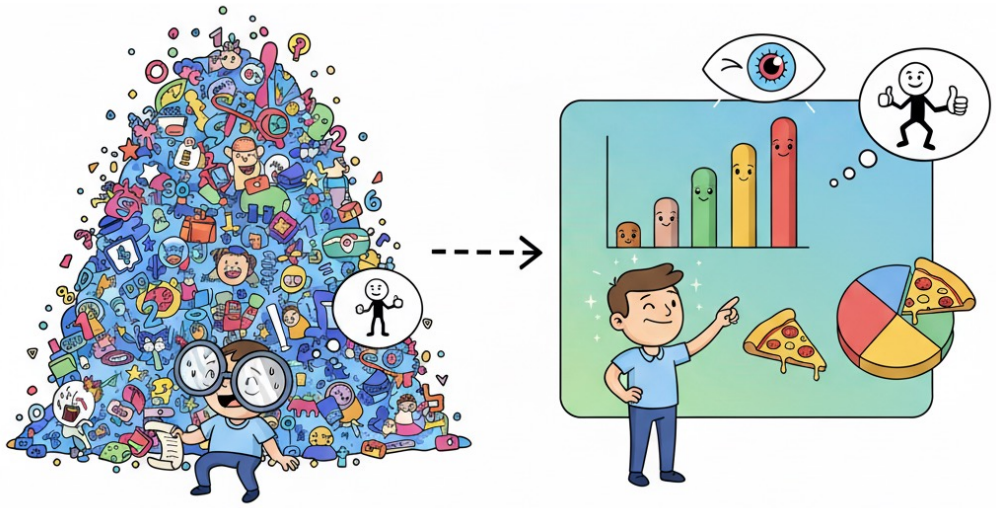
What do you remember


Umsatz
12
10
8
6
4
2
0
10.2
9.9
10
4.5
Setup
Conflict
Resolution
Q1
Q2
Q3
Q4
Umsatz

Why do we visualize?

- Most datasets are far too large to be examined in their raw format.
- Visual analysis uses our **pre-attentive perception** - visual cues that humans process automatically and unconsciously.
- We can perceive and interpret these types of characteristics quickly and without any special effort.

- Example: Using the length of bars to represent sales volumes is an effective choice to indicate differences in sales between categories.



Possibilities of Visual Presentation

Length

- Very good for quantitative variables
- Poorly suited for qualitative variables

Possibilities of Visual Presentation

Width

- Limited to quantitative variables
- Poorly suited for qualitative variablest

Possibilities of Visual Presentation

Orientation

- Limited to quantitative variables
- Poorly suited for qualitative variables

Possibilities of Visual Presentation

Size

- Limited to quantitative variables
- Poorly suited for qualitative variables

Possibilities of Visual Presentation

Form

- Poor for quantitative variables
- Very suitable for qualitative variables

Possibilities of Visual Presentation

Position

- Very good for quantitative variables
- Poorly suited for qualitative variables

Possibilities of Visual Presentation

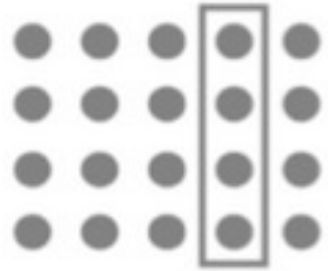
Grouping

- Limited to quantitative variables
- Very suitable for qualitative variables

Possibilities of Visual Presentation

Containment

- Poor for quantitative variables
- Limited suitable for qualitative variables



Possibilities of Visual Presentation

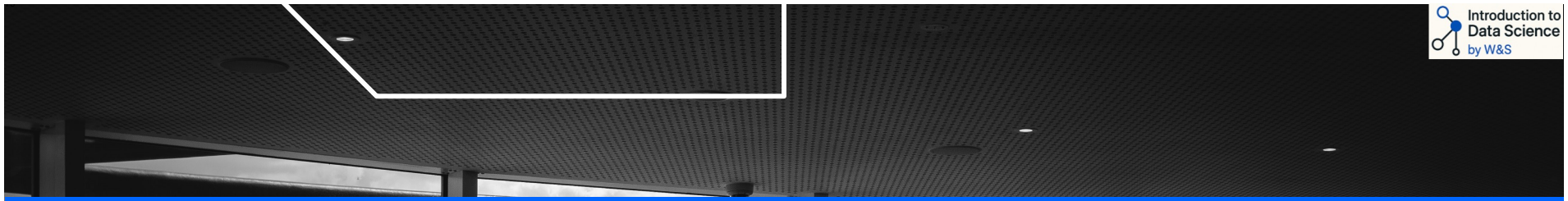
Hue

- Poor for quantitative variables
- Very suitable for qualitative variables

Possibilities of Visual Presentation

Colour intensity

- Limited to quantitative variables
- Poorly suited for qualitative variables



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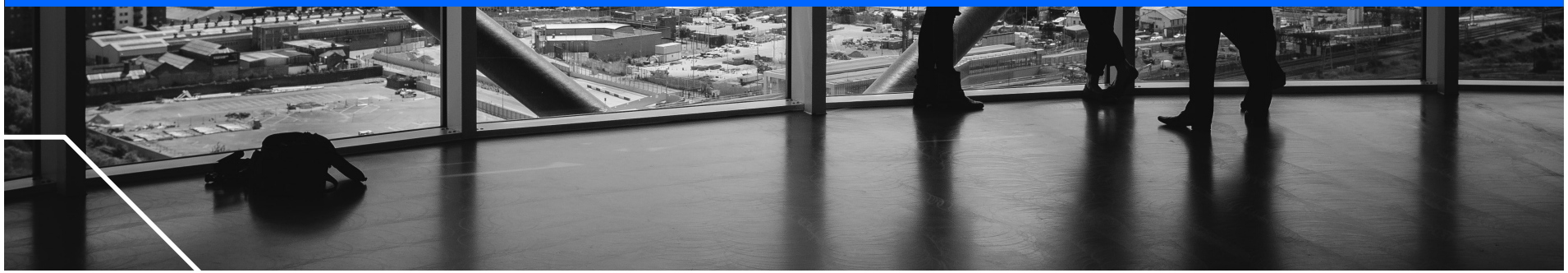
Poor or misleading visualizations



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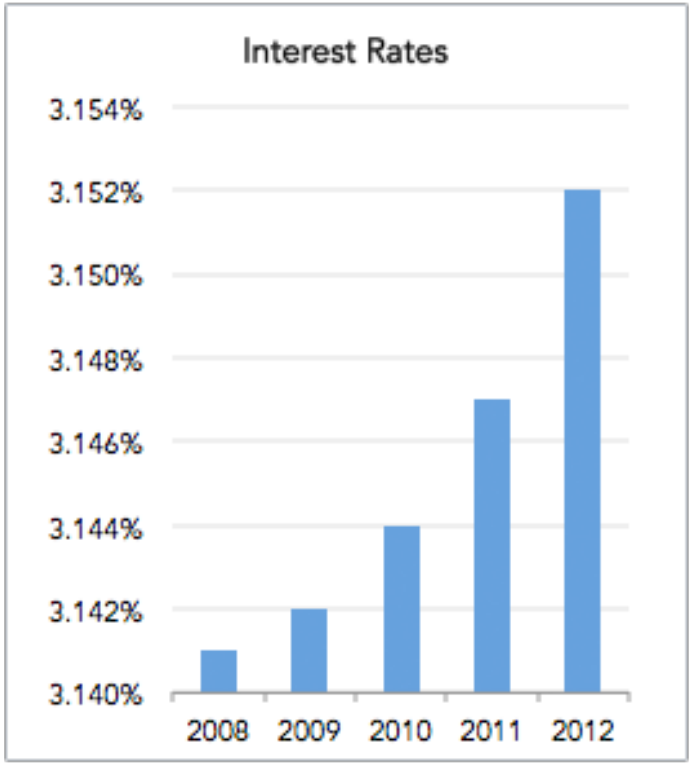
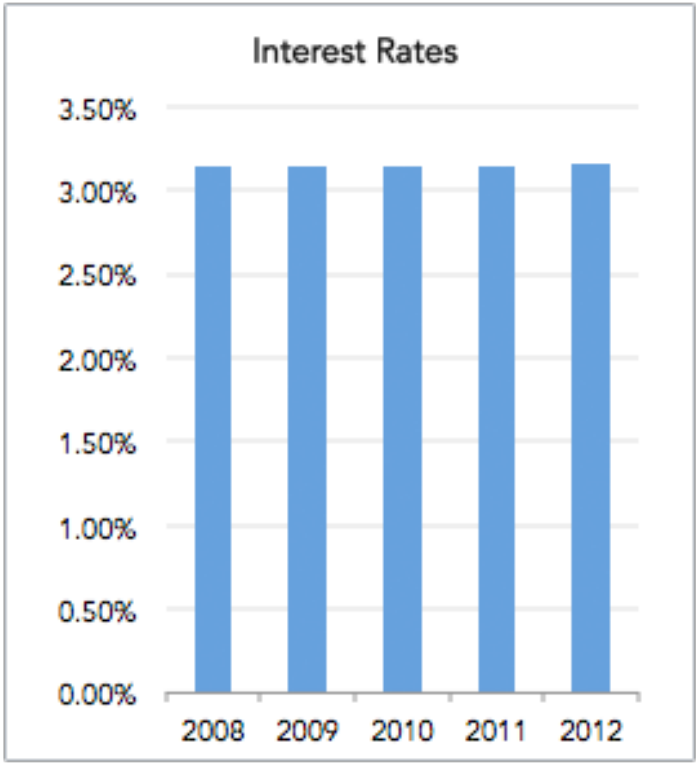
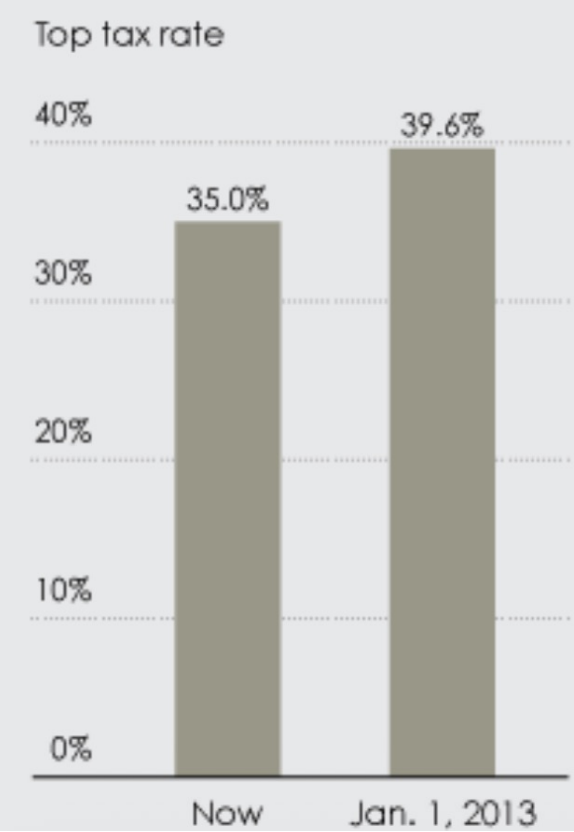
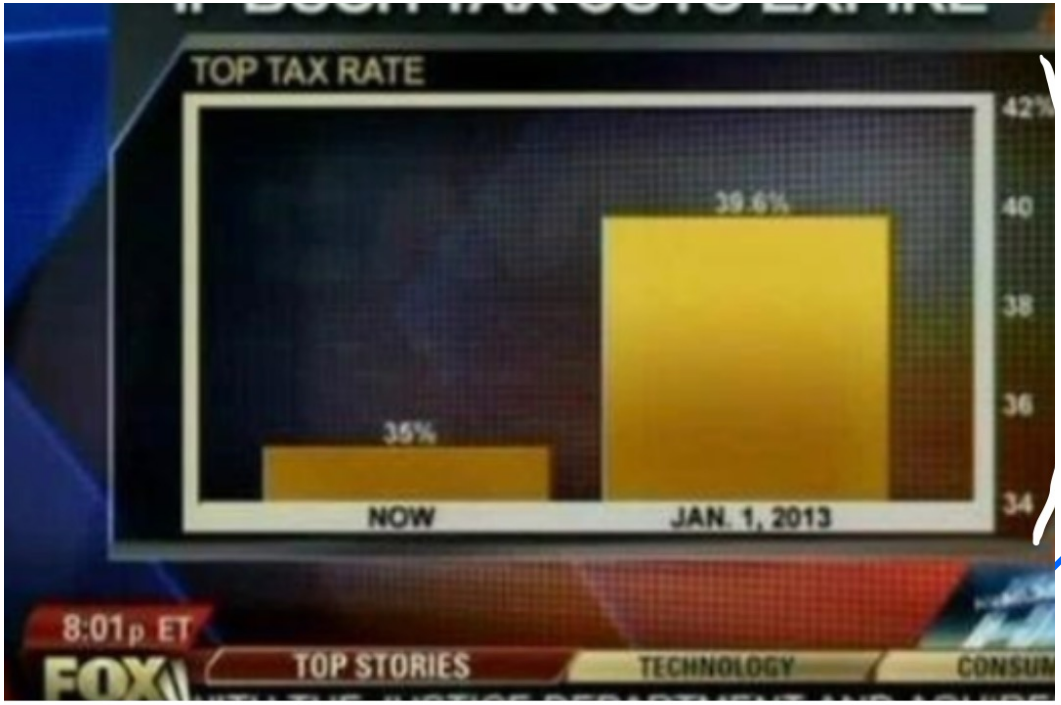




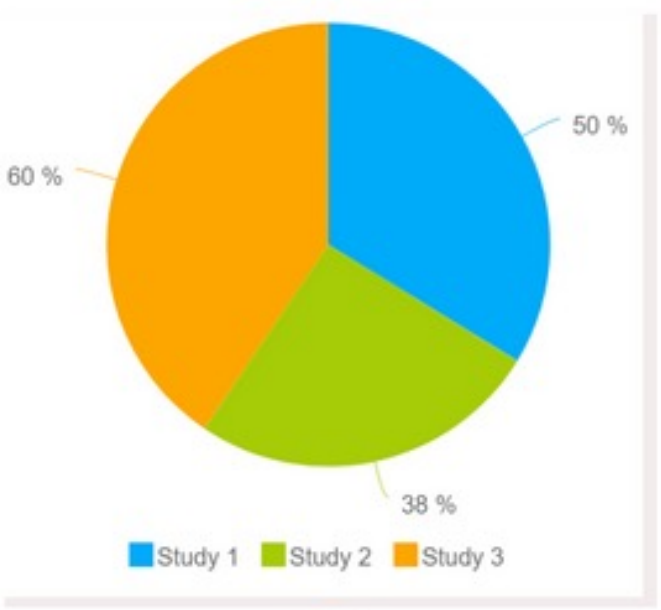
https://www.datapine.com/blog/misleading-data-visualization-examples/
https://blog.csgsolutions.com/6-tips-for-creating-effective-data-visualizations

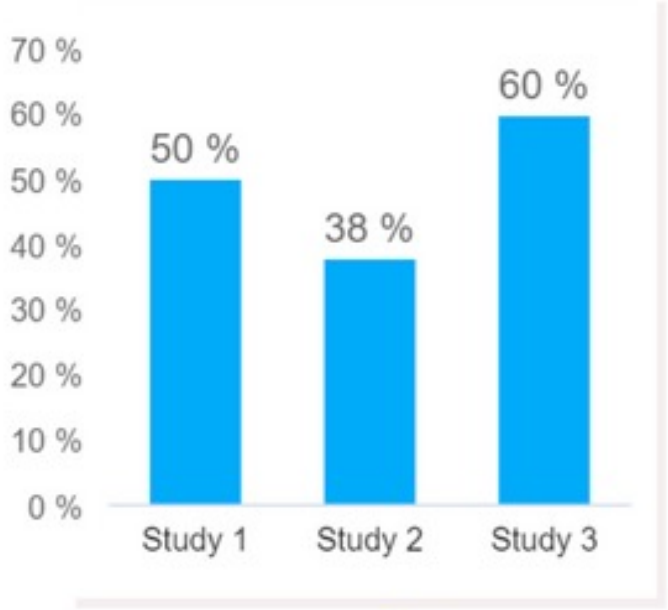
If Bush's tax rate reduction expires ...





Poor or misleading visualizations





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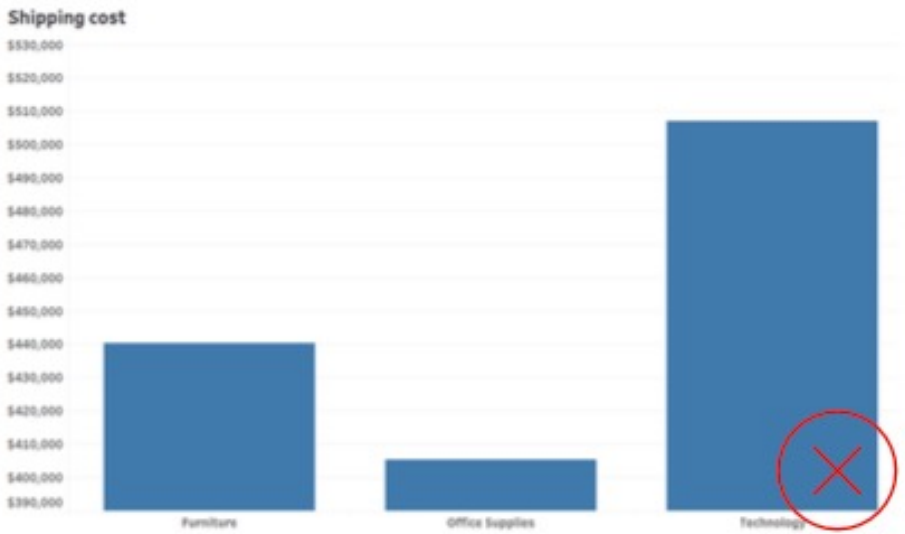
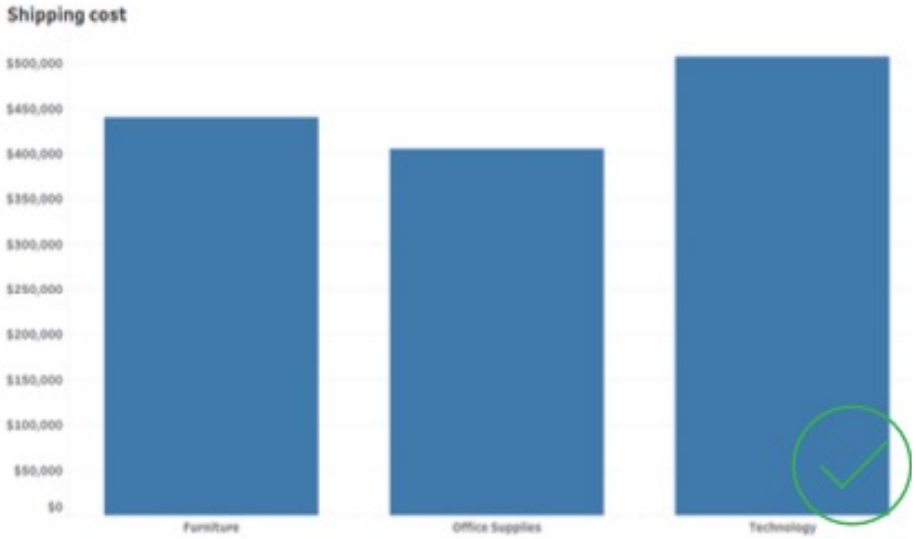
https://blog.csgsolutions.com/6-tips-for-creating-effective-data-visualizations

Poor or misleading visualizations

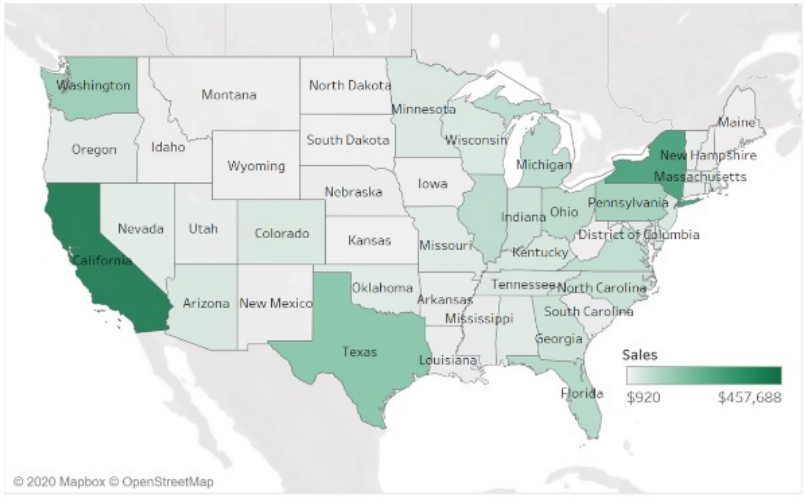




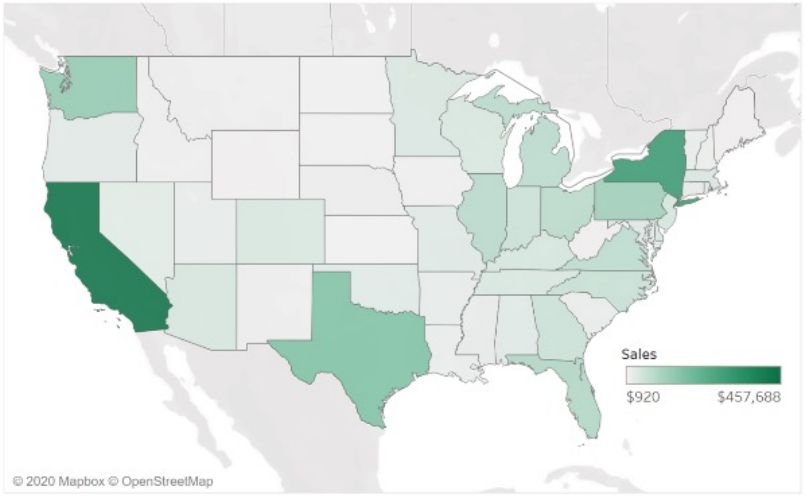
https://www.datapine.com/blog/misleading-data-visualization-examples/
https://blog.csgsolutions.com/6-tips-for-creating-effective-data-visualizations

Poor or misleading visualizations

total sales map



total sales map



ineffective

effective

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Poor or misleading visualizations

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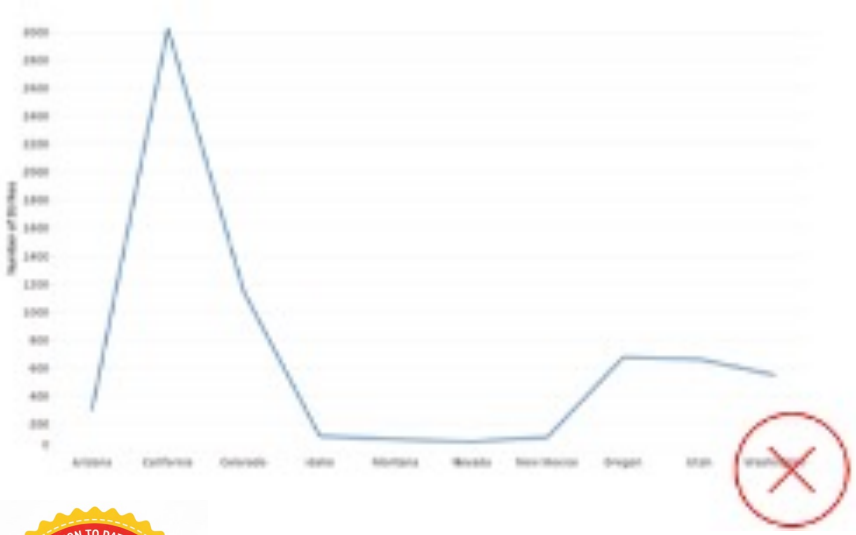

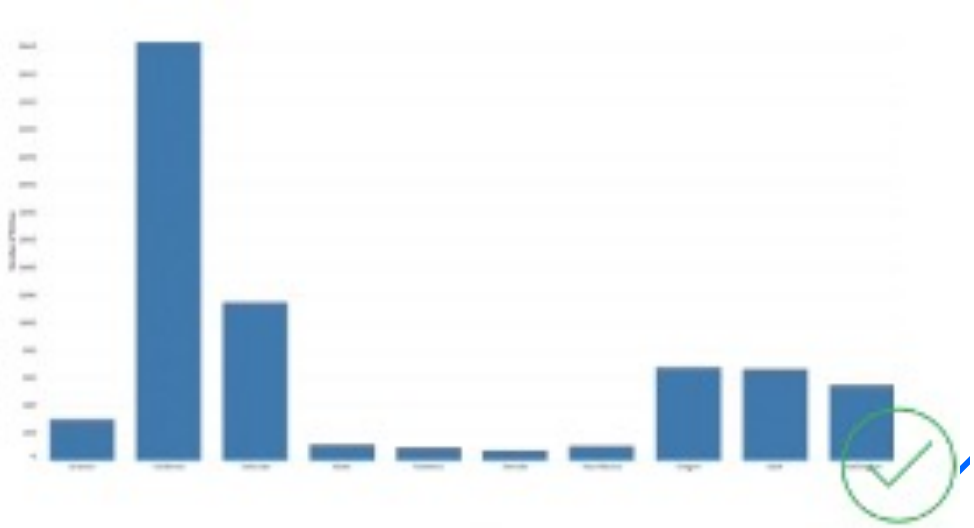

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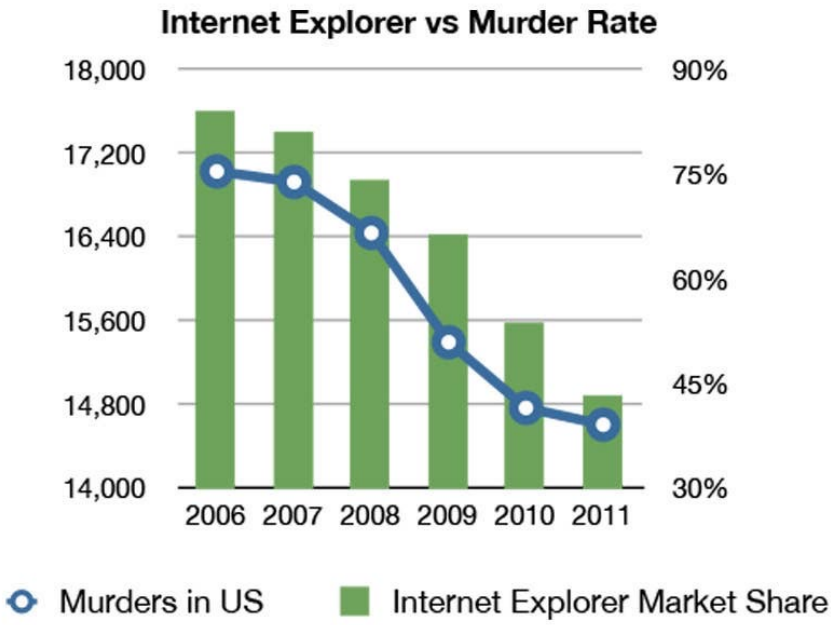
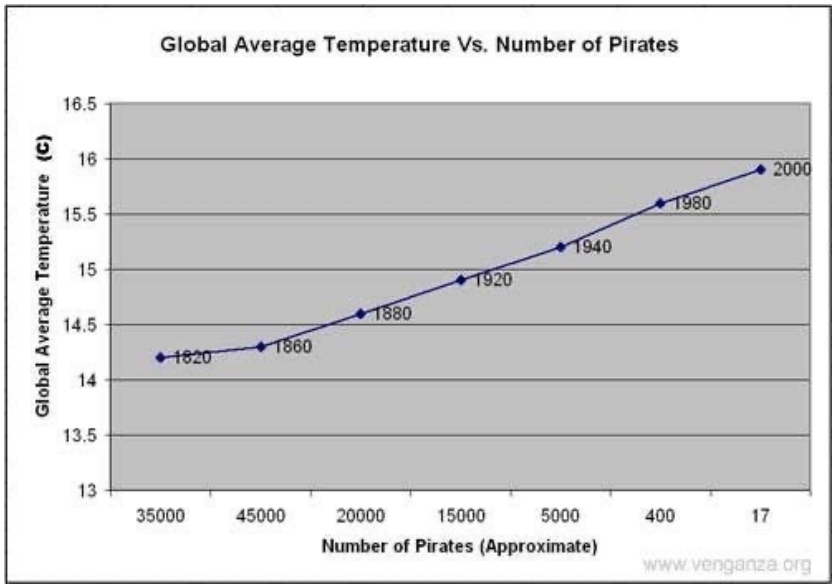
Correlation = causality?



https://www.buzzfeednews.com/article/kih2110/the-10-most-bizarre-correlations



https://www.tylervigen.com/spurious-correlations

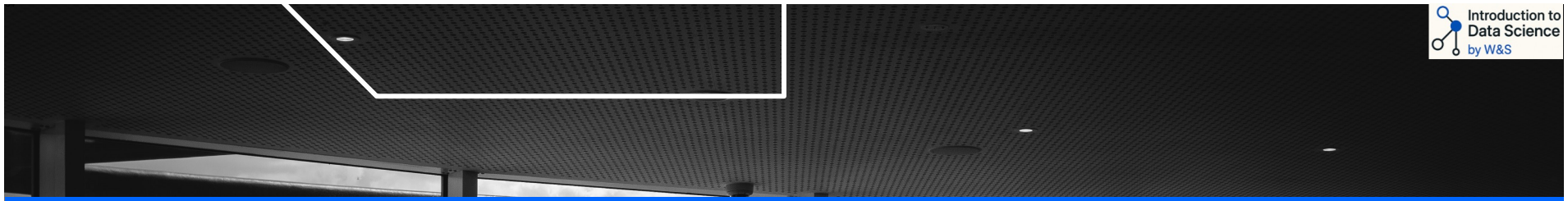


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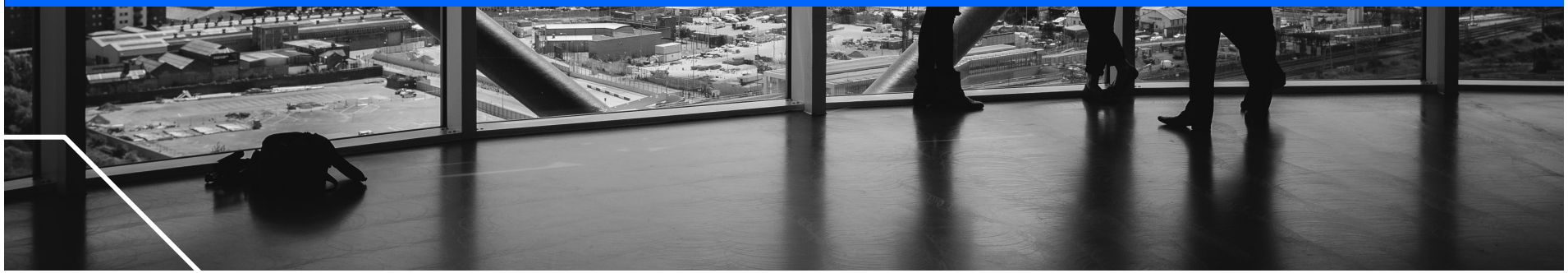
CHART TYPES



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Line Chart

- Displays the change over time for a measure
- What kind of questions does this chart answer?
  - How has this variable changed over the past period?
  - When did this variable change?
  - How quickly did this variable change?
  - What are the trends? Can future trends be derived?
- Example: Stock market prices of the last five years

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Bar Chart (horizontal | vertical)

- Comparison of data of different categories (dimensions)
- What kind of questions does this chart answer?
  - Which of these categories shows the highest/lowest value?
  - Are there any extraordinary categories?
  - What is the gap (deviation) between the lowest and highest values of different categories?

- Example: Sales per department

Bullet Diagram (horizontal | vertical)

- Modification of a bar chart that shows the performance of a primary measure of achievement of key figures.
  - What kind of questions does this chart answer?
  - As with the bar chart
  - Additional: Comparison per bar against a key figure

- Example: What is the actual turnover compared to the expected turnover?

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Histogram

- Representation of the distribution of values
- What kind of questions does this chart answer?
  - Are events grouped around a certain probability?
  - Which group shows the highest values?
  - Which area covers the most observations?
- Example: Students' performance in an exam

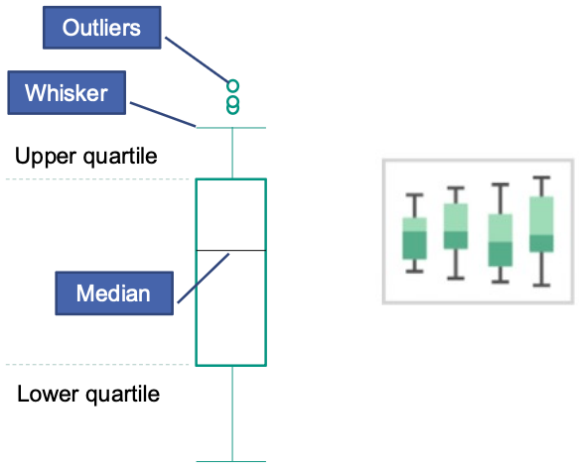
Boxplot

- Representation of the distribution within categories (dimensions)
- What kind of questions does this chart answer?
  - In which range are the values of most of the data in a category located?
  - Are there outliers in the data?
  - What is the median of values in a category?

- Example: Distribution of discounts in different product groups

Boxplot

- Inside the box is the middle 50 percent of the data
- Whiskers (antennas) describe boundaries outside of which we speak of outliers
    - No uniform definition
    - Definition according to John W. Tukey: Length of the whiskers to a maximum of 1.5 times the interquartile distance (IQR)



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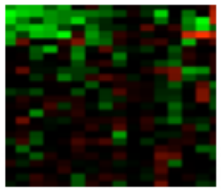
Scatterplot

- Displays relationships between two numeric variables
- What kind of questions does this chart answer?
  - Are there any patterns when looking at the data points?
  - Are there correlation relationships between the variables?
  - Are there exits in the data?

- Example: Relationship between daily calorie intake and a person's body weight.

Heat Map

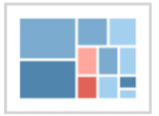
- Comparisons between two variables
- What kind of questions does this chart answer?
  - Is there a relationship between two variables?
  - Are certain areas particularly prominent?
  - Do two variables correlate?



- Example: Which nations won medals at the Olympics (divided into gold, silver,
- bronze)?

Tile Chart (Tree Map)

- Displays the proportion of an overall distribution.
- What kind of questions does this chart answer?
  - How much does this value contribute to the total?
  - How does the distribution of a variable change over time?



- Example: What proportion of total sales do an item's sales by sales region
- provide?
- Alternative chart types: pie charts, area charts, stacked bar charts

Pie Chart

- Displays the proportion of an overall distribution.
- What kind of questions does this chart answer?
  - How much does this value contribute to the total?
  - How does the distribution of a variable change over time?

- Example: What proportion of the votes did a party receive in the last elections?
- Alternative chart types: tree map, area charts, stacked bar charts

Map Charts

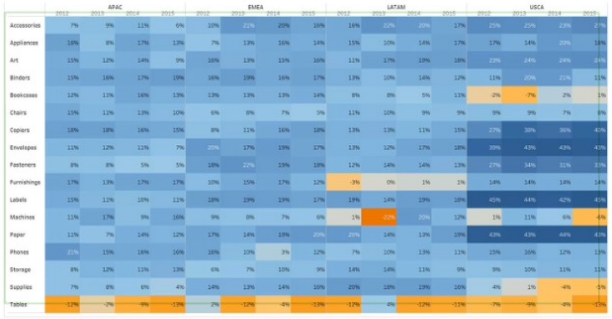
- Map charts represent positions and geographic patterns in the data.
- Variants: filled cards, point distribution cards, symbol cards, density cards...

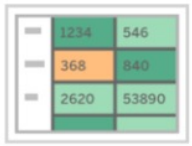
- What types of questions can this diagram answer?
  - Which place has the largest/smallest values?
  - Which region has the largest/smallest values?
  - How do you represent deviations geographically?

- Example: How is COVID-19 spreading worldwide?

Highlight Table

- Data table with color coding
- What kind of questions does this chart answer?
    - Shows all the details of the data points
    - Colors can be assigned to specific dimensions and categories or highlight key figures (quantiles, max/min values, ...)
    - Apply color markers from diagrams and thus display their details.





Tipps and Guidelines

Order your data

When displaying the value of several entities, ordering them makes the graph much more insightful.

To cut or not to cut?

Cutting the Y-axis is one of the most controversial practice in data viz. See why.

The spaghetti chart

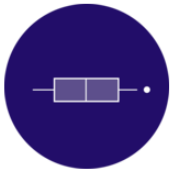
A line graph with too many lines becomes unreadable: it is called a spaghetti graph.

Pie chart

The human eye is bad at reading angles. See how to replace the most criticized chart ever.

Play with histogram bin size

Always try different bin sizes when you build a histogram, it can lead to different insights.



Do boxplots hide information?

Boxplots are a great way to summarize a distribution but hide the sample size and their distribution.

The problem with error bars

Barplots with error bars must be used with great care. See why and how to replace them.

Too many distributions.

If you need to compare the distributions of many variables, don't clutter your graphic.

https://www.data-to-viz.com/caveats.html

Presenting results

Promises

- Enhanced Analyses and Predictions: Leveraging large volumes of data can enable deeper insights and more accurate forecasts than ever before.
- Uncertainty at the Micro Level, Accuracy at the Macro Level: Big Data allows for precise identification of patterns and trends at the macro level, despite uncertainty at the individual level.
- Quality is Crucial: Despite the vast amounts of data, ensuring data quality is essential for drawing valid conclusions.

Risks

- Incorrect Modeling and Conclusions: The complexity and volume of Big Data can lead to errors in data modeling, resulting in false or misleading outcomes.
- Privacy and Individual Rights: Processing large datasets poses risks to privacy and can conflict with individual rights.

Recommendations for Mitigating Risks

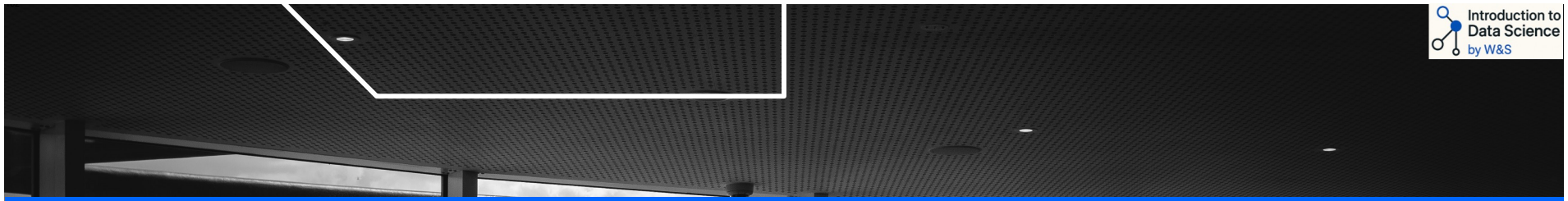
- Rigorous Data Verification: Implement strict data quality verification processes to ensure the integrity of analyses.
- Transparent Modeling: Promote transparency in your modeling processes to build trust and avoid misinterpretations.
- Preserving Privacy: Adhere to privacy regulations and practices to protect individuals' rights and foster trust in Big Data initiatives.
- Reason about results: be able to explain; why have predictions been made?
- Reason about input: data set; metrics

Use of Diagrams

- Usually there are data sets with many variables (characteristics) or
- we want to determine the utility value of other variables

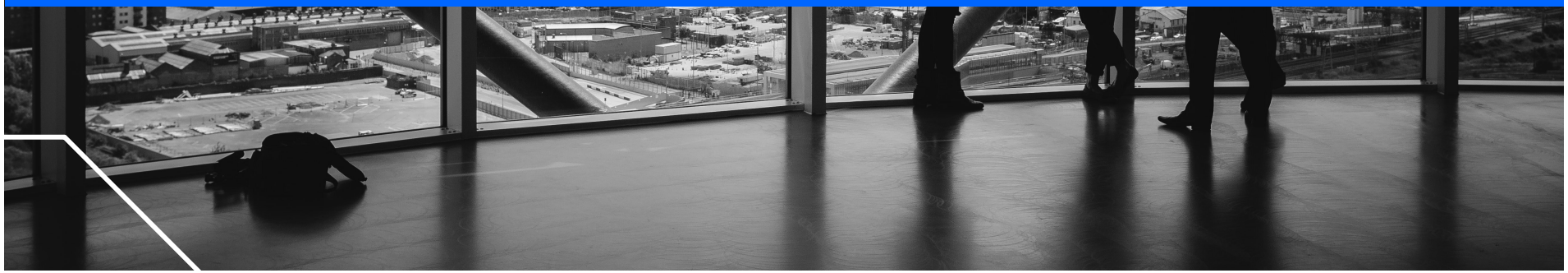
- Application of diagrams
  - Often the same / different diagrams are used one after the other / combined
  - Decision on the type of visualization based on
    - variables,
    - dimensions in our data, and
    - the question asked


HANDS-ON
TIME
INTRODUCTION TO DATA SCIENCE
BY W&S
YOUR TURN!
EXERCISE / QUESTION



Introduction to Data Science by W&S

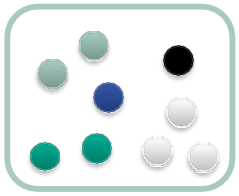
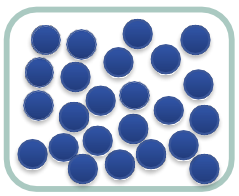
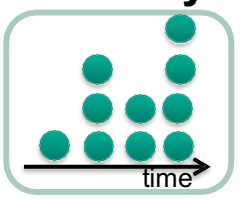
Challenges



Whats hard about data science

- Getting the data (usually)
- Overcoming assumptions
- Communication
  - With domain experts
  - Expectation management for client
- Making ad-hoc explanations of data patterns
- Overgeneralizing
- Not checking enough (validate models, data pipeline integrity, etc.)
- Using statistical tests correctly
- Prototype to Production transition
- Data pipeline complexity (team boundary)

Data Challenges (1)

	Variety	Volume	Velocity
			
Challenge	Handling multiplicity of types, sources and formats	Dealing with large volumes of data	Streams, sensors, near real-time data
Impacted Tasks	Data integration	Storage, processing & analytics	Processing & analytics
Solution	Semantic technologies are a good fit	Distributed storage & parallel processing	Real-time technologies

Data Challenges (2)

- **Data veracity:** coping with uncertainty, imprecision, missing values, misstatements or untruths.

- **Data quality:** determining the quality of datasets and relevance to particular issues. Depends on the use case:
  - How broad/complete is the data?
  - How fine is the sample resolution? How timely are the readings?
  - Does the data contain any “noise” (errors)? Is it representative?

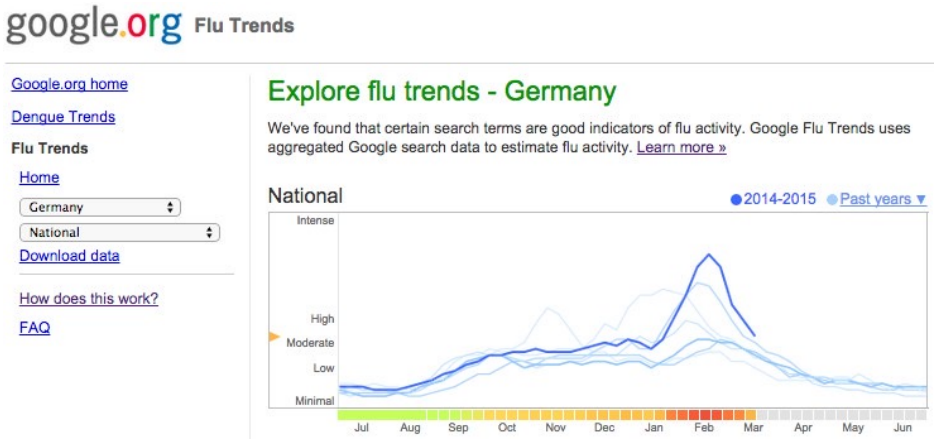
Data Challenges (3)

- **Data discovery:** finding relevant data from enormous amount of data available on the Web.

- **Data dogmatism:** analysis of Big Data can offer remarkable insights. However, data analysis should not entirely replace domain expert knowledge, but act as a tool to support /confirm facts.
    - E.g., Google Flu Trends

Data Challenges (3)

Example: Data dogmatism



Source: https://www.google.org/flutrends/de/#DE

"By counting how often we see these [**flu-related topics] search queries**, we can estimate **how much flu is circulating** in different countries and regions around the world."

Data Challenges (3)

Example: Data dogmatism

Comparison of Google Flu Trends model against medical reports.

SCIENCE BIG DATA

Google's Flu Project Shows the Failings of Big Data

Bryan Walsh @bryanrwalsh | March 13, 2014

A new study shows that using big data to predict the future isn't as easy as it looks—and that raises questions about how Internet companies gather and use information

Source: http://time.com/23782/google-flu-trends-big-data-problems/

The Parable of Google Flu: Traps in Big Data Analysis

David Lazer[1,2,*], Ryan Kennedy[1,3,4], Gary King[3], Alessandro Vespignani[5,6,3]

+ Author Affiliations

*Corresponding author. E-mail: d.lazer@neu.edu.

In February 2013, Google Flu Trends (GFT) made headlines but not for a reason that Google executives or the creators of the flu tracking system would have hoped. *Nature* reported that GFT was predicting more than double the proportion of doctor visits for influenza-like illness (ILI) than the Centers for Disease Control and Prevention (CDC), which bases its estimates on surveillance reports from laboratories across the United States (*1*, *2*). This happened despite the fact that GFT was built to predict CDC reports. Given that GFT is often held up as an exemplary use of big data (*3*, *4*), what lessons can we draw from this error?

Read the Full Text

Source: http://www.sciencemag.org/content/343/6176/1203

Process Challenges (1)

Big-Data Scientists
"Janitor Work"

50% - of data scientists' time
80% - spent in "Data wrangling"

Data acquisition:

Data availability

Data permissions

Aligning/integrating data from different sources:

Syntactic challenge: Data in different formats

Semantic challenges: Resolving when two objects are the same, describing relationships between data points, resolving inconsistencies

Transforming, cleaning and organizing the data into a form suitable for analysis

Source: "For Big-Data Scientists, 'Janitor Work' is Key Hurdle to Insights" in The New York Times. 2014.

Process Challenges (2)

Modeling data:

Mathematically: mathematical models to describe the data Statistical methods or Machine Learning

Simulations

Knowledge representation: ontologies and rules

Understanding the output:

Interpreting the results

Visualizing

Sharing the results

Data privacy, security, and Governance:

- Ensuring that data is used correctly (abiding by its intended uses and relevant laws).
- Tracking how the data is used, transformed, derived, …
- Managing data lifecycle.

*"Many data warehouses contain sensitive data such as personal data. There are **legal** and **ethical concerns** with accessing such data. So the data must be secured and access controlled as well as logged for audits".*

Michael Blaha, Modelsoft Consulting Corporation, 2012

Source: http://www.odbms.org/blog/2012/03/data-modeling-for-analytical-data-warehouses-interview-with-michael-blaha/

Data science – two sides of the same coin

Opportunities	Risks
• Discover potential • Develop new services • Informed decisions based on forecasts • Service and product improvement	• Surveillance • Manipulation • Uselessness • Data protection

Bis Donnerstag

samuel.schlenker@hpe.com