MBA Digital Business & AI

Master of Business Administration in Digital Business & AI
2024-2026

Business Analytics & Data Science

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FAU Friedrich-Alexander-Universität Erlangen-Nürnberg

Agenda

Business Analytics

- Introduction
- Types of Data and Databases
- Data Models
- Entity Relationship Model
- Case 1: Reverse Engineer a Database Model
- The Star and Snowflake Schema
- Analyzing Data with Power BI
- Case 2: Analyzing Procurement Transactions

Data Science

Agenda

Business Analytics

Introduction

Types of Data and Databases

Data Models

Entity Relationship Model

Case 1: Reverse Engineer a Database Model

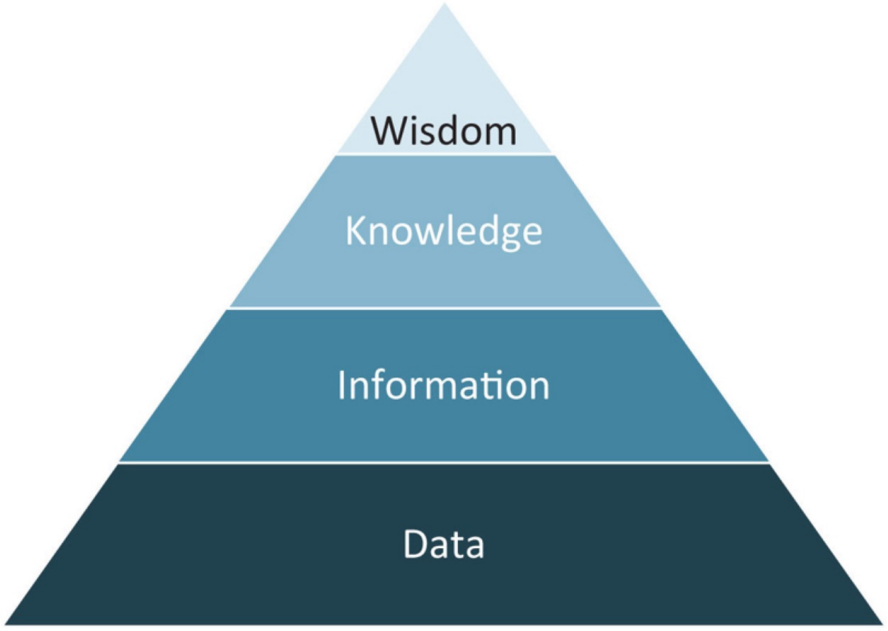
The Star and Snowflake Schema

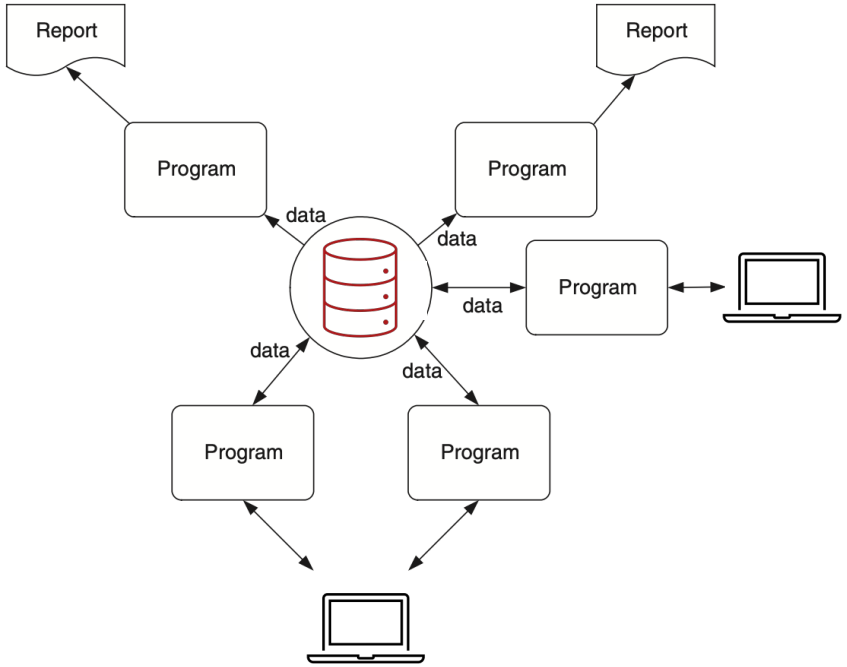
Analyzing Data with Power BI

Case 2: Analyzing Procurement Transactions

Data Science

Every Information System Is Built on Data





Why Efficient Data Management Is Important

Data Sources

Steadily growing sources of data

Advanced Analytics

Non-domain experts such as data scientist need to be able to work efficiently with data (e.g., data catalogues)

Customer Experience

Amazon found for every 100 milliseconds of latency; they lost 1% revenue.*

*Source: https://glinden.blogspot.com/2006/11/marissa-mayer-at-web-20.html

Why Data Management Has Become More Challenging - Corporate Planning Process

Sales Planning

Forecast 1 Forecast 2 Forecast 3

31.3 30.6 30.9

Land	Product Category	Sales (kEUR)
Germany	Face Cream	100,000
France	Face Cream	50,000
…	…	…

Production Planning

Site	Product Category	Quantity
Hamburg	Face Cream	10.000
Leipzig	Face Cream	2.000

Purchase Planning

Material	Supplier	ML
Glycerin	Neutro GmbH	50.000
Panthenol	Chemie AG	85.000

Why Data Management Has Become More Challenging - Corporate Planning Process

	Type of Data	Source System
1	Forecasted sales quantity existing products	SAP
2	Forecasted sales quantity new products	SAP
3	Prices	SAP
4	Marketing Budget	Excel

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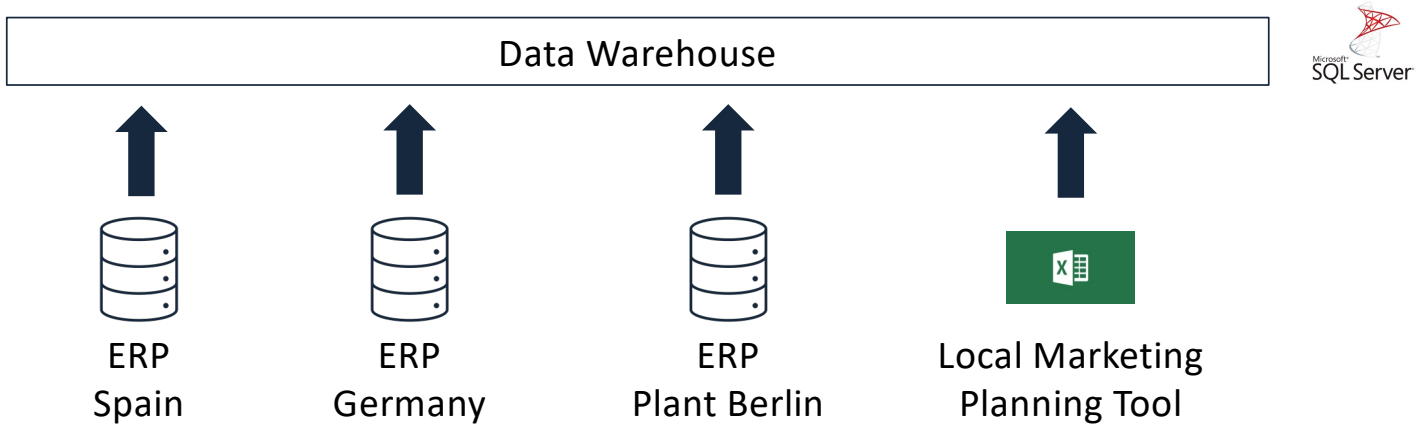

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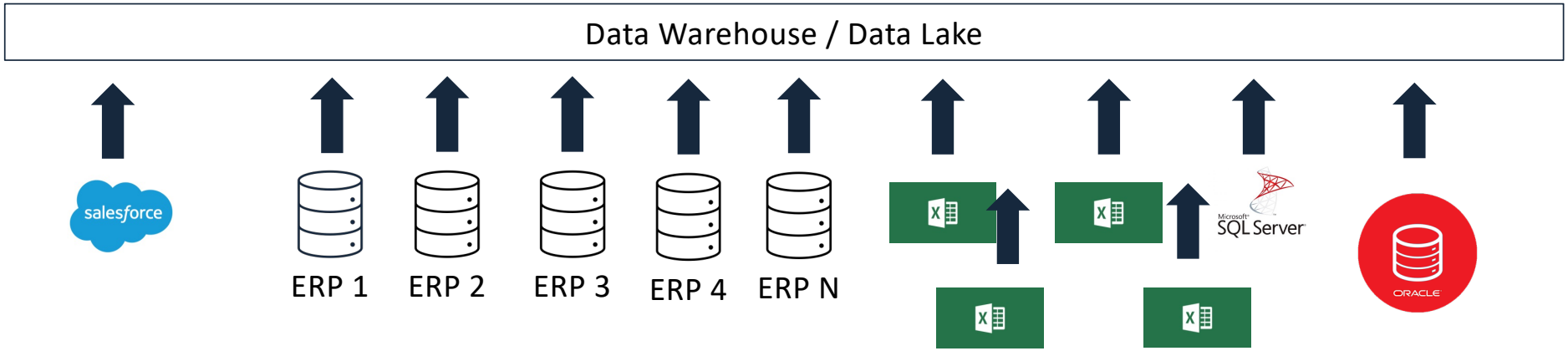

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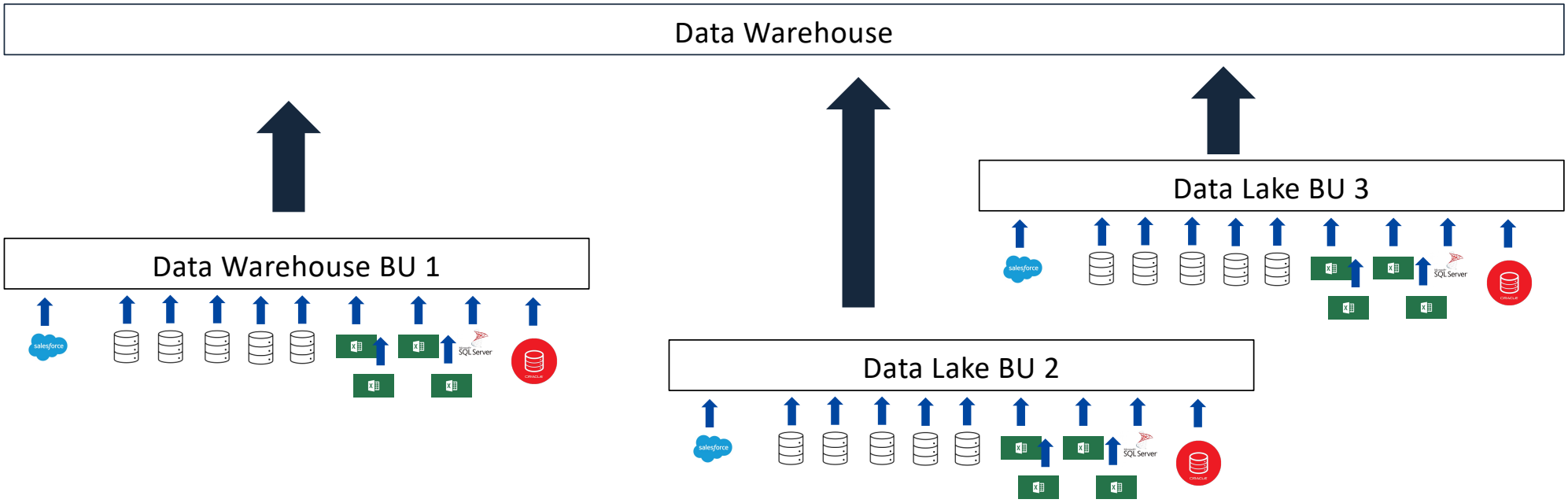


How many ERP-Systems is Siemens AG using?

How many PB of data are saved in their core platform

Drivers of Complex Data Landscapes

Technical and Architectural Factors

- **Legacy Systems:** Incompatible formats, missing APIs, outdated technology.
- **Hybrid IT** (Cloud + On-Prem): Data is spread across environments with different integration capabilities.
- **Tool Proliferation**: Overuse of specialized tools leads to fragmented data without a shared model.
- **Vendor Lock-in**: Proprietary systems discourage data portability and integration.

Organizational and Operational Factors

- **Departmental Autonomy ("Shadow IT")**: Teams independently adopt tools, creating silos.
- **Mergers & Acquisitions**: Inherited systems and inconsistent architectures.
- **Lack of Central Data Strategy**: Growth and tool adoption without enterprise-wide alignment.
- **Cultural Silos**: Reluctance to share or harmonize data across business units.

Advanced Analytics as a Driver for a Complex Data Landscapes

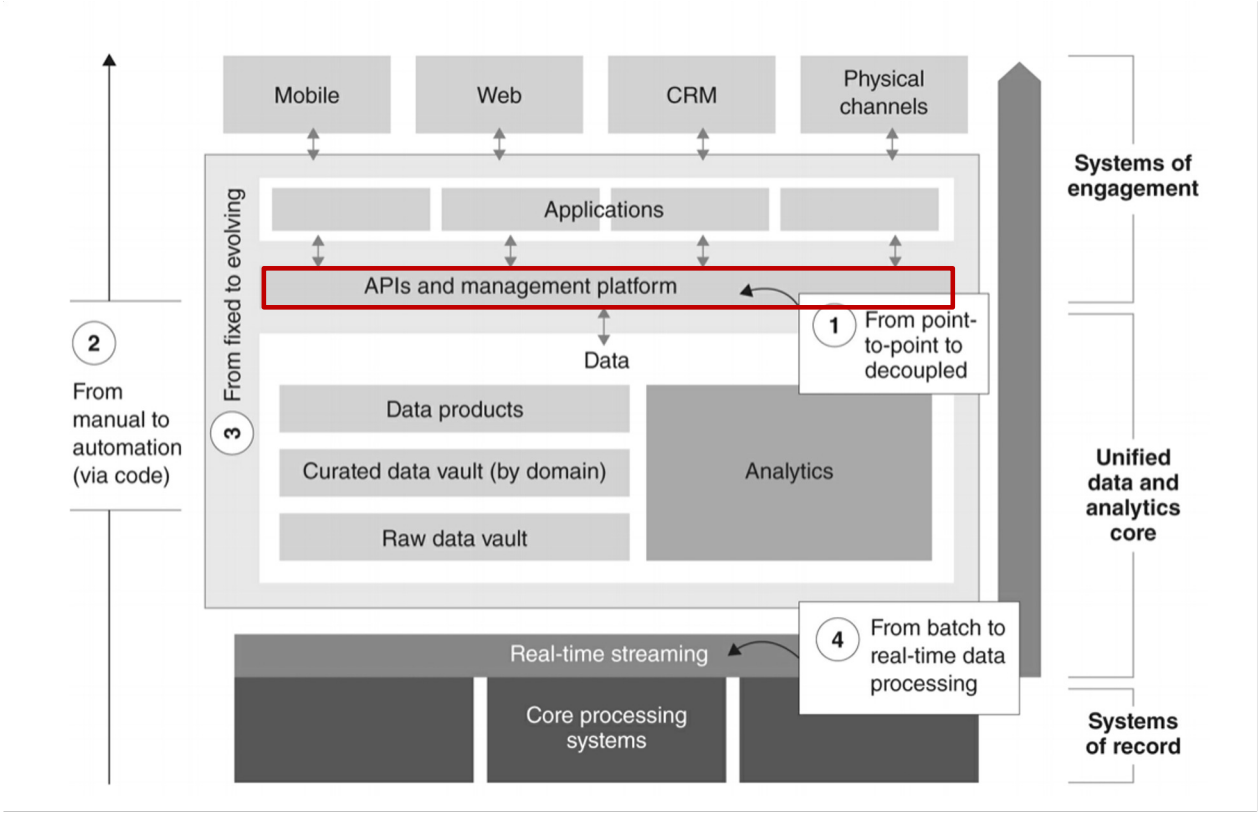
Large number of sources

Each use case requires different data

Scattered Data

Data is often copied and scattered in different applications

Given the Number of Systems Companies Try to Get Beyond Point-to-point Communication



Source: Lamarre et al (2023).

Evolving Data Landscape of Data Platforms

		Data Warehouse	Data Lake	Data Fabric	Data Mesh
Architecture		• Central • Focus on modeling and analysis	• Central • Focus on scalability	• Central layers on top of distributed data • Focus on data management, integration and access	• Decentralized & distributed • Focus on product thinking • Focus on organizational change
Data	**Format**	• Primarily structured format	• Structured format • Unstructured format	• Any format	• Data as a product • Any format
	Status	• Mostly pre-processed • Consolidated	• Mostly Raw	• Any status	• According to data product • How customer needs it
	Types	• Primarily internal data • Mostly ERP / CRM / PLM	• Internal and external data • Various data sources	• Internal and external data • Various data sources	• Internal and external data • Various data sources
	Sourcing & Storage	• Data replication (ETL) • Data is centrally stored (in the data warehouse)	• Data replication (ELT) • Data is centrally stored (in the data lake)	• Either data replication (ETL or ELT) with central data storage (in the data fabric) • Or data virtualization with decentral data storage (original data sources)	• Data is stored decentrally (original data sources) but are logically integrated into the data mesh
	Access	• Central access	• Central access	• Central access (self-service) through fabric (API) layer, using data catalog or knowledge graph data model	• Decentral access (self-service) where data is produced
Ownership & Governance		• Central	• Central	• Central (empowered by strong metadata foundation)	• Decentral (empowered by domain or product owners)

Data Mesh

Data ownership by domain

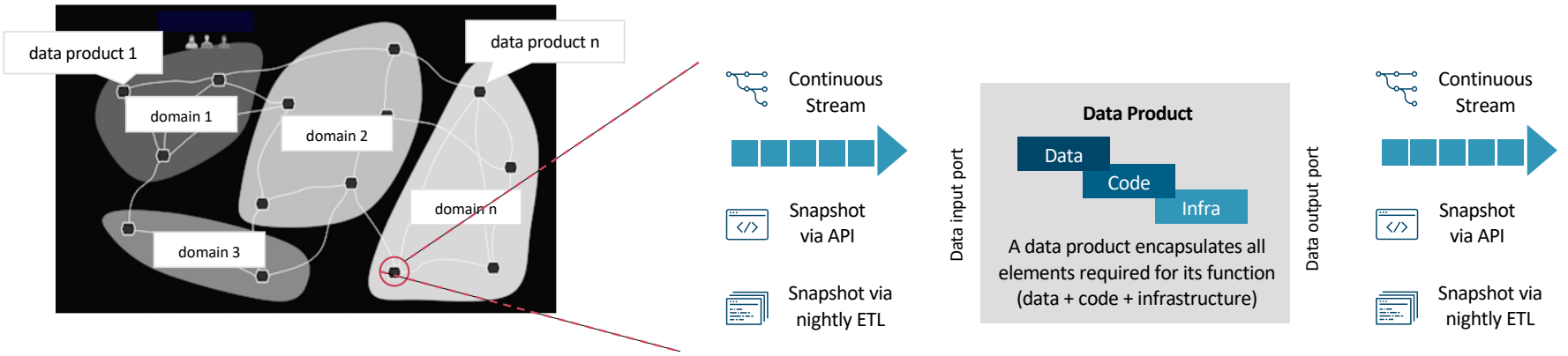
- Data "lives" where it's created and is owned by those who understand its structure and value the best
- Domain-driven decentralization of responsibility for data
- Data is governed where it is created

Data as a product

- Data owners think product-orientated and customer-centric
- The data owner is responsible for all aspects of the data (e.g., quality, form, pre-processing)

Data available everywhere

- Data is locally produced and made available in a decentral way (e.g. via event streaming), to be consumed by other teams in the company
- From everywhere in the company, all data is accessible via self-service



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Data Science

Tabular Data Can Be Saved in Various Formats

	A	B	C
1	**name**	**price**	**volume**
2	a	10.12	20
3	b	90.5	100
4	c	8.99	40

Tabular Data Can Be Saved in Various Formats

CSV

```
name, price, volume
a, 10.12, 20
b, 90.5, 100
c, 8.99, 40
```

XML

```
<?xml version='1.0' encoding='utf-8'?>
<data>
 <row>
  <index>1</index>
  <name>a</name>
  <price>10.12</price>
  <volume>20</volume>
 </row>
 <row>
  <index>2</index>
  <name>b</name>
  <price>90.5</price>
  <volume>100</volume>
 </row>
 <row>
  <index>3</index>
  <name>c</name>
  <price>8.99</price>
  <volume>40</volume>
 </row>
</data>
```

JSON

```
{
  "1":{"name":"a","price":10.12,"volume":20},
  "2":{"name":"b","price":90.5,"volume":100},
  "3":{"name":"c","price":8.99,"volume":40}
}
```

Example for Encoding an Image

The "Grinning Face" emoji, from the Twemoji set

Base64 encoded image

iVBORw0KGgoAAAANSUhEUgAAAoAAAAKACAYAAAAMzckjAAAABmJLR0QA/wD/AP+gvaeTAAAgAElEQVR4nOzdeX
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AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAgNRjXAcAgESxLy8tVG4ofOIPukPFCsVP/
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....
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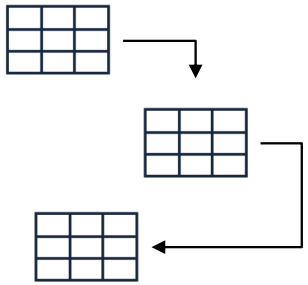
Types of Database

Key-Value Database

Key	Value
Paul	87077
Mike	8179

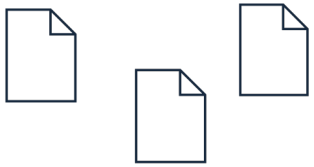
Redis,
DynamoDB

Relational Databases



SQL-Server, Postgres,
MySQL,

Document Databases



MongoDB, CouchDB,
CosmosDB

Graph Databases

Neo4j,
Amazon Neptune

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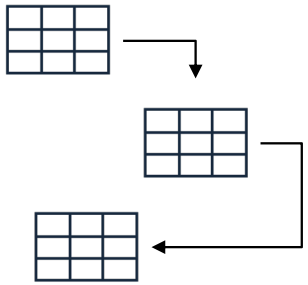

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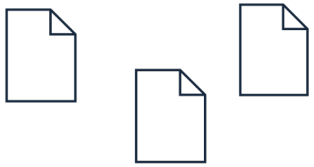

MongoDB, CouchDB,
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Graph Databases

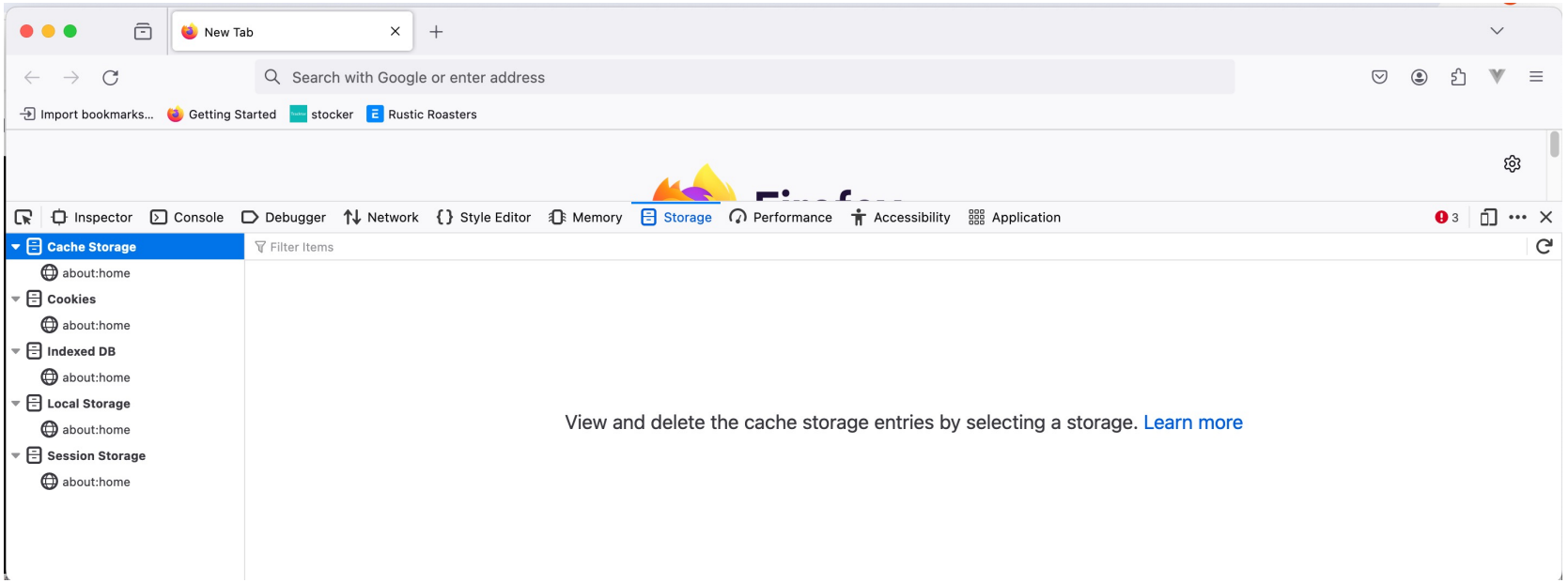
Neo4j,
Amazon Neptune

Key-value Store – Simplest Version of Database

Key	Value
Steven	001 - 4797797
Maria	0030 - 2312321

```
product_prices = {
        "Apple": 0.5,
        "Banana": 0.25,
        "Cherry": 0.75,
        "Date": 1.0
        }
```

Key-value Store – Simplest Version of Database



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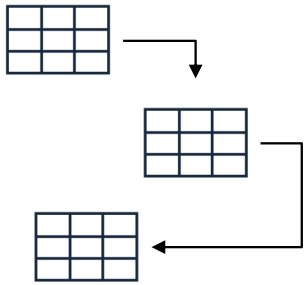

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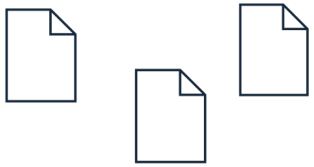

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Example for a Linked in Profile with a Relational Database

http://www.linkedin.com/in/williamhgates

Bill Gates

Greater Seattle Area | Philanthropy

Summary

Co-chair of the Bill & Melinda Gates Foundation. Chairman, Microsoft Corporation. Voracious reader. Avid traveler. Active blogger.

Experience

Co-chair • Bill & Melinda Gates Foundation
2000 – Present

Co-founder, Chairman • Microsoft
1975 – Present

Education

Harvard University
1973 – 1975

Lakeside School, Seattle

Contact Info

Blog: thegatesnotes.com
Twitter: @BillGates

id	first_name	last_name	summary	region_id	industry_id
251	Bill	Gates	Co-chair of ..	us:91	131

id	region_name
us:7	Greater Boston Area
Us:91	Greater Seattle Area

id	industry_name
43	Financial Services
48	Construction
131	Philanthropy

Source: Kleppmann, M. (2017).

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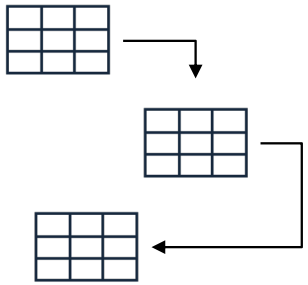

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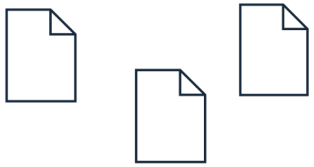

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```
{
  "user_id":     251,
  "first_name":  "Bill",
  "last_name":   "Gates",
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    {"school_name": "Lakeside School, Seattle", "start": null, "end": null}
  ],
  "contact_info": {
    "blog":    "https://www.gatesnotes.com/",
    "twitter": "https://twitter.com/BillGates"
  }
}
```

Source: Kleppmann, M. (2017).

The Document Structure Is Very Easy to Handle with Object-oriented Programming: Example Mapping a Documents to a Python Class

```python
class Customer:
    def __init__(self, name, balance, address):
        self.name = name
        self.balance = balance
        self.address = address
```

```
{
    "name": "Isabell Wang",
    "balance": 200,
    "address": {
        "city": "San Francisco",
        "state": "CA",
        "zip": 94107,
        "street": "123 Main St"
 }
```

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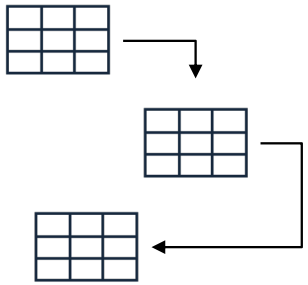

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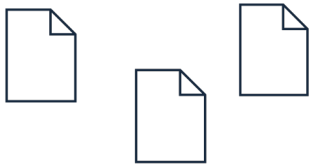

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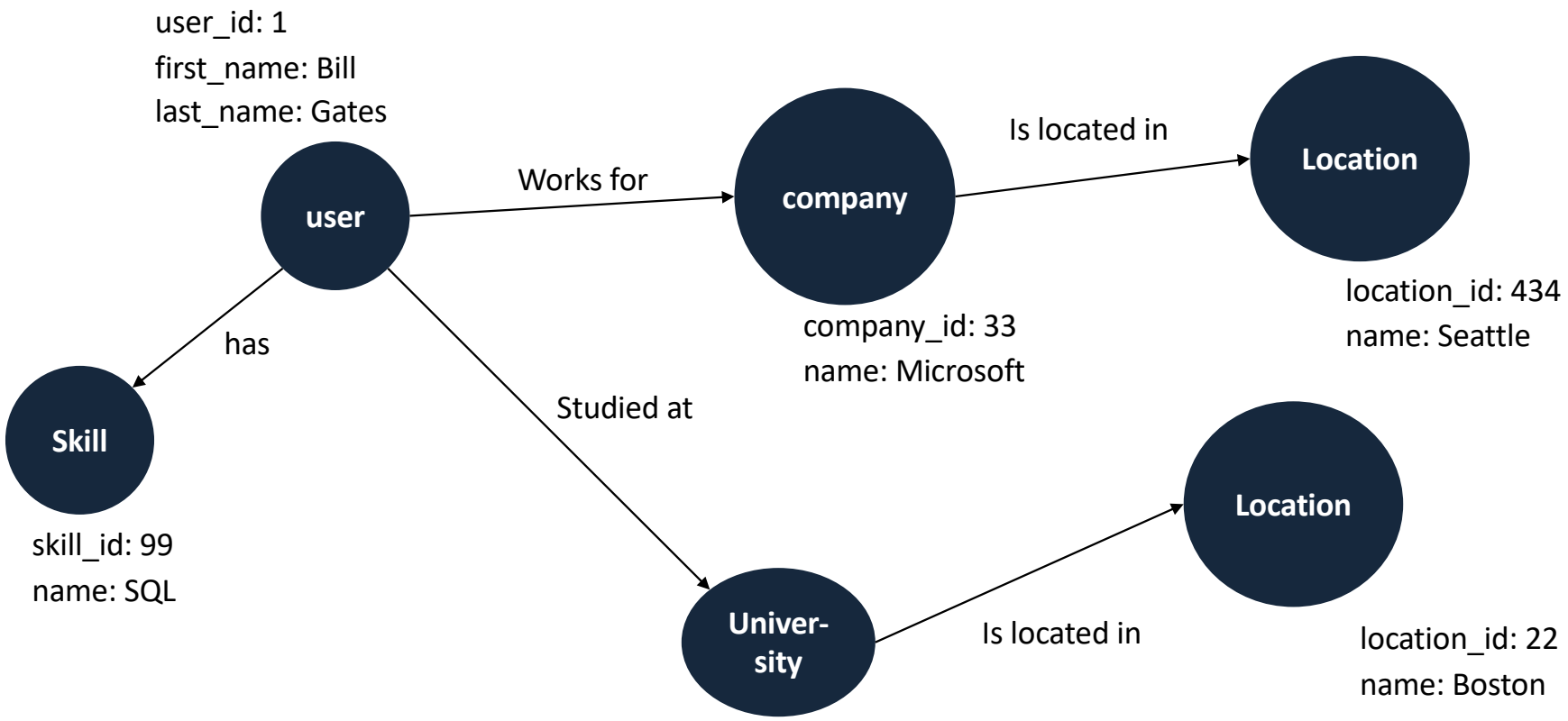
Amazon Neptune

Example for a Graph Database Model



Each Database Type Has Different Strength and Weaknesses

Database Type	Pros	Cons	Use Cases
Key-value	Simple, fast, and scalable	Limited query capabilities and data relationships	Real-time analytics, content management, caching, session management
Relational	Data integrity and complex queries	Schema rigidity and scalability challenges	Financial systems, inventory management, Transaction-based systems
Document	Schema flexibility and rich data structures	Data duplication and consistency issues	Content management, IoT, blogging, web analytics, mobile applications
Graph	Data relationships and traversal performance	Data size and complexity limitations	Fraud detection, social networks, route planning

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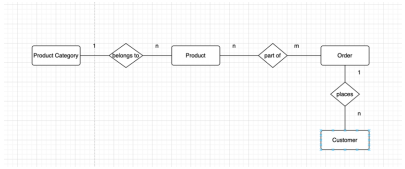
Data Science

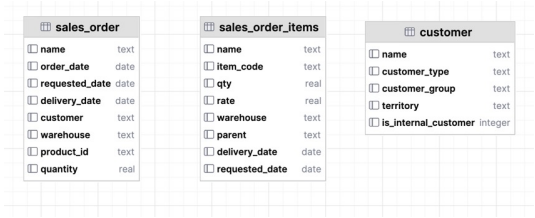
What Is a Data Model

Conceptual data model



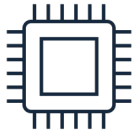
- Technology- independent specification of the data to be held in the database
- Used for communication between the data modeler and business stakeholders

Logical data model



- Translation of the conceptual model into structures that can be implemented using a database management system (DBMS)
- Typically specifies tables and columns

Physical data model



- Incorporates any changes necessary to achieve adequate performance and is also presented in terms of tables and columns
- Together with a specification of physical storage and access mechanisms

Simsion, G., & Witt, G. (2004), p 17.

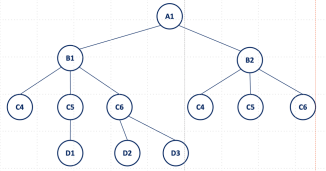
A Conceptual Database Model Essentially Defines Relationships

One-to-one

One-to-many

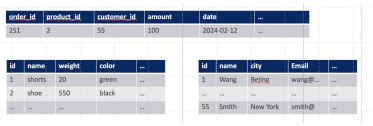
many-to-many

Conceptiual Data Models



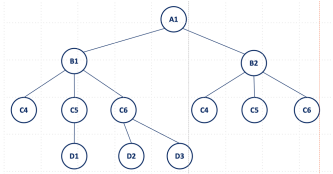
Hierarchical Data Model

Network Data Model



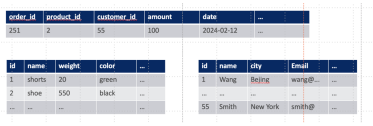
Relational Data Model

Conceptiual Data Models



Hierarchical Data Model

Network Data Model



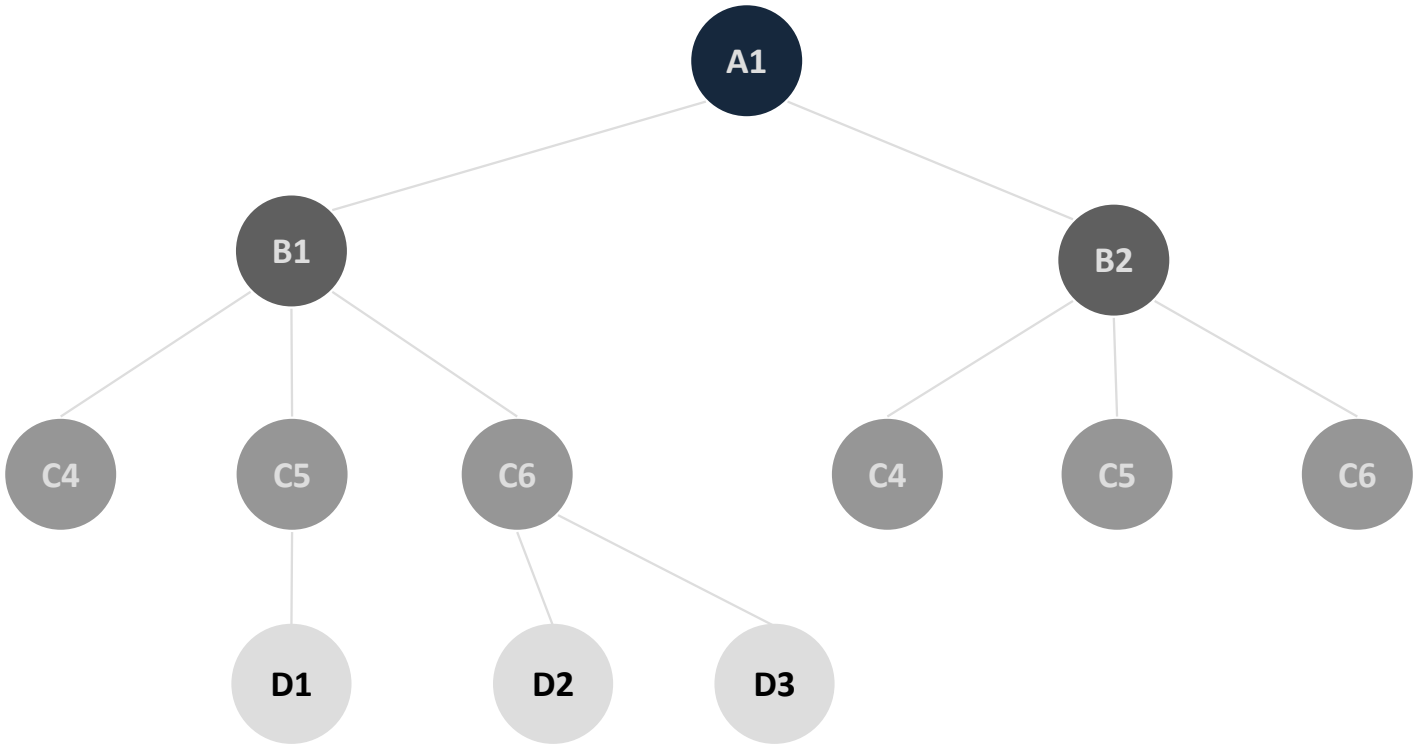
order_id	product_id	customer_id	amount	date	...
251	2	55	100	2024-02-12	...

id	name	weight	color	...
1	shorts	20	green	...
2	shoe	550	black	...
...	...	...		...

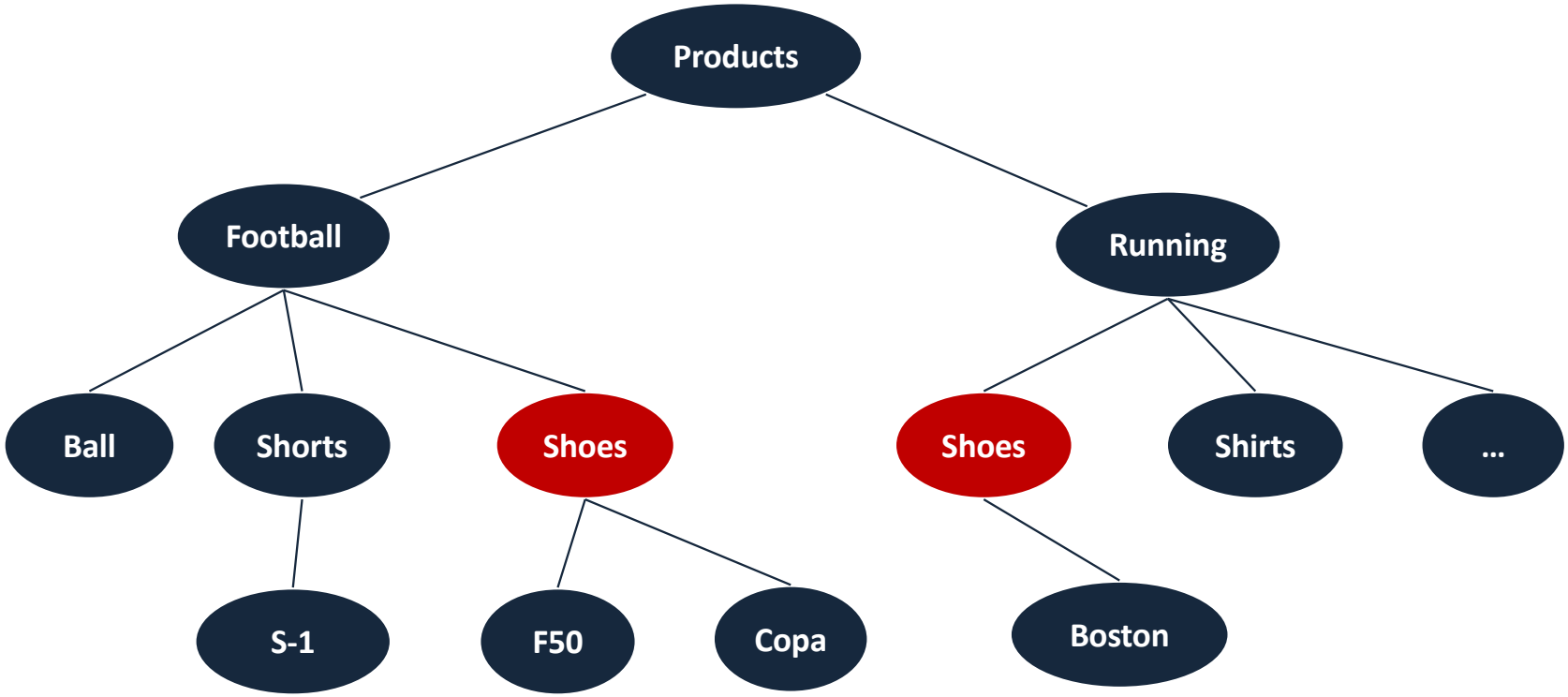
id	name	city	Email	...
1	Wang	Beijing	wang@...	...
...	...	...	...	...
55	Smith	New York	smith@	...

Relational Data Model

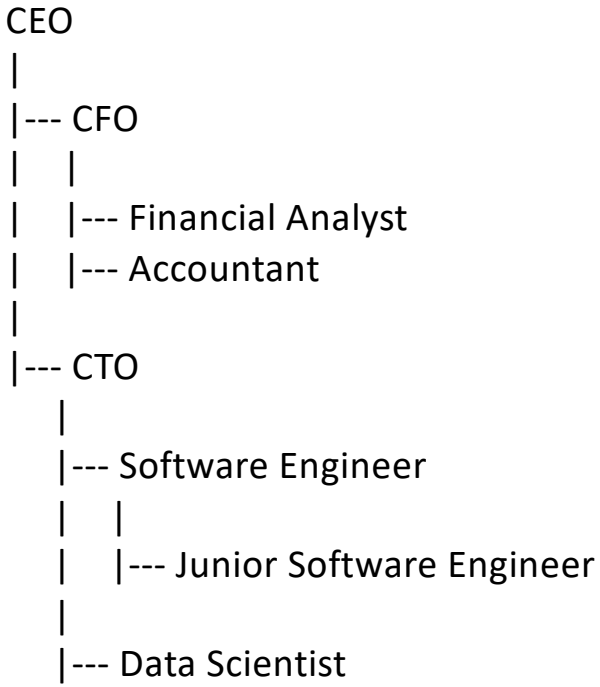
Hiearchical Database Model



Hiearchical Database Model



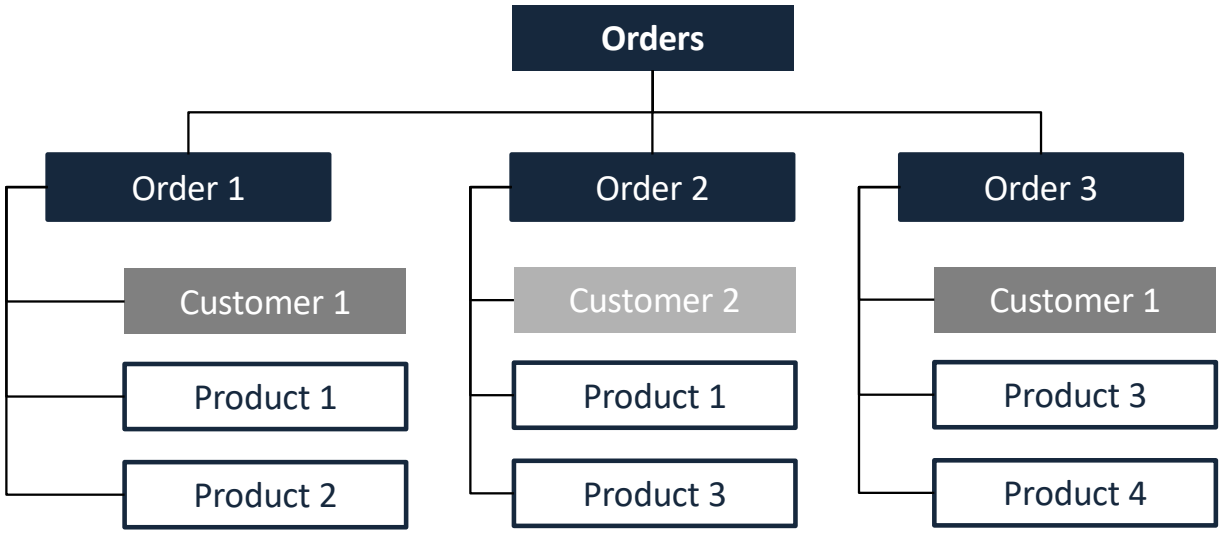
The Windows System Registry Follows a Hierarchical Model



Local File System Can Be Considered as a Hierarchical Database

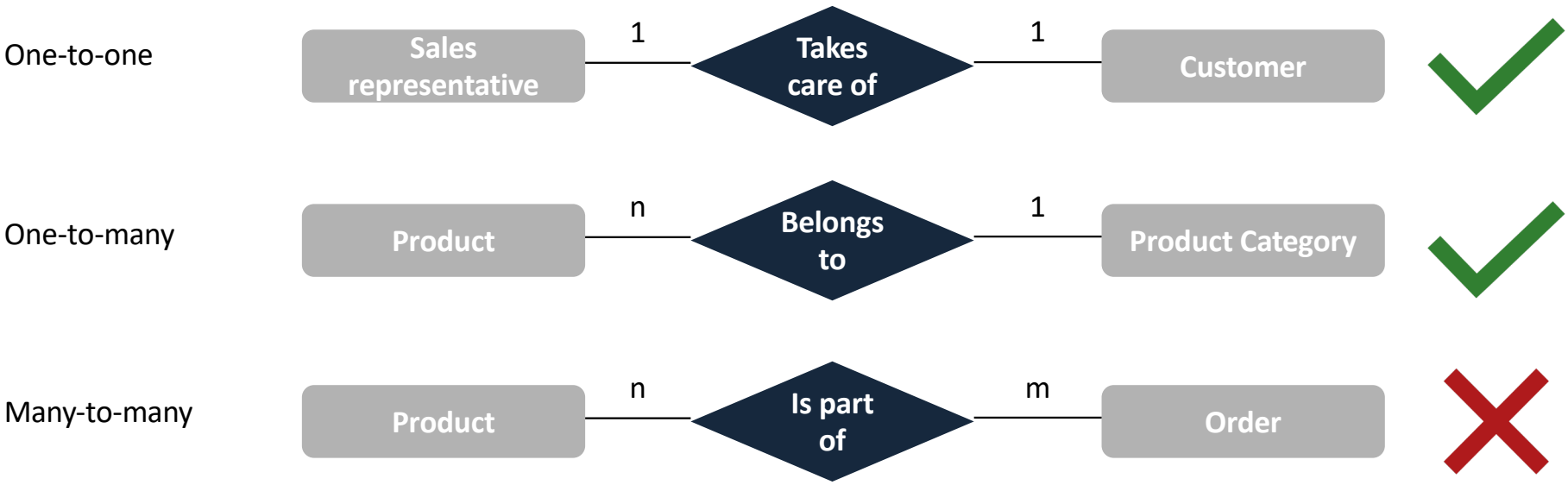
```
C:\
|
|--- Program Files
|    |
|    |--- Microsoft Office
|    |--- Google
|    |    |
|    |    |--- Chrome
|
|--- Users
     |
     |--- User1
     |    |
     |    |--- Documents
     |    |--- Pictures
     |
     |--- User2
          |
          |--- Documents
          |--- Pictures
```

Limitations of the Hierarchical Database Model

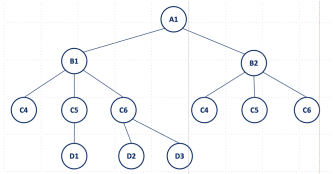


- **High data redundancy**
- **Complex queries**

Many-to-many Relationships Can Not Be Handled Well with Hierarchical Data Models

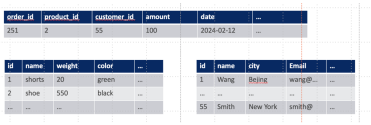


Conceptiual Data Models



Hierarchical Data Model

Network Data Model



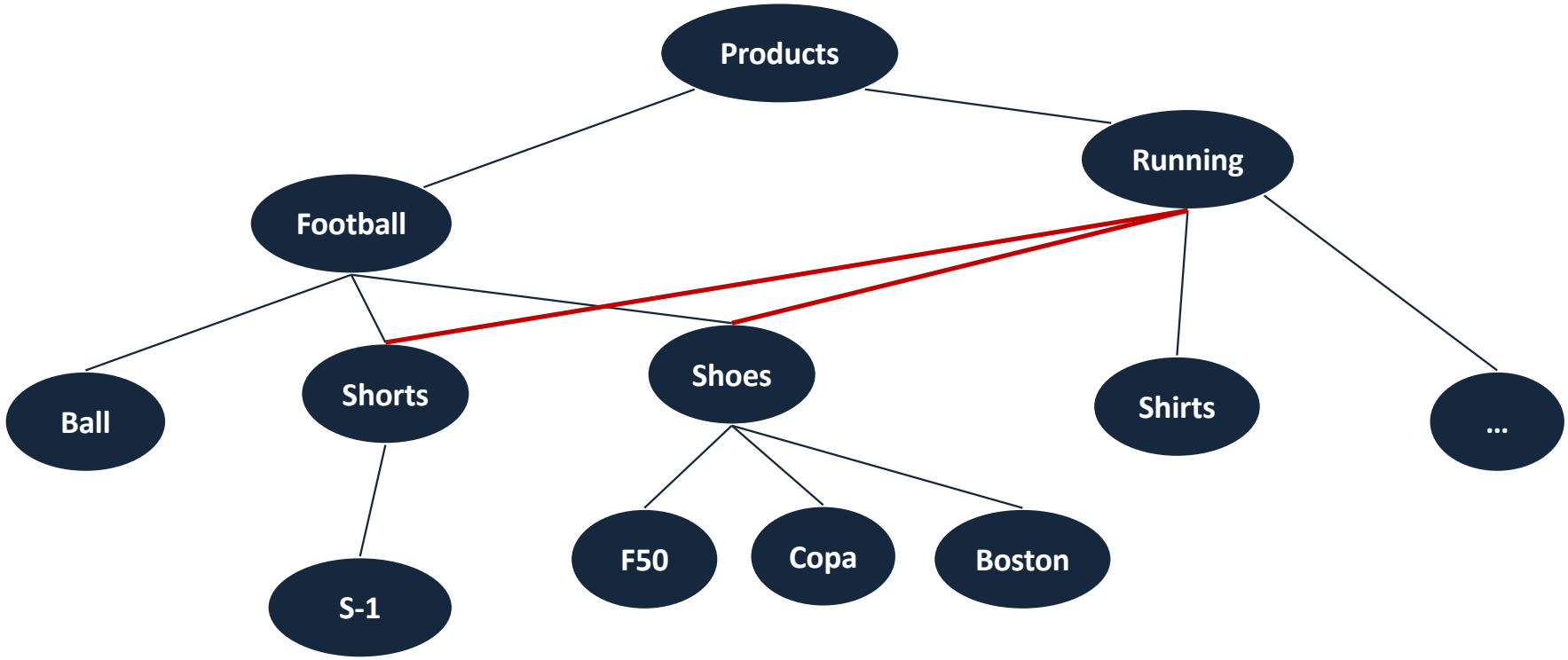
order_id	product_id	customer_id	amount	date	...
251	2	55	100	2024-02-12	...

id	name	weight	color	...
1	shorts	20	green	...
2	shoe	550	black	...
...	...	...		...

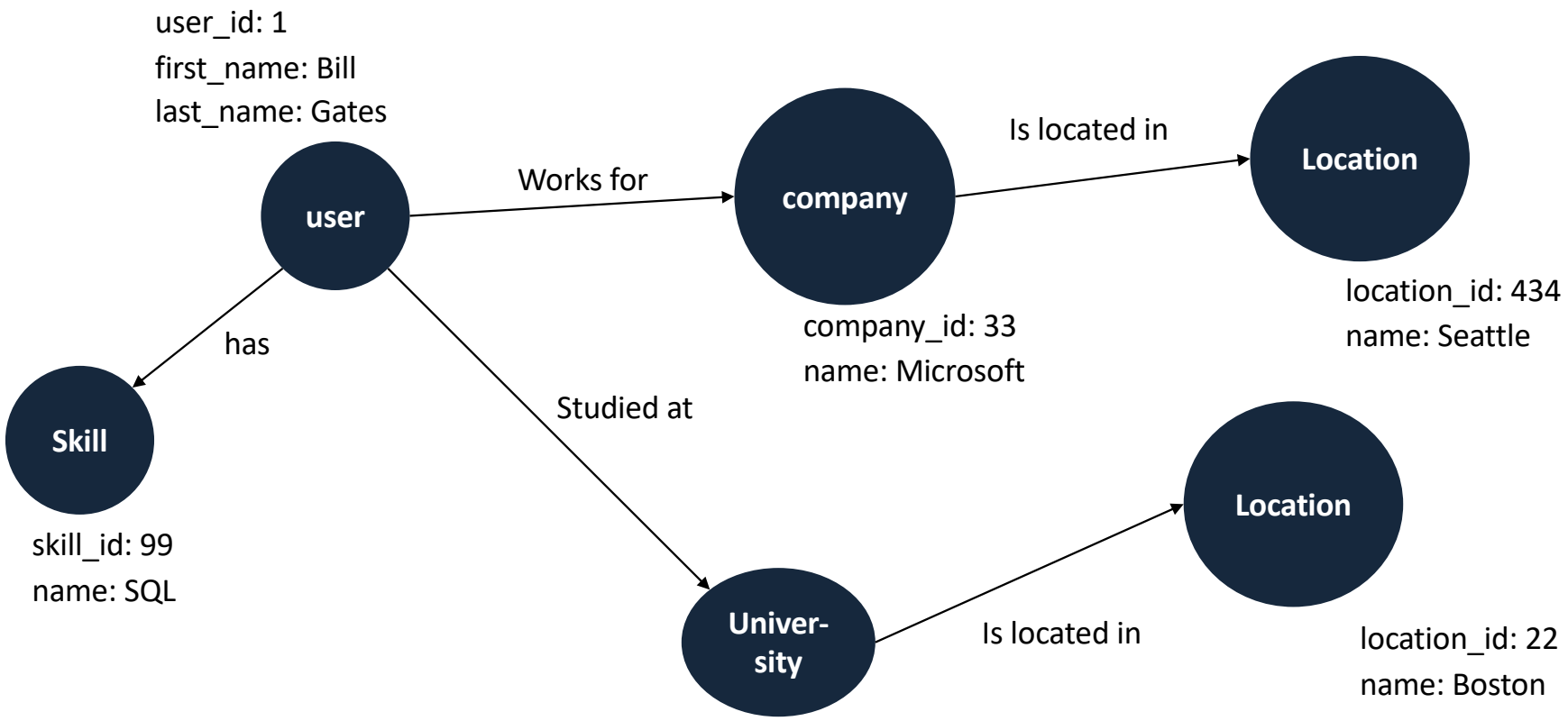
id	name	city	Email	...
1	Wang	Beijing	wang@...	...
...	...	...	...	...
55	Smith	New York	smith@	...

Relational Data Model

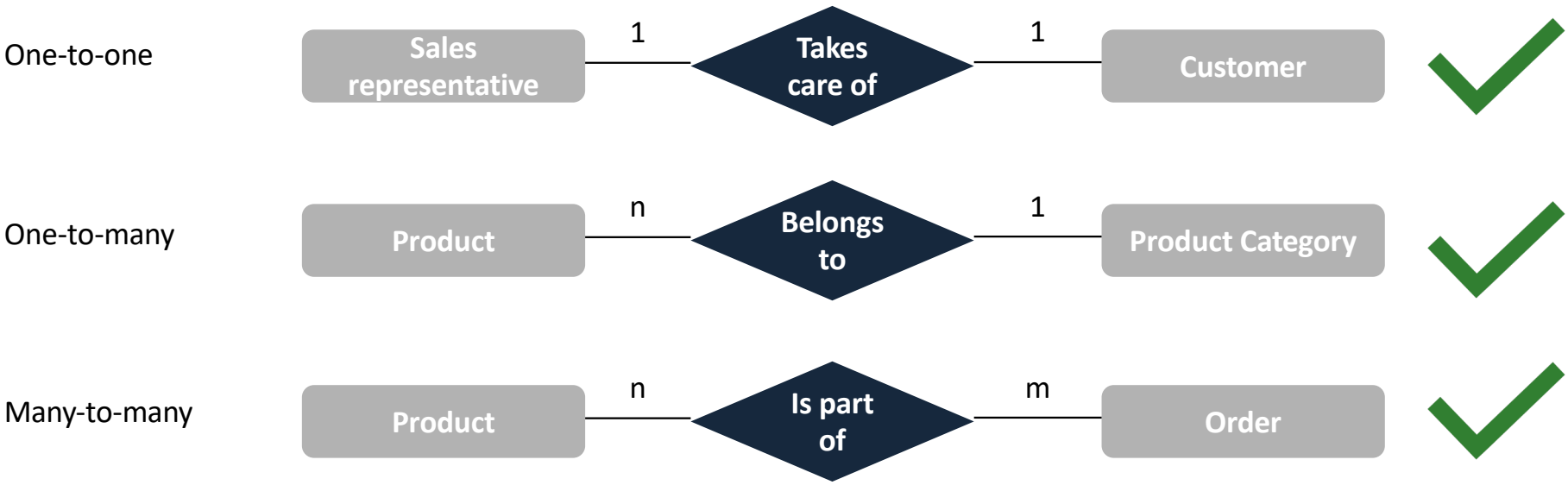
Network Database Model Emerged From Hierarchical Database Model



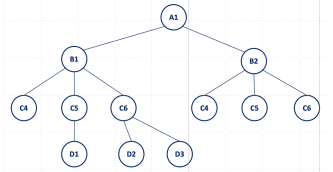
Network Database Model Emerged From Hierarchical Database Model



Network Data Model Can Handle All Three Relations

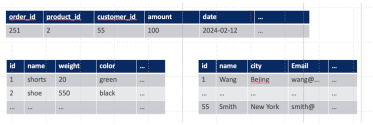


Conceptiual Data Models



Hierarchical Data Model

Network Data Model



Relational Data Model

Relational Database Model

Order Table

order_id	product_id	customer_id	amount	date	…
251	2	55	100	2024-02-12	…

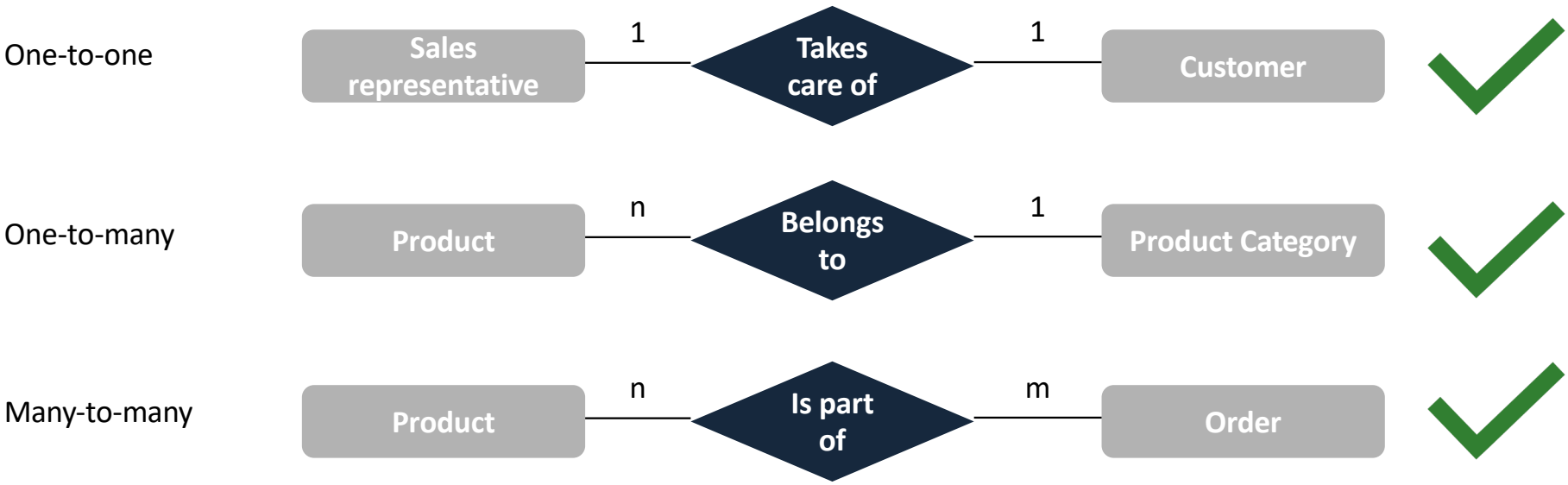
Product Table

id	name	weight	color	…
1	shorts	20	green	…
2	shoe	550	black	…
…	…	…		…

Customer Table

id	name	city	Email	…
1	Wang	Bejing	wang@...	…
…	…	…	…	…
55	Smith	New York	smith@	…

Many-to-many Relationships Can Not Be Handled Well with Hierarchical Data Models



Agenda

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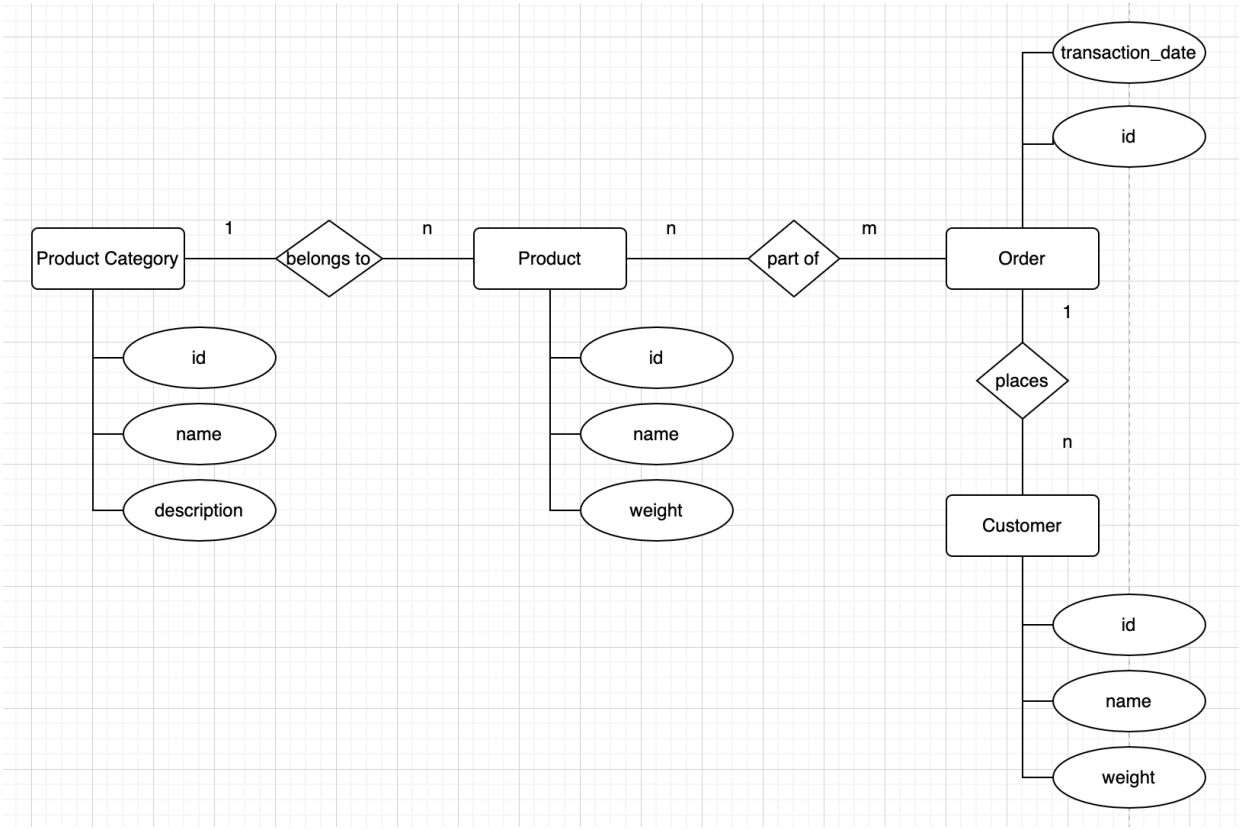
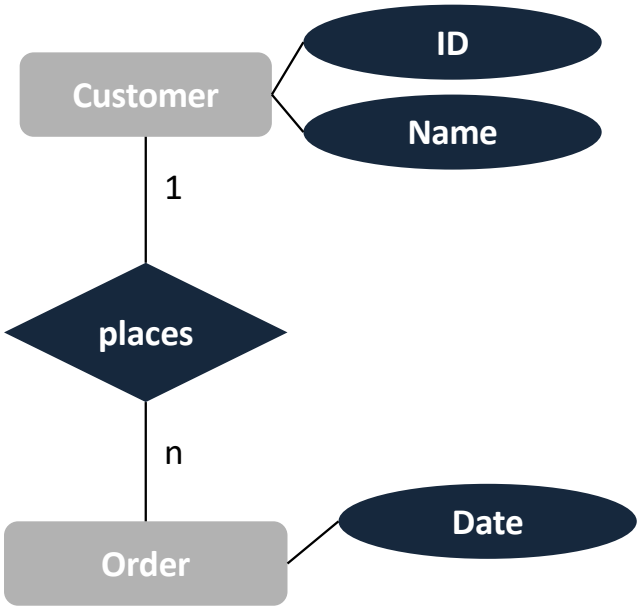
Data Science

The Entity-relationship Approach Is an Example for a Conceptual Data Model

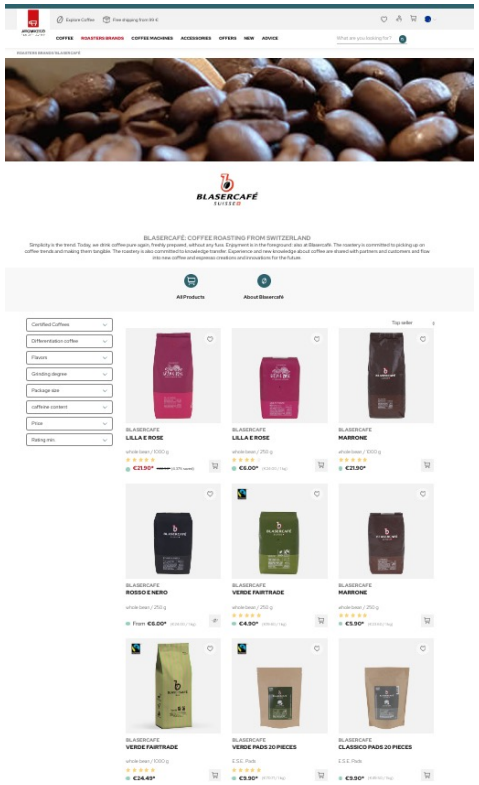


The Entity-relationship Approach Is an Example for a Conceptual Data Model

- E/R diagrams allow to visualize an organization's data elements as well as the relationships between them
- **Rectangles** identify **entities** about which the organization collects data
- **Diamonds** enclose and name **relationships** between entities
- **Lines** connecting entities to the diamond show whether the relationship is exclusive or not (cardinality)
- **Ellipses** show **attributes** of entities and relationships



An Entity Is a Real-world Class of Things Such as Product or Customer

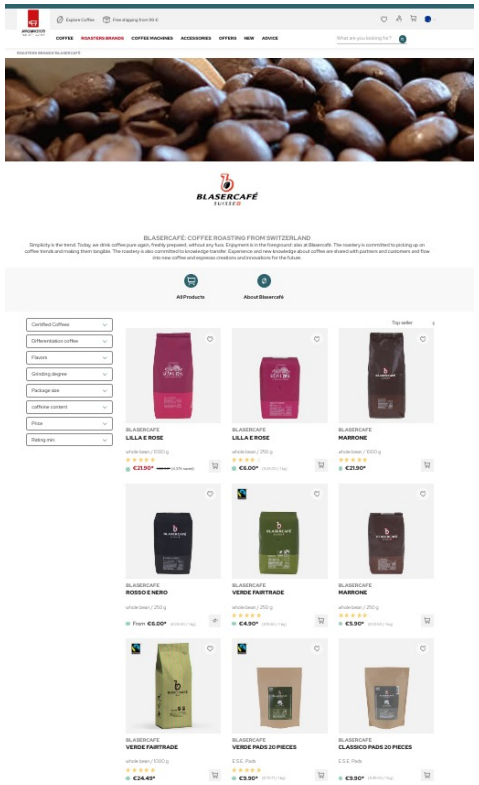


Product

Customer

Order

What Are the Entities in This Diagram?



Product

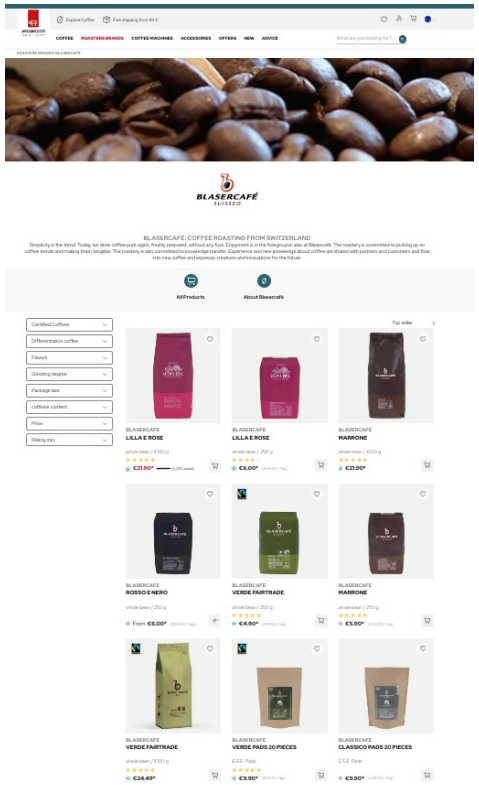
- ID
- Name
- Description

ID	Name	Description
...	...	...

Customer

Order

What Are the Entities in This Diagram?



Product

Customer

Order

ID

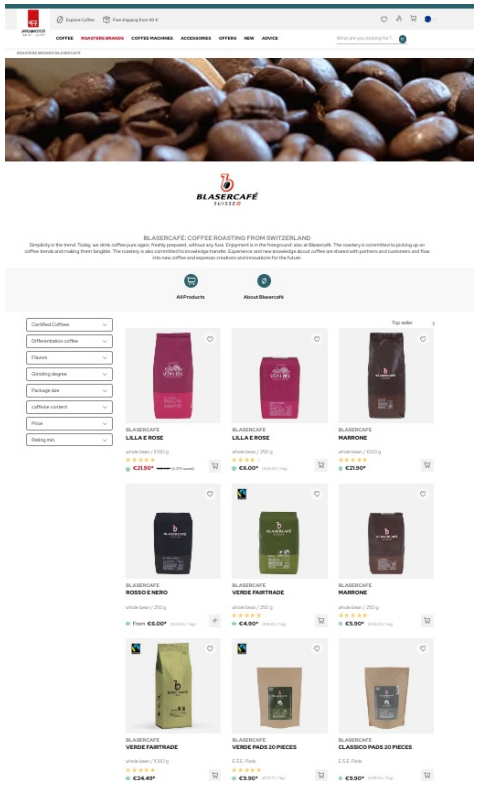
Name

City

Email

ID	Name	City	Email
...	...	...	...

Attributes Typically Correspond to Columns



Product

Customer

Order

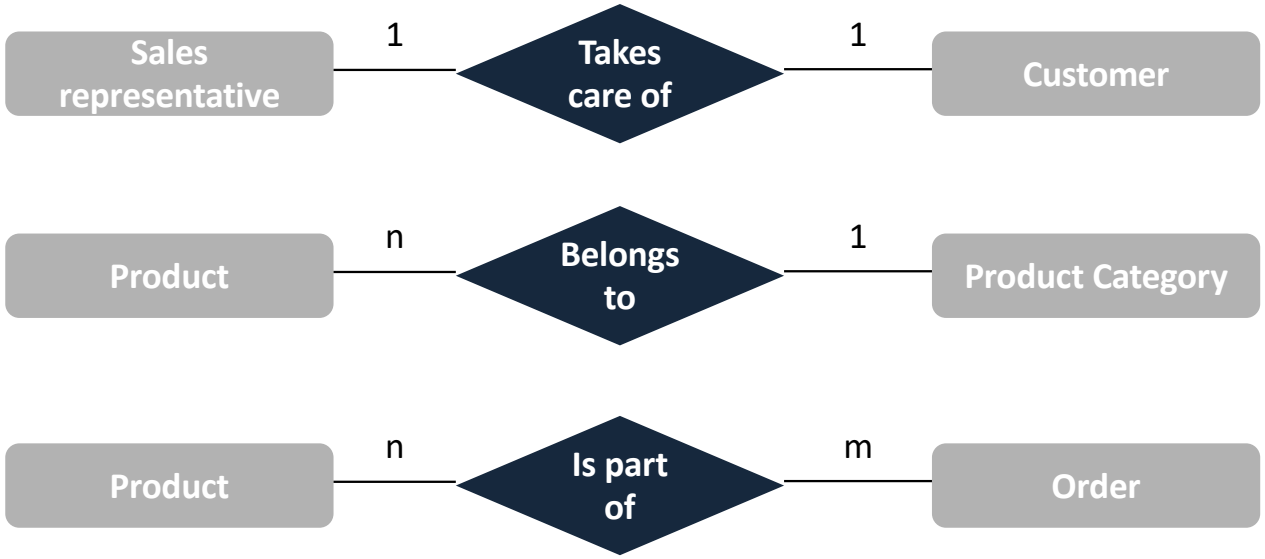
ID

Date

Amount

ID	Date	Amount
...	...	...

Types of Relations - Cardinalities



Types of Relations - Cardinalities

ID	Last Name	…
1	Manson	…
2	Kim	…
3	Johnson	…

ID	Last Name	Sales Rep.	…
1	Muram	3	…
2	Jameson	2	…
…	….	….	…

Types of Relations - Cardinalities

ID	Name	Category	…
1	Harmony	2	…
2	New York	1	…
3	Jamaican	3	…
…	…	…	…

ID	Name	…
1	Standard	…
2	Premium	…
3	Luxury	…
…	…	…

Types of Relations – Cardinalities N:m

ID	Name	Category	…
1	Harmony	2	…
2	New York	1	…
3	Jamaican	3	…
…	…	…	…

ID	Date	Amount	Products
1	2023-11-01	150	[1, 3]
2	2023-06-15	200	[4, 6]
3	2023-08-31	250	1
…	…	…	…

Types of Relations – Cardinalities N:m

Product Table

ID	Name	Category	…
1	Harmony	2	…
2	New York	1	…
3	Jamaican	3	…
…	…	…	…

Order Table

ID	Date	Amount
1	2023-11-01	150
2	2023-06-15	200
3	2023-08-31	250
…	…	…

Types of Relations – Cardinalities N:m

Product Table

ID	Name	Category	…
1	Harmony	2	…
2	New York	1	…
3	Jamaican	3	…
…	…	…	…

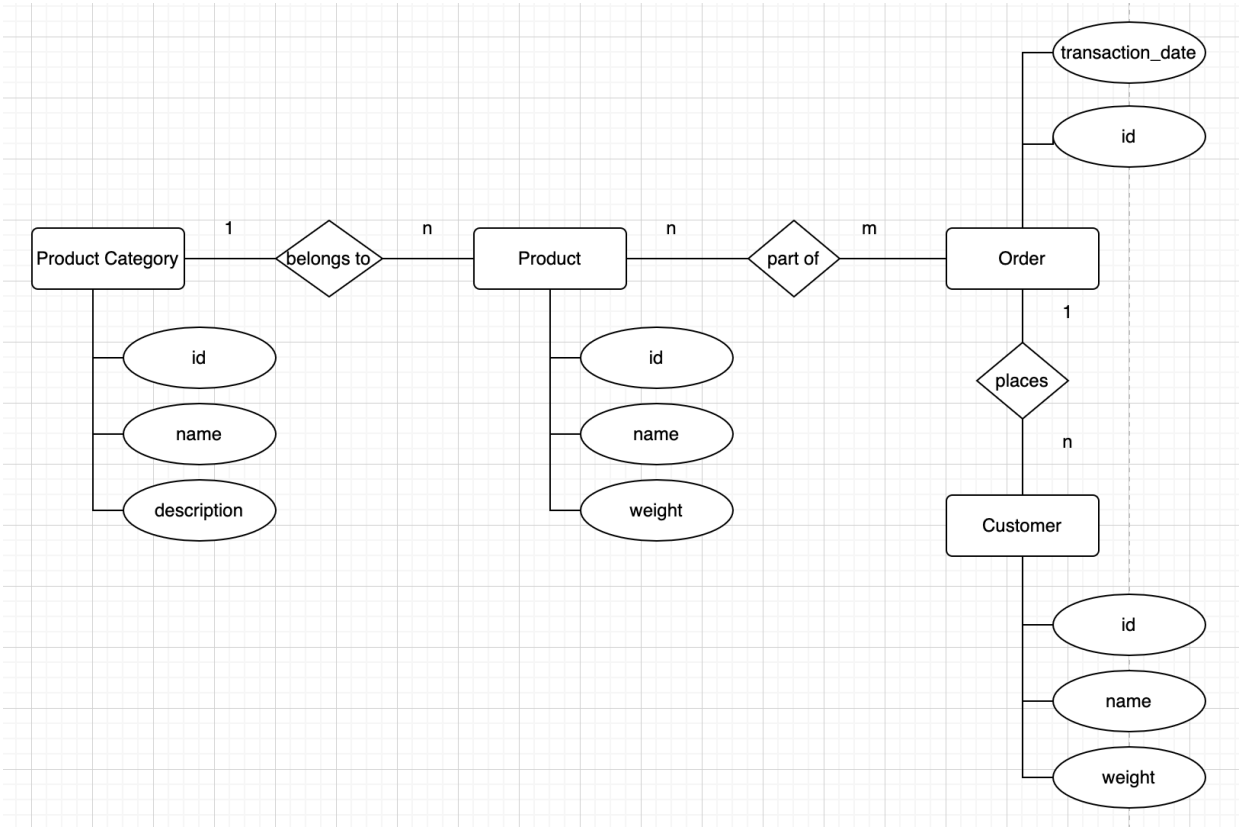
Order Lines Table

ID	OrderID	ProductID	Kg
1	1	1	10
2	1	2	20
3	1	5	2
…	…	…	

Order Table

ID	Date	Amount
1	2023-11-01	150
2	2023-06-15	200
3	2023-08-31	250
…	…	…

There Is One Error in This Diagram Š



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Data Science

Case 1: Reverse Engineer a Database Model

You are provided with five xlsx / csv files:

- customesr.xlsx / customers.csv
- products.xlsx / customers.csv
- order_items.xlsx / order_items.csv
- sales_orders.xlsx / orders.csv
- products.xlsx / products.csv

Your task is to build an Entity-Relationship Model:

1. Identify the entities which need to be included
2. Identify the primary and foreign keys which can be used to link the tables
3. Identify the type of cardinality between the entities
4. Add the attributes to each entity

A Comment on Real World Products Keys

Key	value
GTIN*	4005900933034
DM-Article	710736
Amazon-Article	B09XF4T5V8

*Global Trade Item Number

Generating Unique Keys with Universally Unique Identifier (uuid)

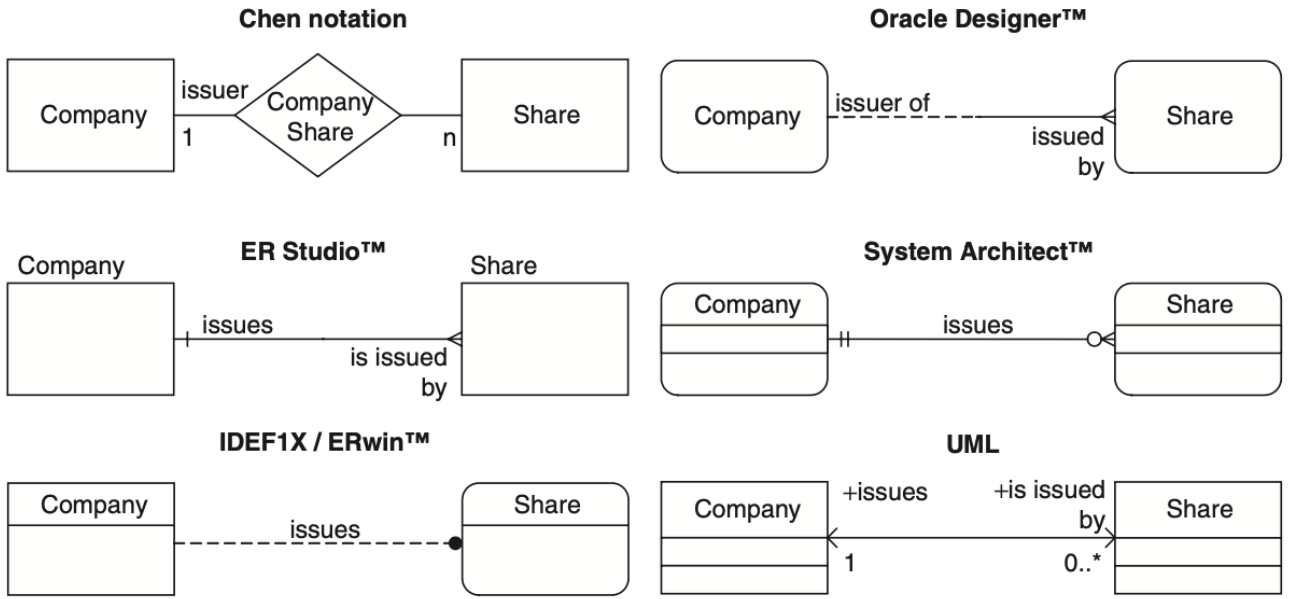
Example UUID: `13806bf6-1541-479c-94ed-ba0fd2bb05f5`

Online-Generator: https://www.uuidgenerator.net/

Python:

```
import uuid
uuid.uuid4()
```

Examples for Other Types of Notations



- Simsion & Witt, p. 83.

The Logical Data Model Also Defines the Types of Data in Each Table

Product table

name	type
id	integer
name	text
description	text
weight	float
price	float
categoryI_id	integer

Category table

name	type
id	integer
name	text
description	text

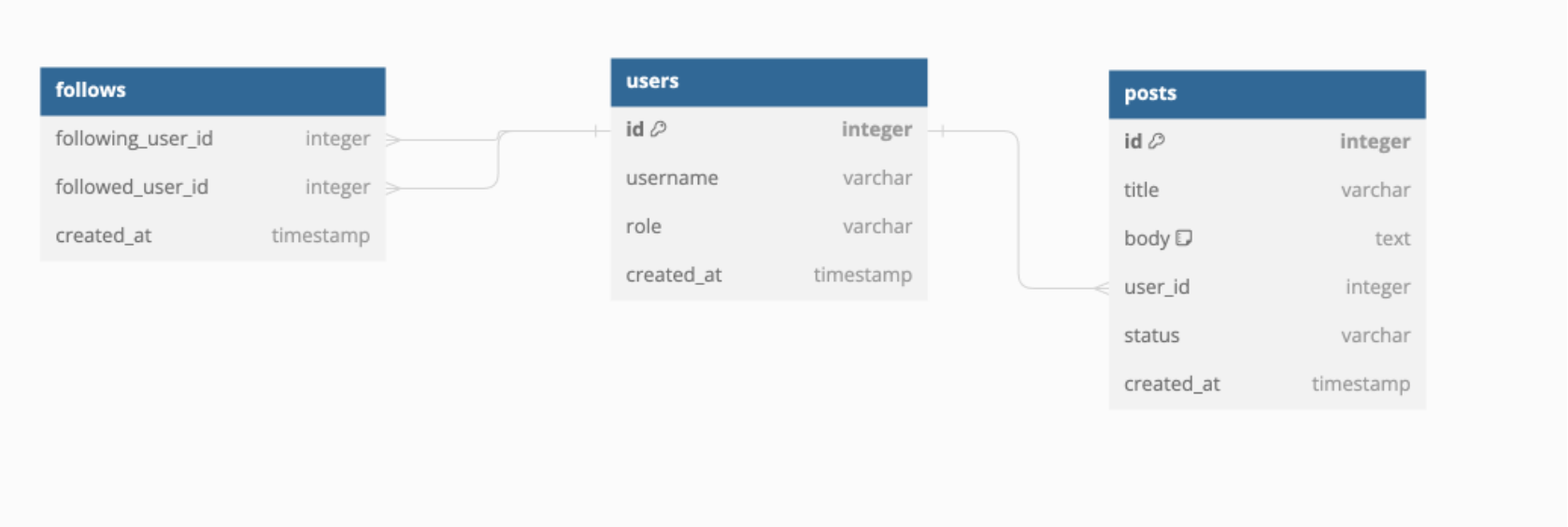
Primary Key

Foreign Key

Case 1: Reverse Engineer a Database Model

Please highlight the primary and secondary key in your database model

Tools – for the Building a Logical Data Model - DBdiagram



https://dbdiagram.io

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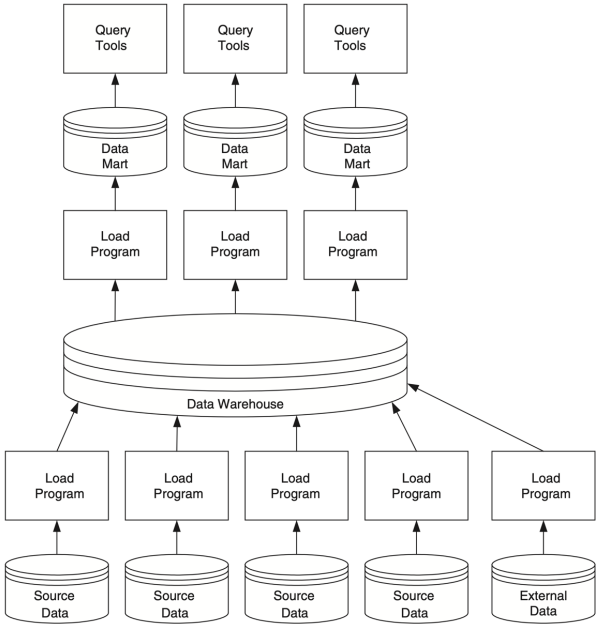
Data Science

Data Warehouses and Data Marts



Simsion & Witt, p. 474

Key Features of data marts

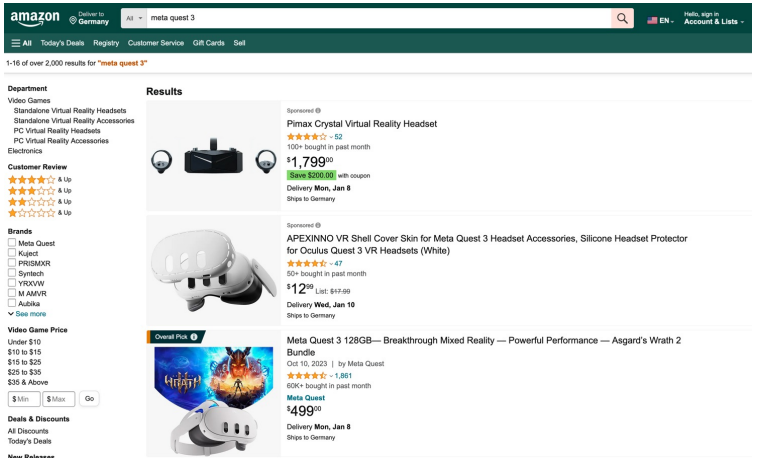
- Present data in a form that it is understandable for people in business functions
- Often structured by business domain, e.g., sales, procurement, logistics, finance
- Common data structure for Tableau, PowerBI or Qlik reporting (dashboards)
- Two common data modeling schemas:
  - **star schema**
  - **snowflake schema**

Star and a Snowflake Schemas Consist of Two Types of Tables:

- Fact Tables
- Dimension Tables

A Fact Tables Consist of Measurements, Metrics or Facts of a Business Process, E.g., Sales Transactions

- Fact Tables
- Dimension Tables



#	Date	Amount	Product	Customer	…
06B5278A-…	2024-02-23	499.99	B0C8VKH1ZH	5CD779AB-…	….
…	….	….	….	….	….

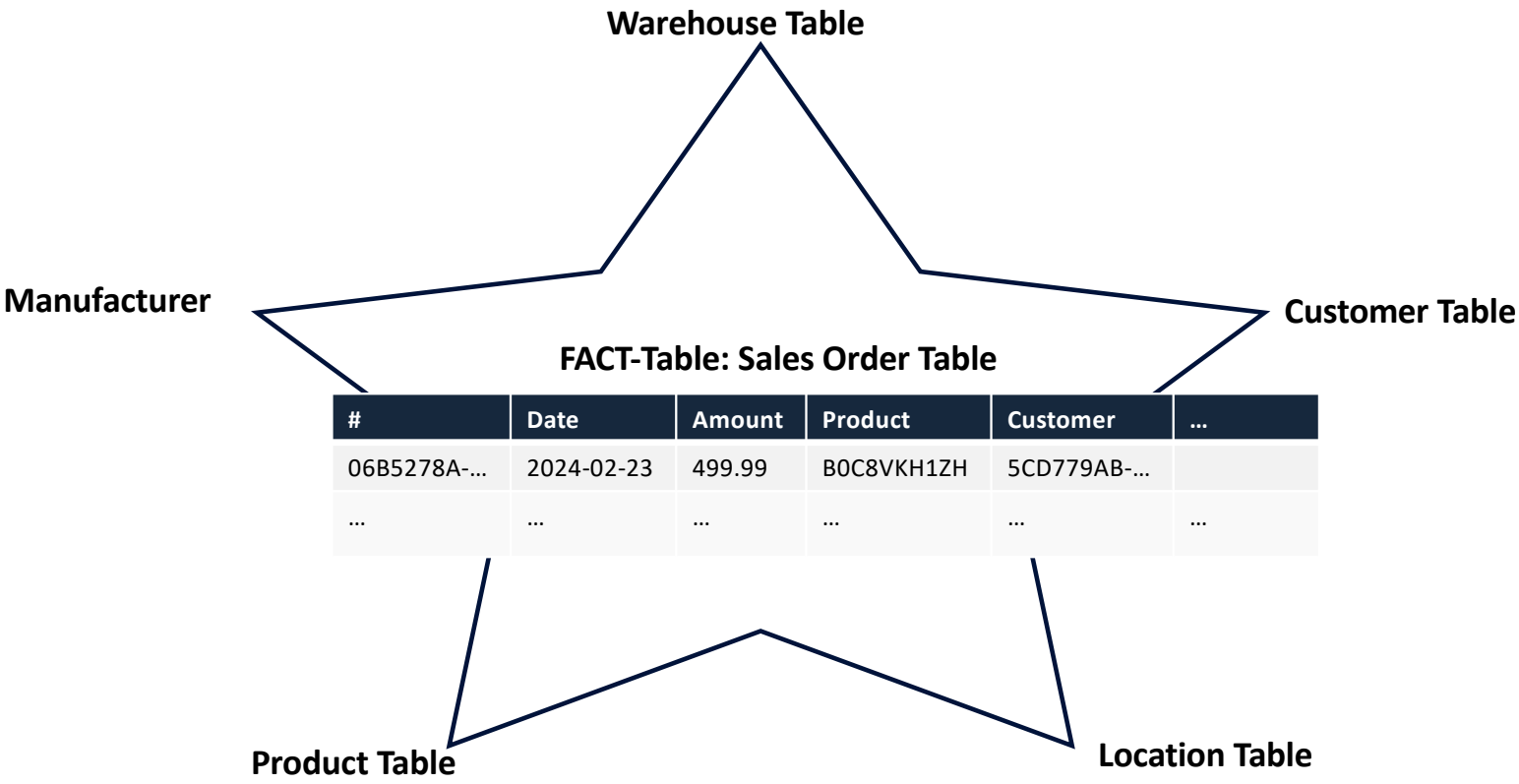
A Fact Tables Consist of Measurements, Metrics or Facts of a Business Process, E.g., Sales Transactions

- Fact Tables
- Dimension Tables

Manufacturer ID	Name	City	Postal Code	Contact	…
0CF1EA9C-…	Meta	…	…		

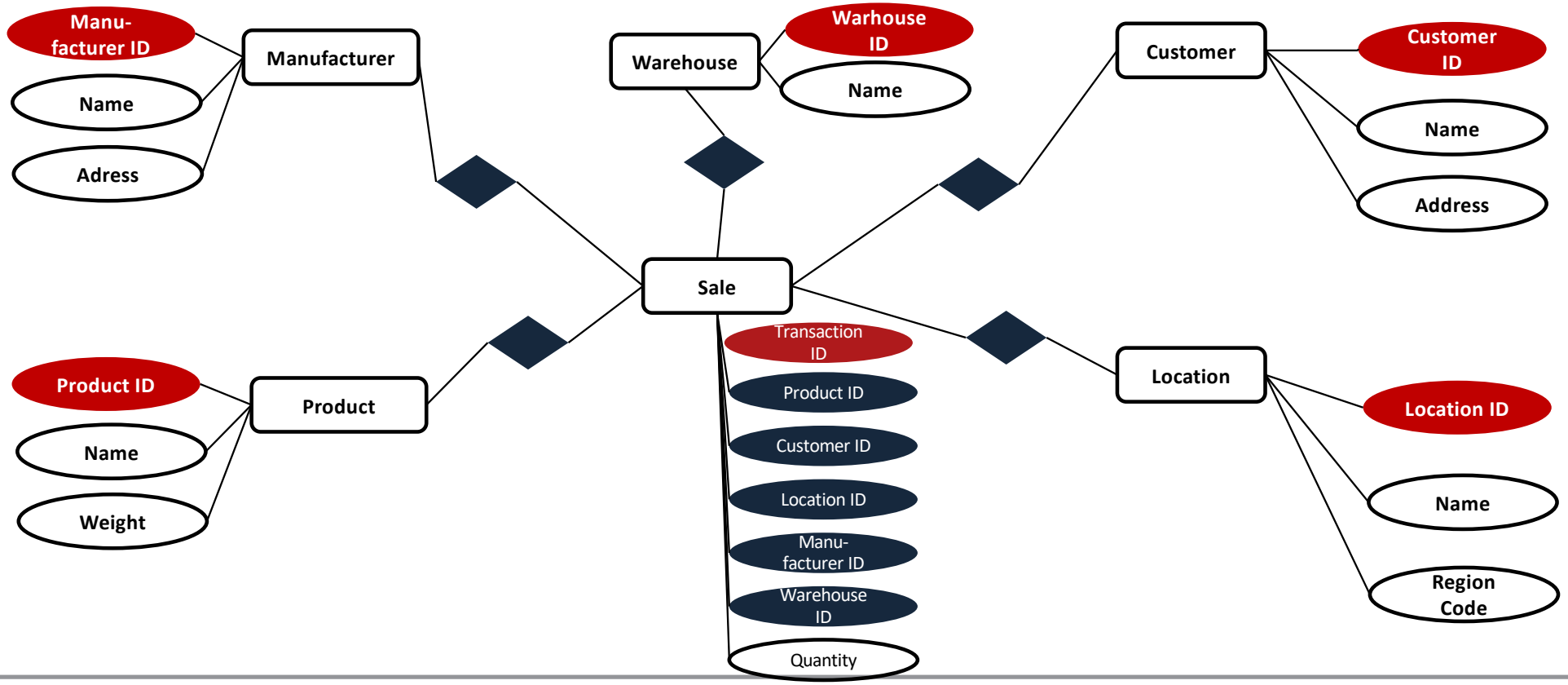
Customer ID	Name	City	Postal Code	Contact	…
7Xq1DP13-…	Wang	…	…		

Star-schema



#	Date	Amount	Product	Customer	…
06B5278A-…	2024-02-23	499.99	B0C8VKH1ZH	5CD779AB-…	
…	…	…	…	…	…

Star-schema


Manu-facturer ID
Name
Adress
Manufacturer
Warehouse
Warhouse ID
Name
Customer
Customer ID
Name
Address
Sale
Transaction ID
Product ID
Customer ID
Location ID
Manu-facturer ID
Warehouse ID
Quantity
Product ID
Name
Weight
Product
Location
Location ID
Name
Region Code

Summary Star-schema

- Common data modeling approach for Data-Marts, organize data in a way that it can be understood by people form the business functions
- Common approach for data models behind dashboard (e.g., PowerBI, Tableau, Qlik)
- Fact table is surrounded by several dimensions table
- Only one fact table can be part of the star schema
- True star schema only supports on level of dimension

Product Table in a Star-schema

Columns
Product Key
Product Description
Category Name
Brand Name
Storage Type
Package Type
Shelf Lifetime
Weight

Snowflaked Product Dimensions

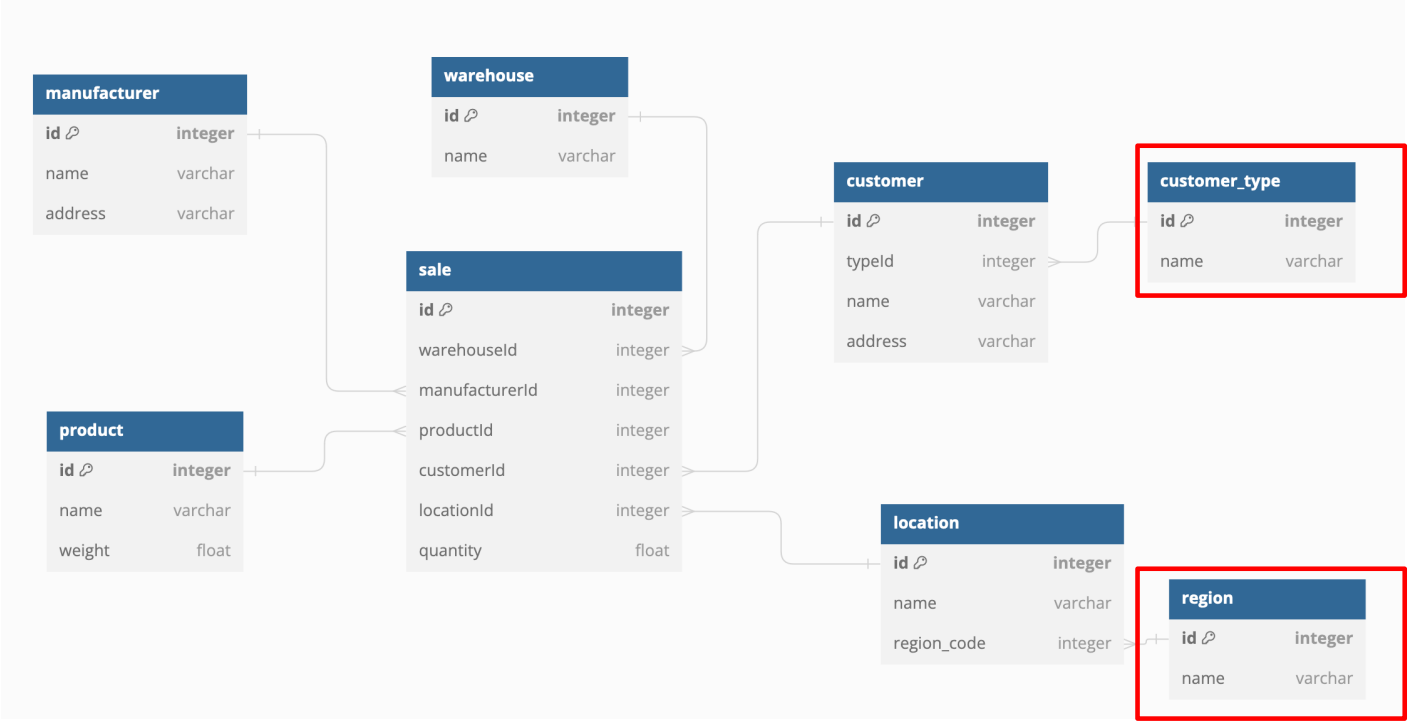
Product Table
Product Key
Product Description
Brand Key
….
Shelf Key

Brand Table
Brand Key
Brand Name
Category Key

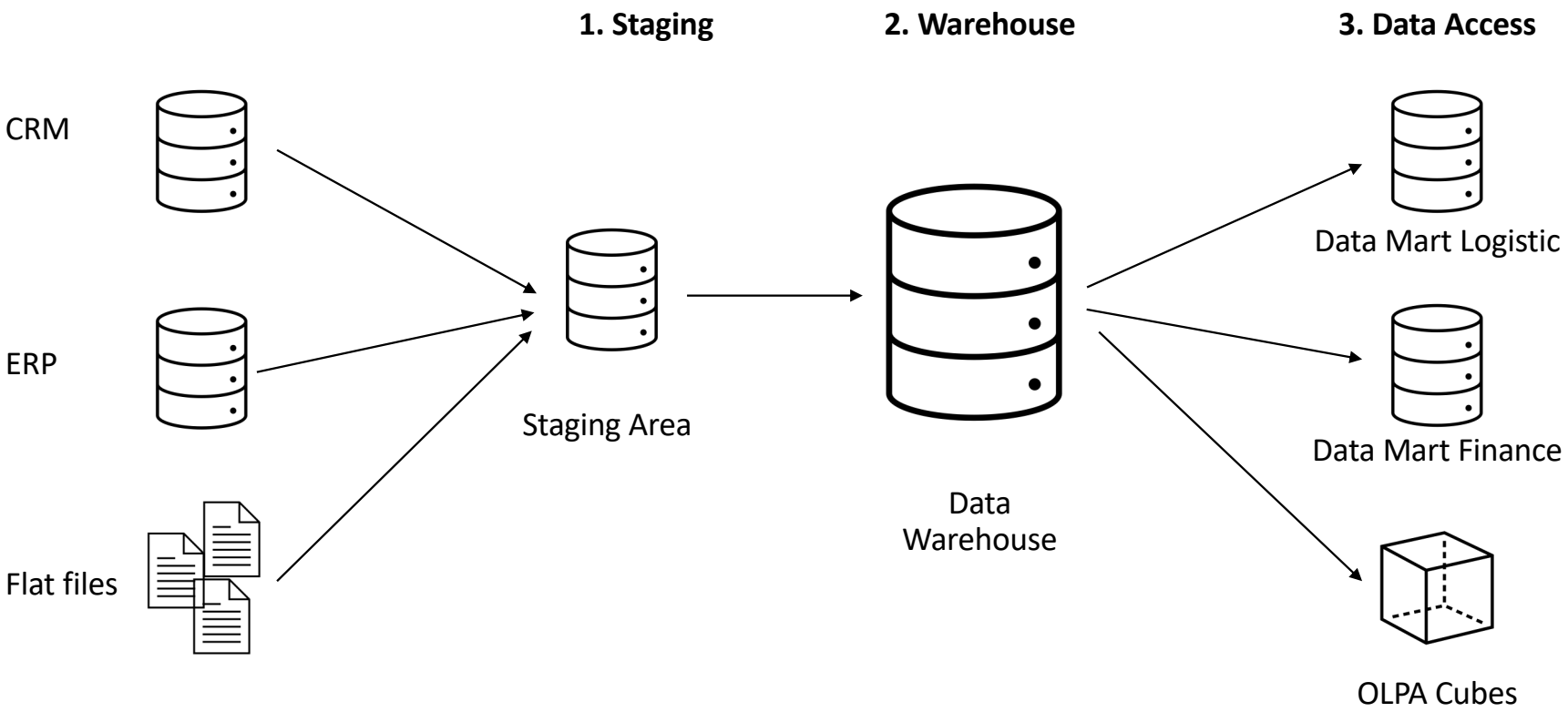
Category Table
Category Key
Category Name
Category Description

Shelf Lifetime Table
Shelf Key
Name
Lifetime

Snowflaked Product Dimensions



Typical 3-layer Architecture



Source: Abramson, I. Data Warehouse: The Choice of Inmon vs. Kimball. IAS Inc.

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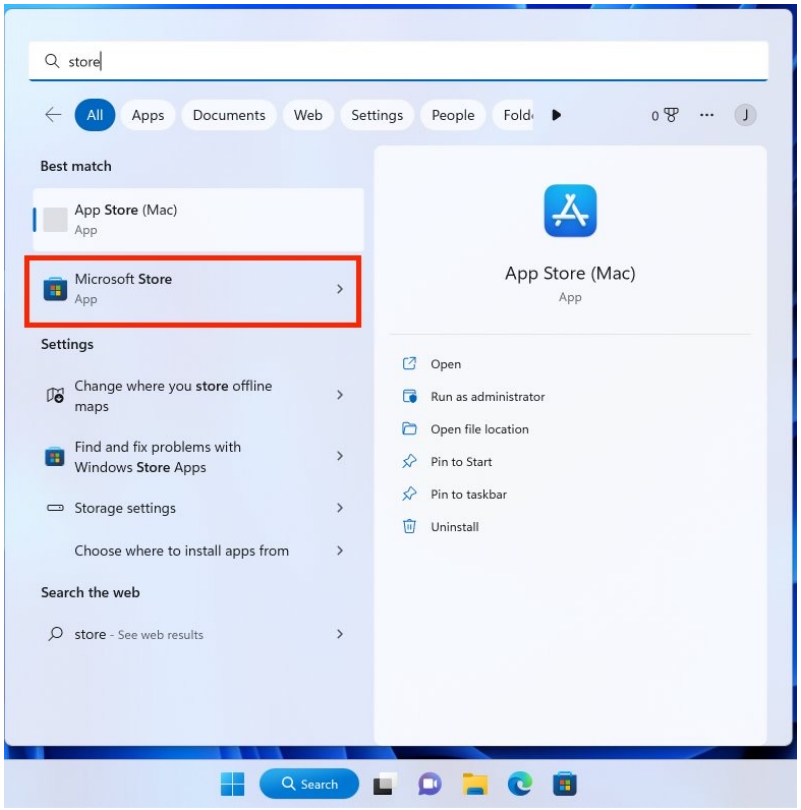
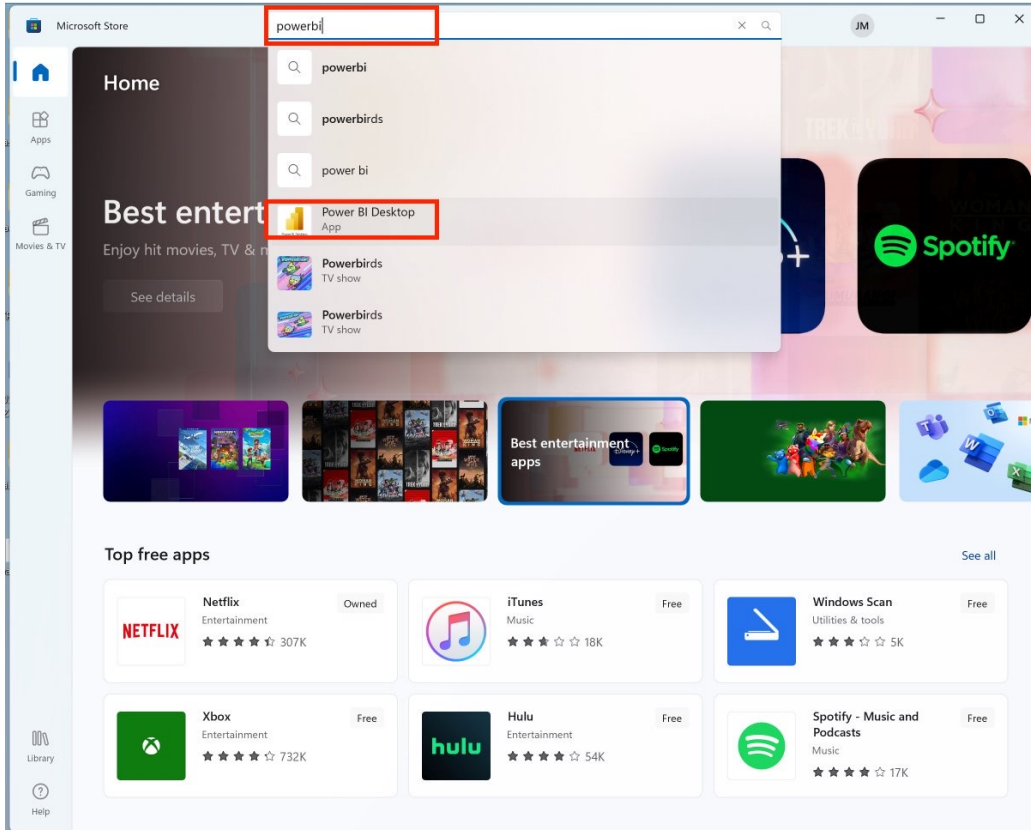
Data Science

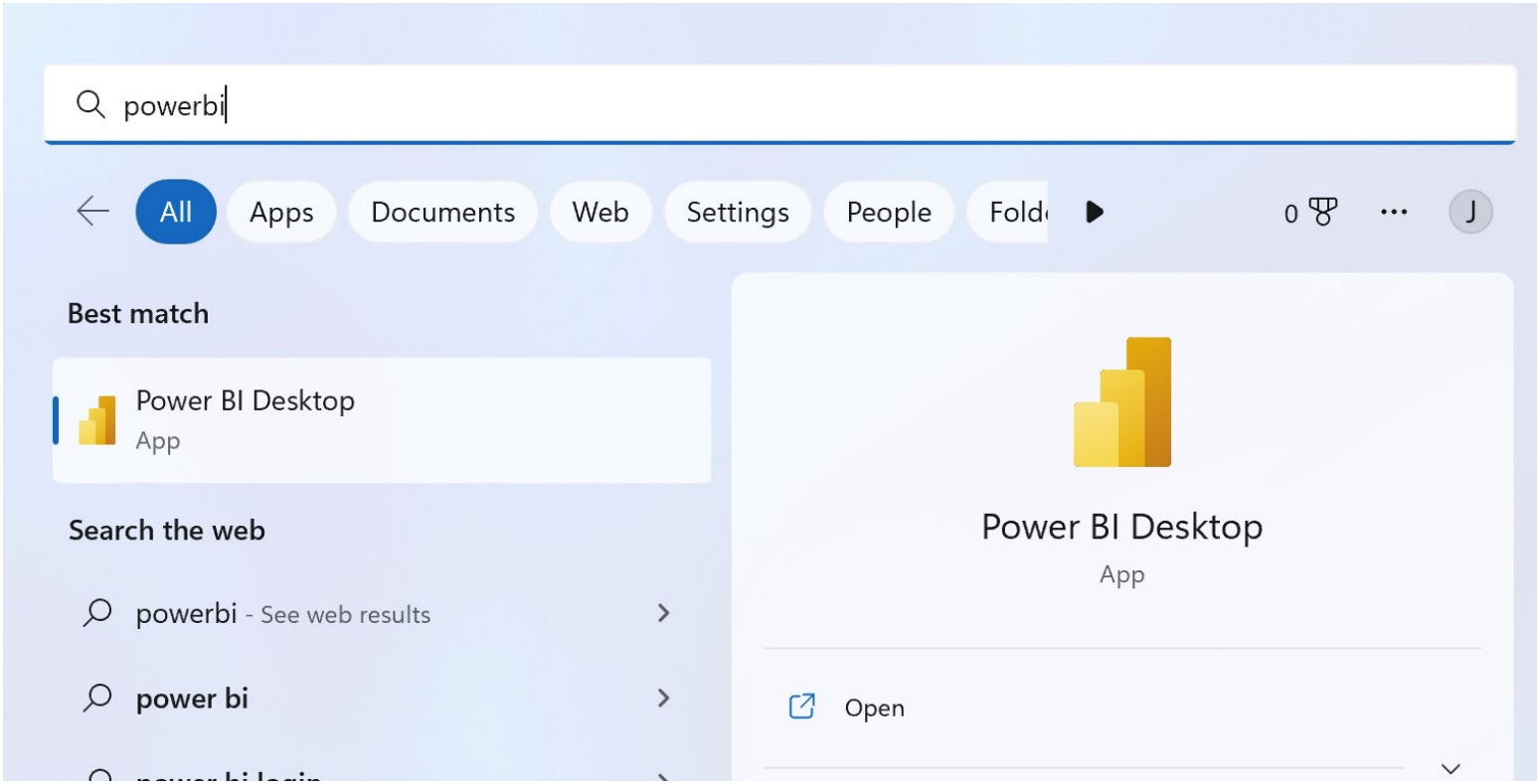
Installation (1): Open Microsoft Store



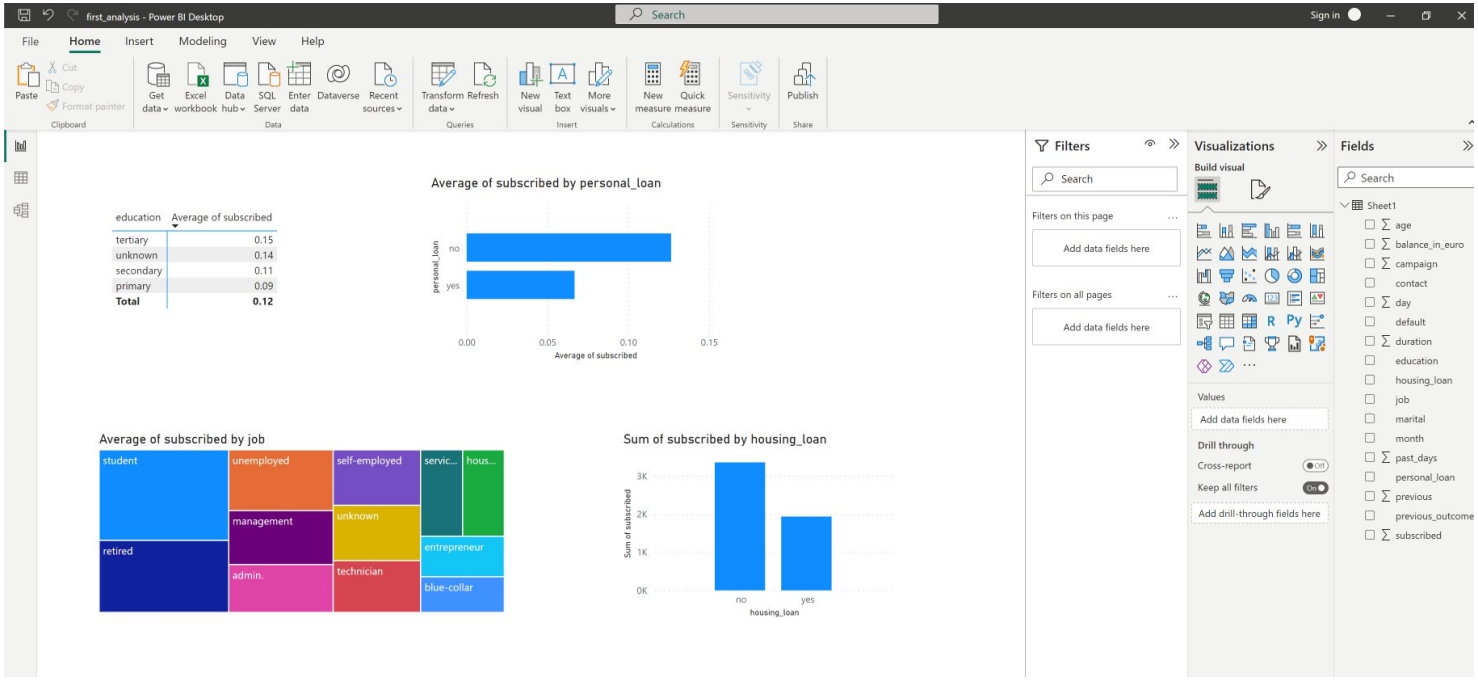
Installation (2): Search for “powerbi Desktop”



Installation (3): Verify Installation

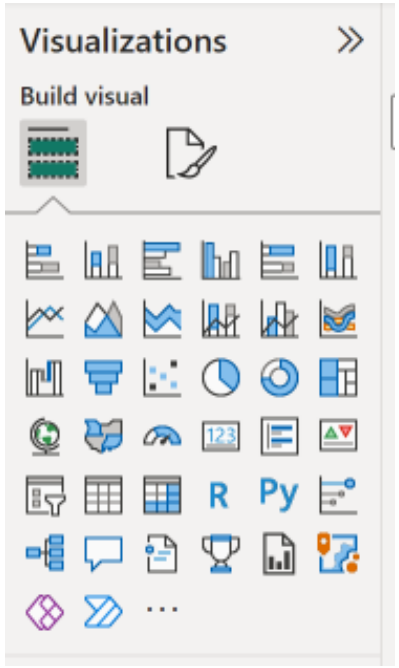


Creating Visuals



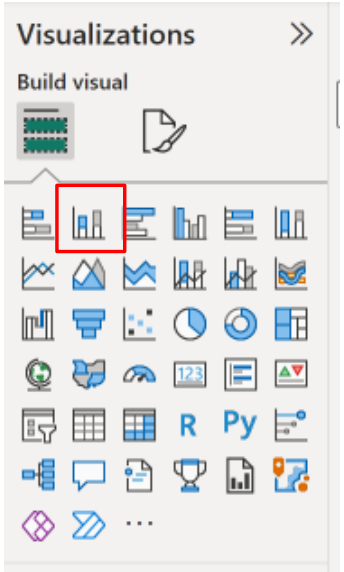
Creating Visuals

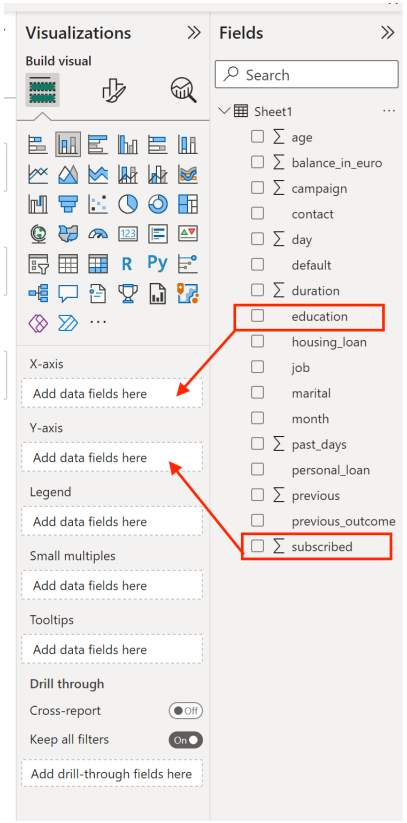
- Power BI has several types of visuals integrated
- The market place offers further visuals



Creating Visuals – Stacked Column Chart

1 Select stacked column chart

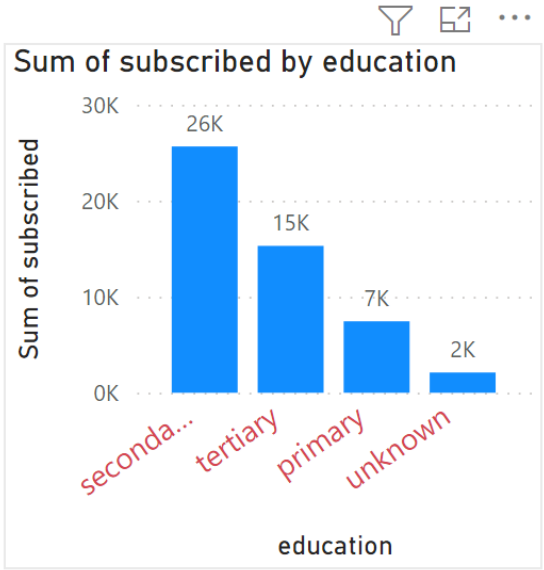


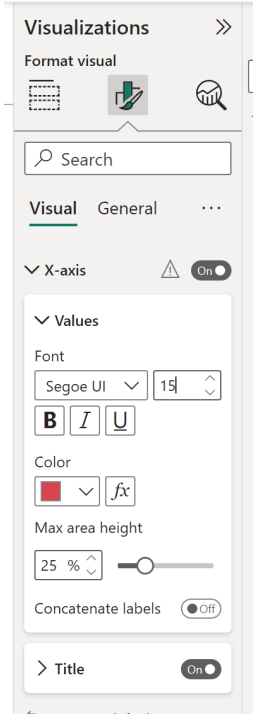


2 Drag & Drop education on x-axis

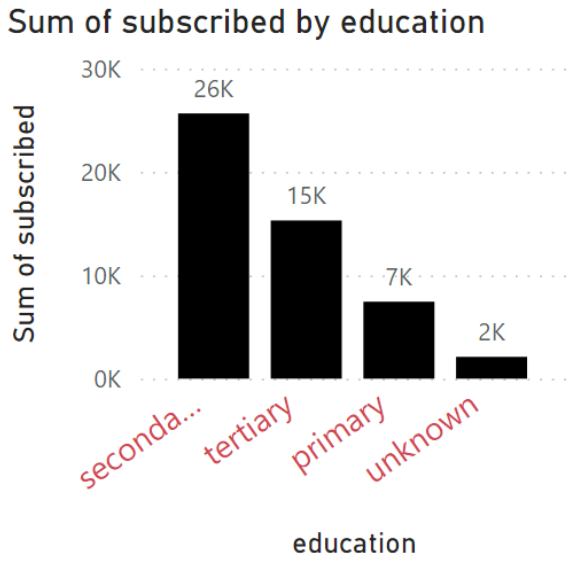
3 Drag & Drop subscribed on y-axis

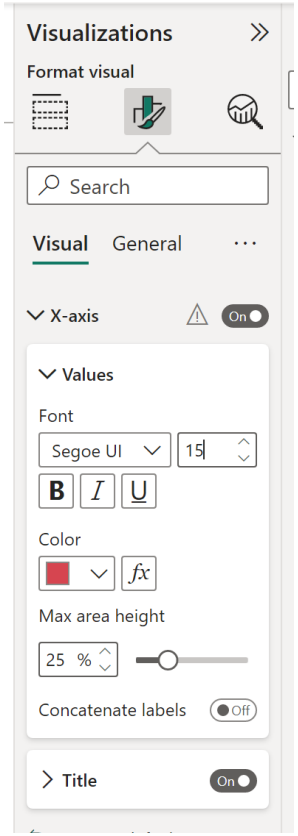
Creating Visuals – Stacked Column Chart



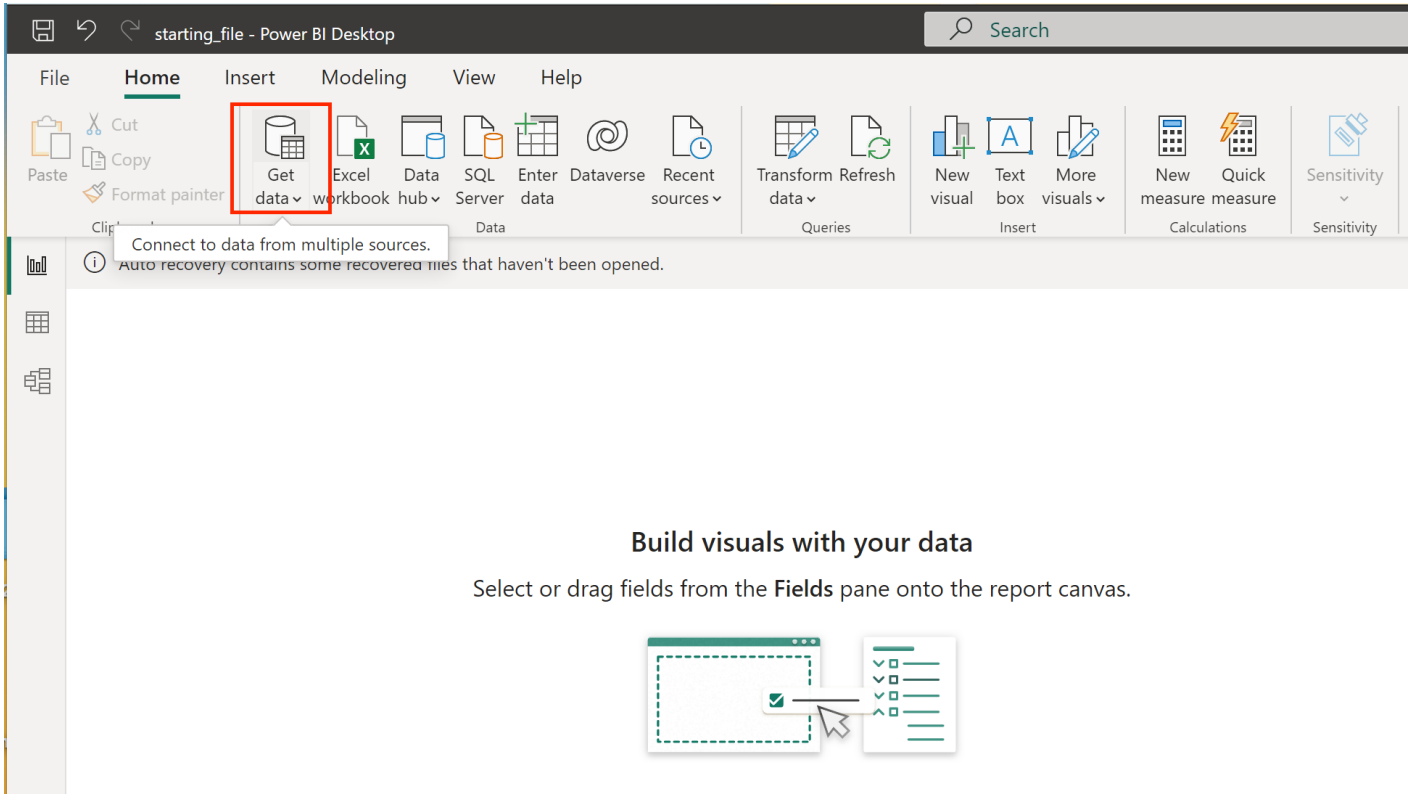


Creating Visuals – Stacked Column Chart

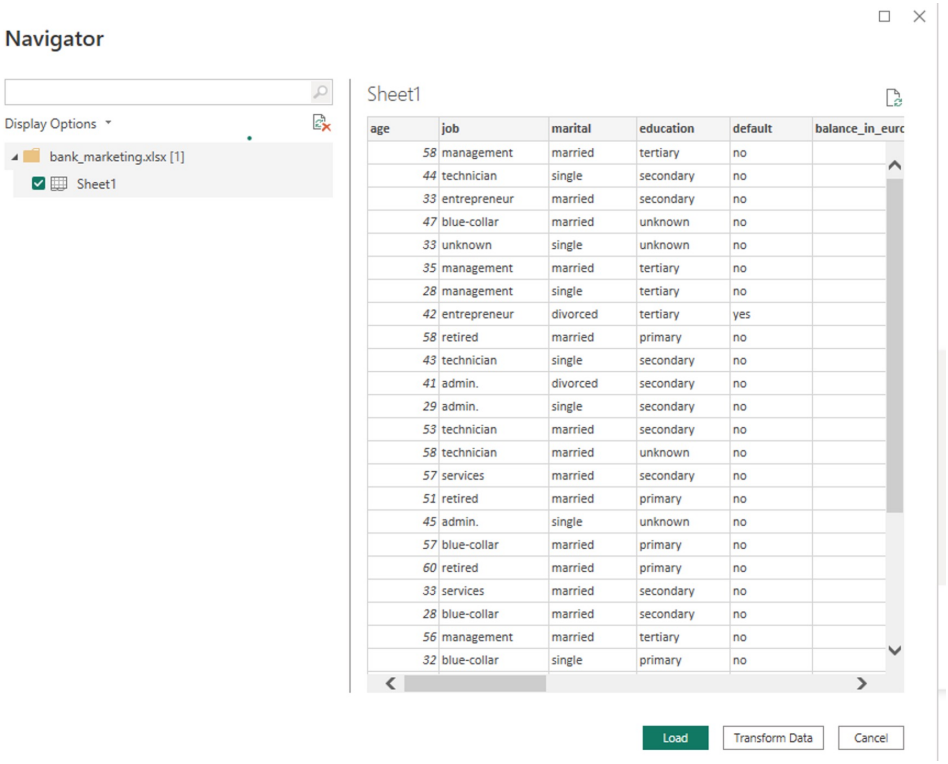




Loading Data

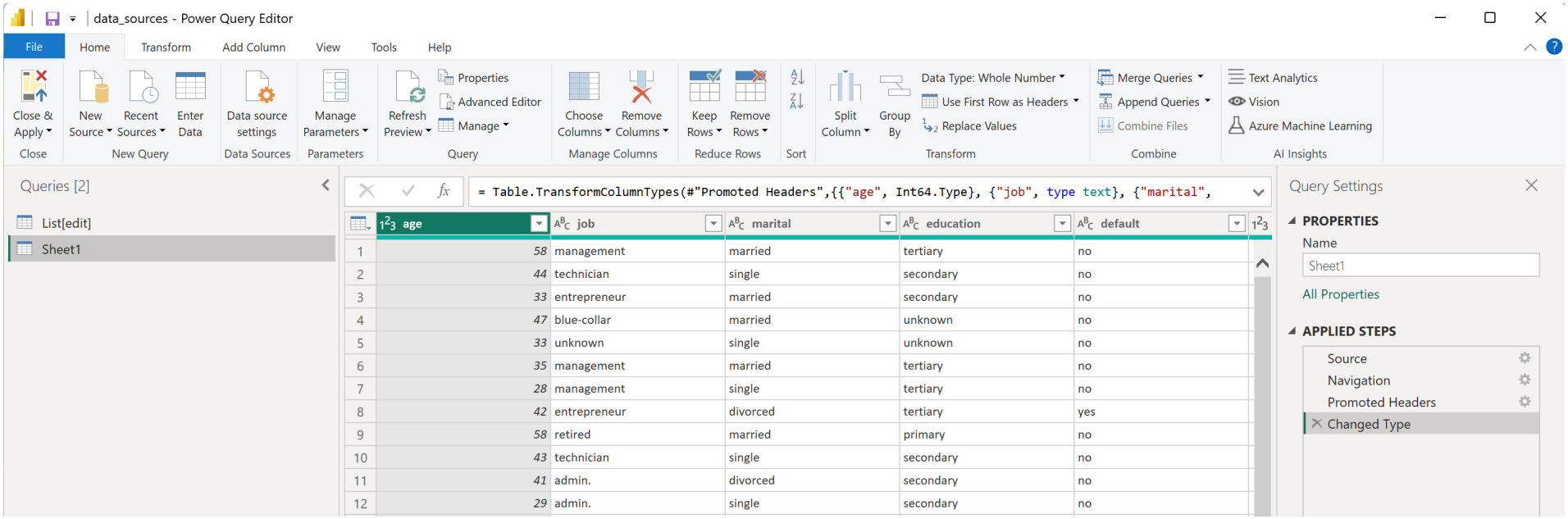


Loading Data – Ms Excel File



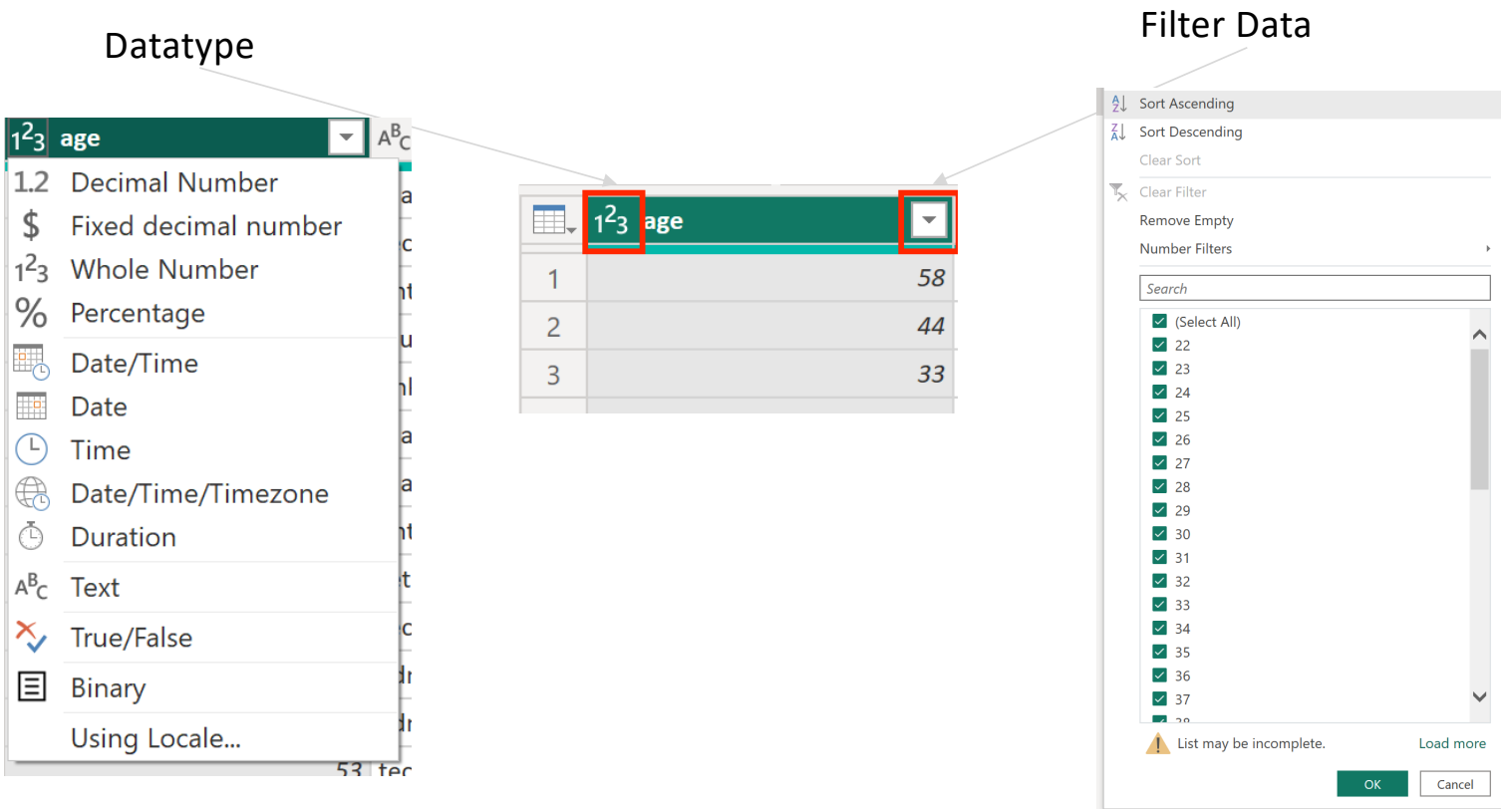
age	job	marital	education	default	balance_in_eurc
58	management	married	tertiary	no	
44	technician	single	secondary	no	
33	entrepreneur	married	secondary	no	
47	blue-collar	married	unknown	no	
33	unknown	single	unknown	no	
35	management	married	tertiary	no	
28	management	single	tertiary	no	
42	entrepreneur	divorced	tertiary	yes	
58	retired	married	primary	no	
43	technician	single	secondary	no	
41	admin.	divorced	secondary	no	
29	admin.	single	secondary	no	
53	technician	married	secondary	no	
58	technician	married	unknown	no	
57	services	married	secondary	no	
51	retired	married	primary	no	
45	admin.	single	unknown	no	
57	blue-collar	married	primary	no	
60	retired	married	primary	no	
33	services	married	secondary	no	
28	blue-collar	married	secondary	no	
56	management	married	tertiary	no	
32	blue-collar	single	primary	no	

Loading Data – Ms Excel File



	age	job	marital	education	default
1	58	management	married	tertiary	no
2	44	technician	single	secondary	no
3	33	entrepreneur	married	secondary	no
4	47	blue-collar	married	unknown	no
5	33	unknown	single	unknown	no
6	35	management	married	tertiary	no
7	28	management	single	tertiary	no
8	42	entrepreneur	divorced	tertiary	yes
9	58	retired	married	primary	no
10	43	technician	single	secondary	no
11	41	admin.	divorced	secondary	no
12	29	admin.	single	secondary	no

Loading Data – Ms Excel File



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Data Science

Case 2: Build a BI-report in Power Bi

You are tasked with building a Business Intelligence report for the Procurement Department of Rustic Roasters, a coffee trading company. The company is experiencing significant challenges with late purchase orders arriving at their warehouses. The Procurement Department wants to gain deeper insights into this issue and identify potential causes for these delays.

You have been provided with the following data files:

- customer.xlsx
- material.xslx
- logistics_partners.json
- procurement_transactions_part_A.xlsx
- procurement_transactions_part_B.xlsx
- supplier.xlsx
- Territory.xlsx
- warehouse.xlsx

Your report should leverage these datasets to analyze the current situation and support data-driven decision making for the Procurement Department.

Case 2: Build a BI-report in Power Bi – Task Part 2

- Many companies faced significant transport challenges during the COVID-19 pandemic. Did Rustic Roasters also experience similar issues? Please analyze the data to identify any pandemic-related disruptions.

- Additionally, there was a workers' strike in the past. Can you determine which warehouse(s) were affected by the strike?

Agenda

Business Analytics

Data Science

Classification vs. Regression

Prediction Models

Case 3: Building a Prediction Model for Purchase Order Delivery

Measuring the Quality of a Prediction Model

Feature Engineering

Explainable AI

Agenda

Business Analytics

Data Science

Classification vs. Regression

Prediction Models

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Explainable AI

Predictive Analytics - Target

Past:

Order	Confirmed Date	Delivered Date
#1	2024-06-14	2024-06-18
#2	2024-07-16	2024-07-25
#3	2024-07-14	2024-07-14

Present:

Order	Confirmed Date	Delivered Date
#1	2025-08-14	?
#2	2025-09-16	?
#3	2025-09-14	?

Models

- Linear and Logit Regression
- Decision Tree
- Random Forest
- Boosted Trees
- Neural Network

Classification Vs Regression

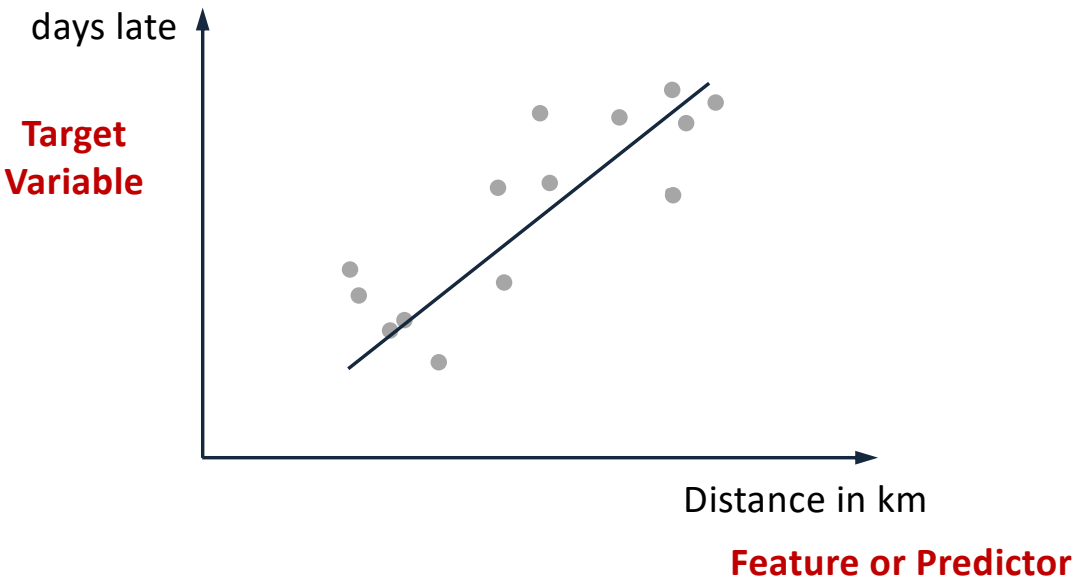
Present:

Order	Confirmed Date	Delivered Date	Late	Days late
#1	2025-06-14	?	?	?
#2	2025-07-16	?	?	?
#3	2025-07-14	?	?	?

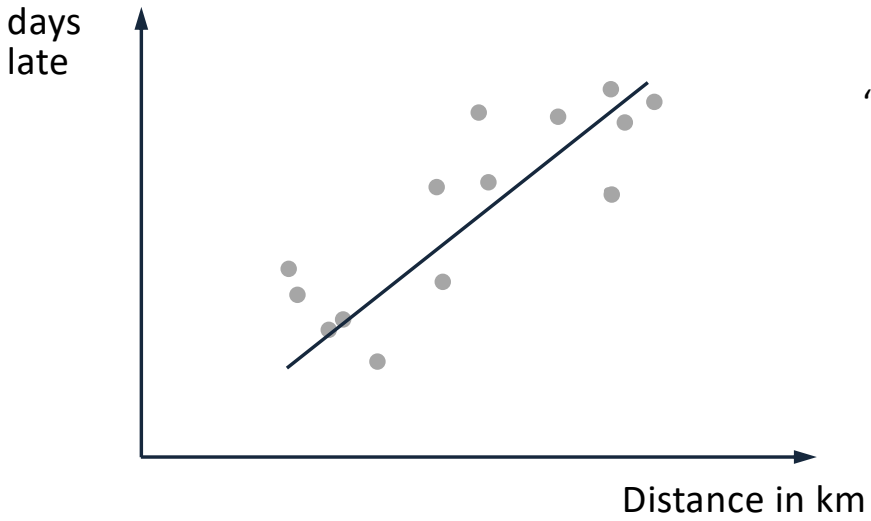
Which One Is a Classification Problem?

- Predict raw material consumption to optimize stocks
- Predict risk of suppliers going bankrupt
- Predict if a picture shows a t-shirt

Regression


days late
Target Variable
Distance in km
Feature or Predictor

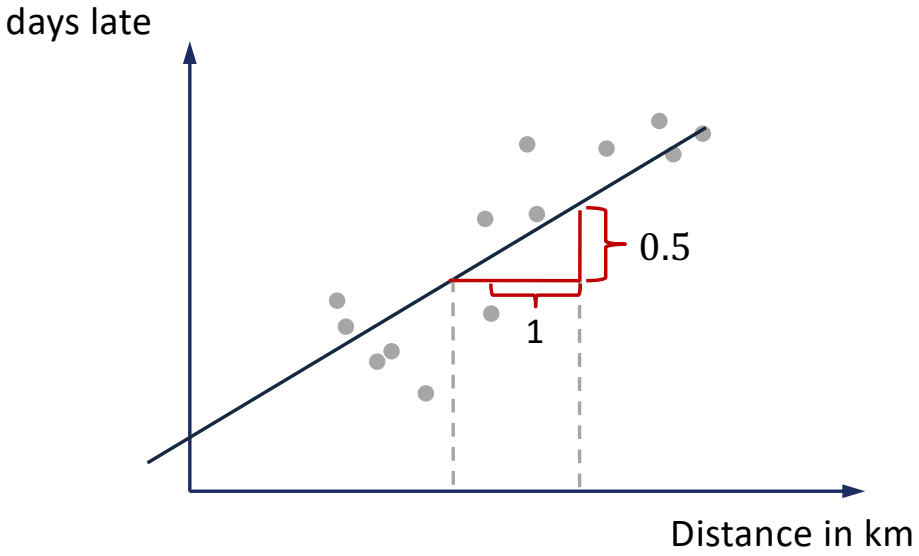
Example Regression Analysis



"Abstract Model": $y = \beta_0 + \beta_1 x$

Specific Model: $days\ late = \beta_0 + \beta_1 Distance\ in\ km$

Example Regression Analysis

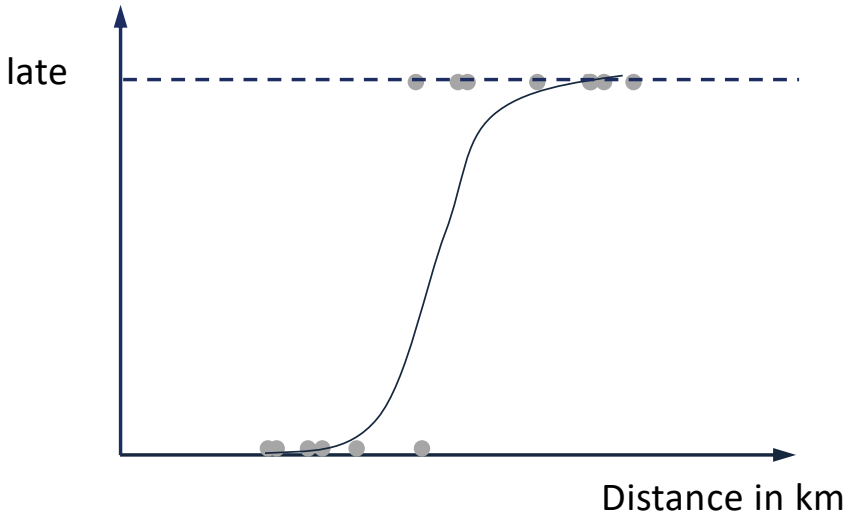


Specific Model with estimated parameters:

$$days\ late = 0.1 + 0.5\ Distance\ in\ km$$

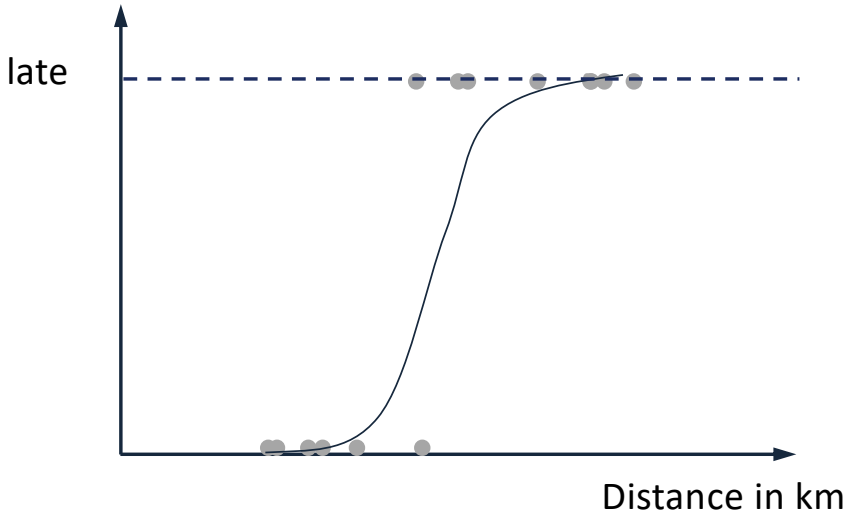
Order ID	Distance in km	Predicted days late
1	10	5.1
2	5	2.6
…	..	..

Classification



$$p(x) = \frac{e^{\beta_0+\beta_1 x}}{1+e^{\beta_0+\beta_1 x}}$$

Classification



$$p(x) = \frac{e^{0.1+0.5Distance\ in\ km}}{1+e^{0.1+0.5Distance\ in\ km}}$$

Order ID	Distance in km	Predicted probability late
1	10	84%
2	5	72%
…	..	..

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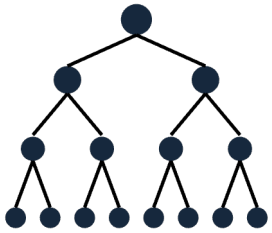
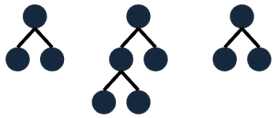
- Feature Engineering
- Explainable AI

Ensemble Learning

Decision Tree



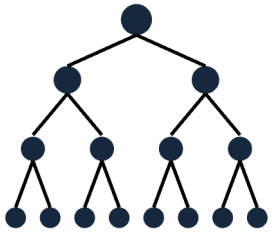
Random Forest



Boosted Trees

Ensemble Learning

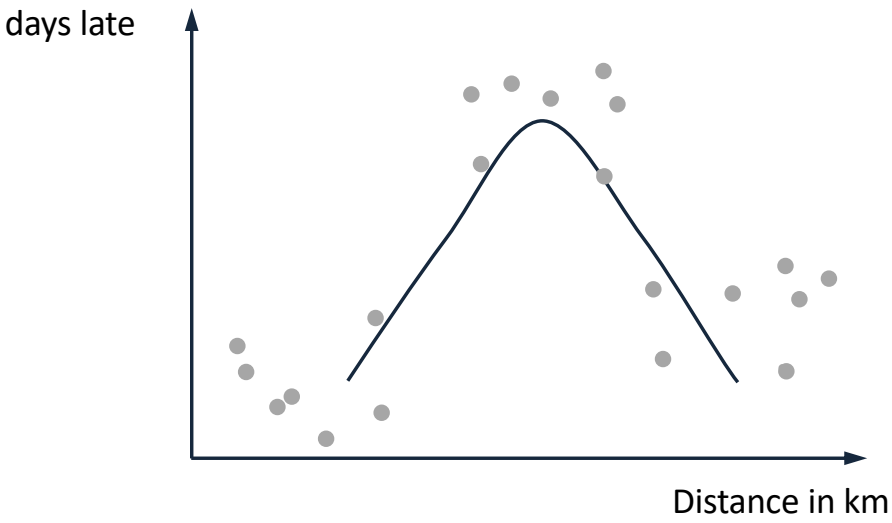
Decision Tree

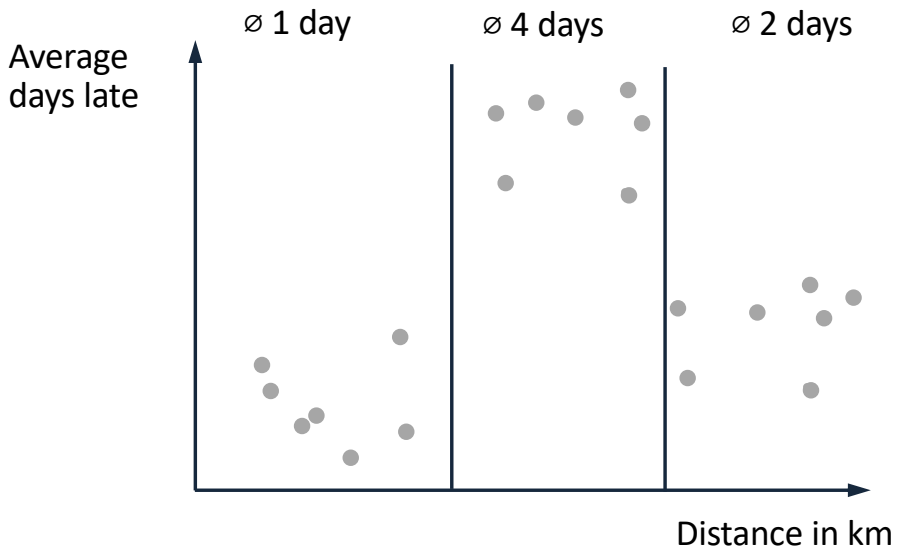


Random Forest

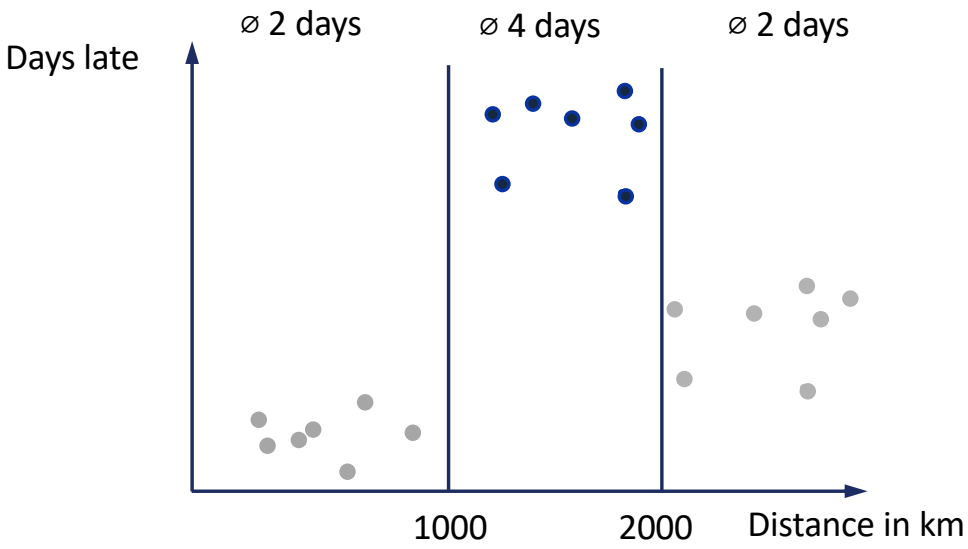
Boosted Trees

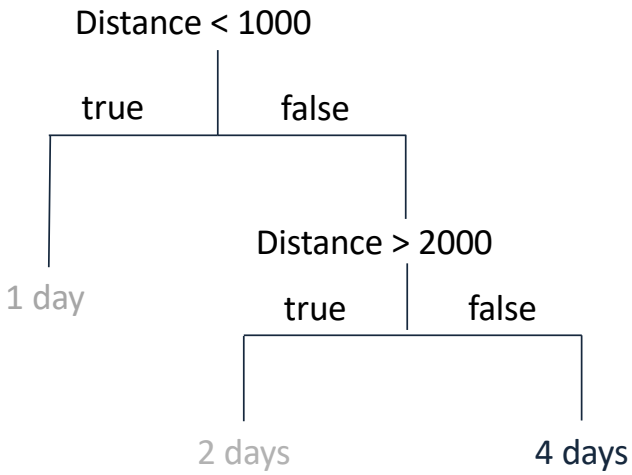
Limitations of Linear and Logistic Regression



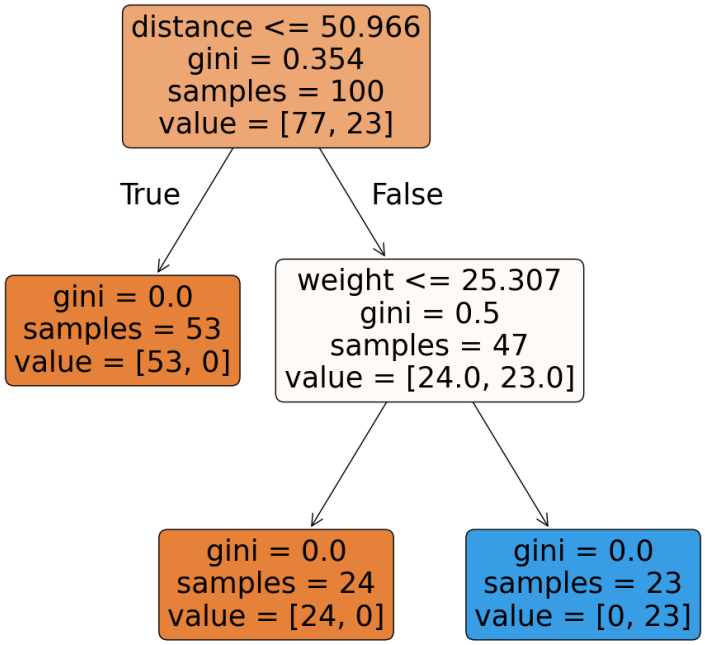


Decision Tree for Regression

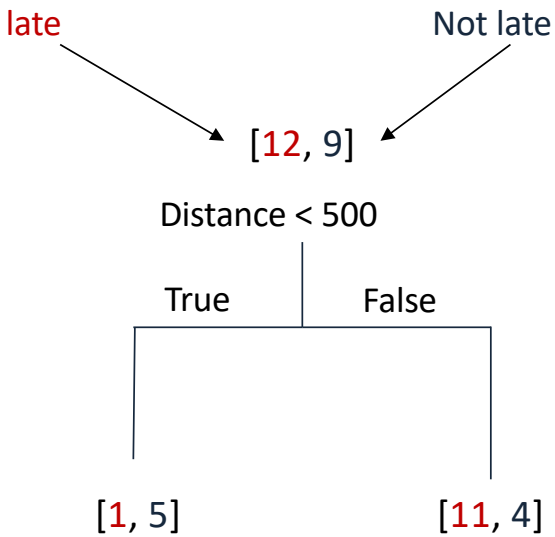




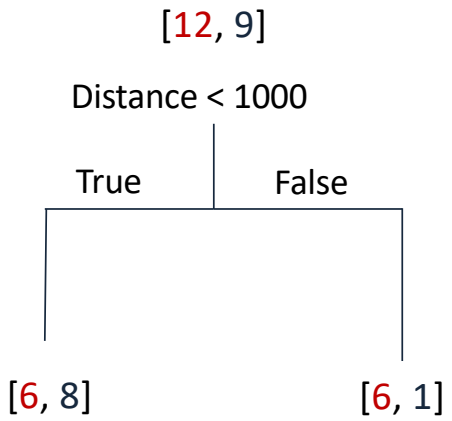
Example for Decision Tree in Python



Decision Tree for Classification - Finding Splits



Does the split improve our classification?



Which split is better?

Decision Tree for Classification - Finding Splits by Measuring Purity

$$Gini\ index = \sum_{k=1}^{K} \hat{p}_k(1 - \hat{p}_k)$$

[True(s), False(s)]

[4, 0] $Gini\ index = \frac{4}{4}\left(1 - \frac{4}{4}\right) + \frac{0}{4}\left(1 - \frac{0}{4}\right) = 0$

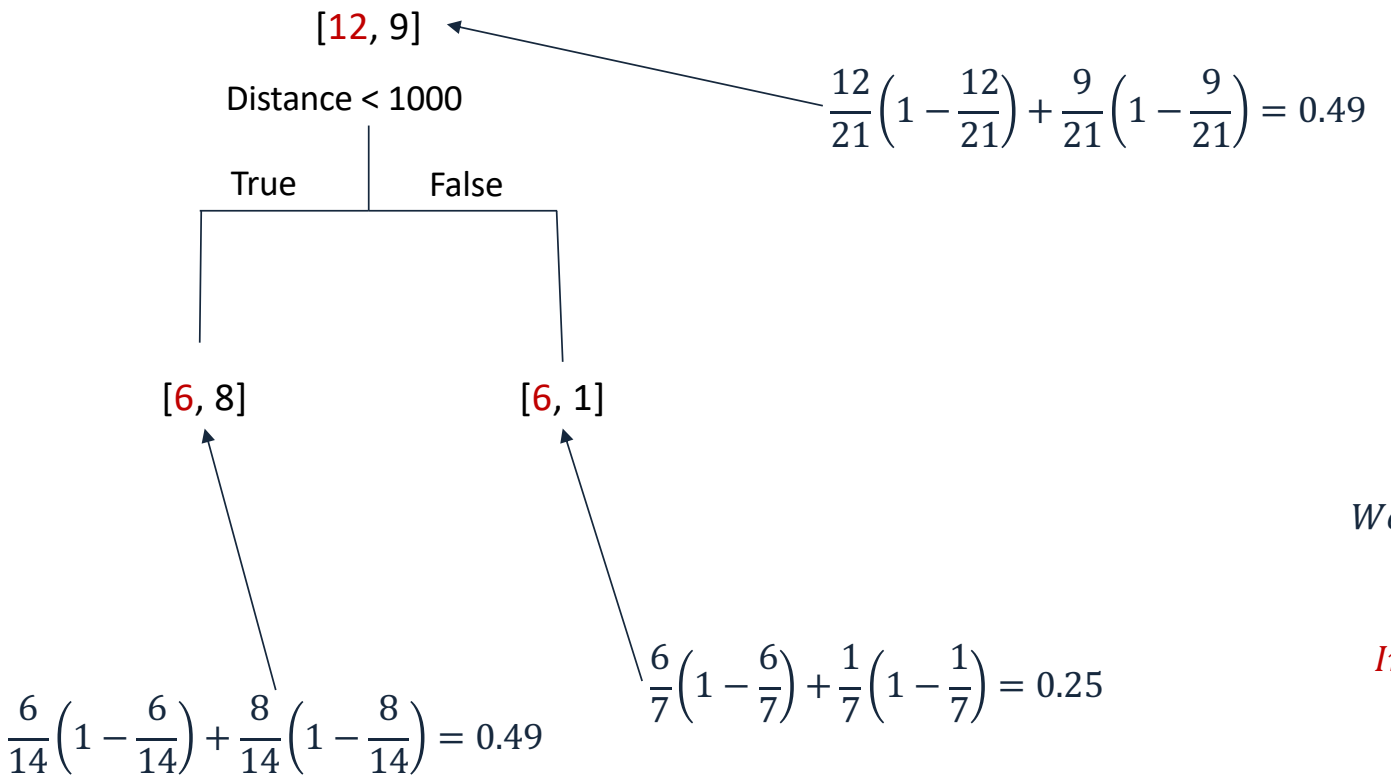
[2, 2] $Gini\ index = \frac{2}{4}\left(1 - \frac{2}{4}\right) + \frac{2}{4}\left(1 - \frac{2}{4}\right) = \frac{1}{2}$

[1, 3] $Gini\ index = \frac{1}{4}\left(1 - \frac{1}{4}\right) + \frac{3}{4}\left(1 - \frac{3}{4}\right) = \frac{3}{8}$

» Smaller value if a node is purer.

Q: What is the max value (max impurity) of Gini if we have two classes?

Decision Tree for Classification - Finding Splits by Measuring Purity



$$\frac{12}{21}\left(1-\frac{12}{21}\right)+\frac{9}{21}\left(1-\frac{9}{21}\right)=0.49$$

$$\frac{6}{14}\left(1-\frac{6}{14}\right)+\frac{8}{14}\left(1-\frac{8}{14}\right)=0.49$$

$$\frac{6}{7}\left(1-\frac{6}{7}\right)+\frac{1}{7}\left(1-\frac{1}{7}\right)=0.25$$

$$Weighted\ Gini=\frac{14}{21}0.49+\frac{7}{21}0.25=0.41$$

$$Improvement=0.49\ -\ 0.41=0.08$$

Alternative Measures for Finding Splits

$$Entropy = -\sum_{k=1}^{K} \hat{p}_k log_2 \hat{p}_k$$

- Like the Gini index, the entropy will take on a small value if a node is pure.
- The natural logarithm can also be used
- Max Value for log2 with two classes is 0.5

Measures for Finding Splits for Regression Trees

- Squared Difference between true value (y_i) and predicted value ($\hat{y}_i$)

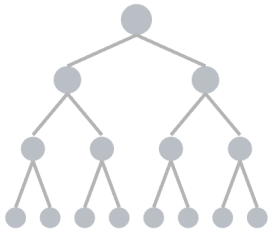
$$Squared\ Error = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

- Absolute Difference between true value (y_i) and predicted value ($\hat{y}_i$)

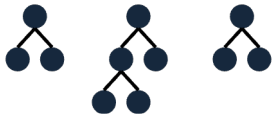
$$Absolute\ Error = \sum_{i=1}^{n} |y_i - \hat{y}_i|$$

Ensemble Learning

Decision Tree



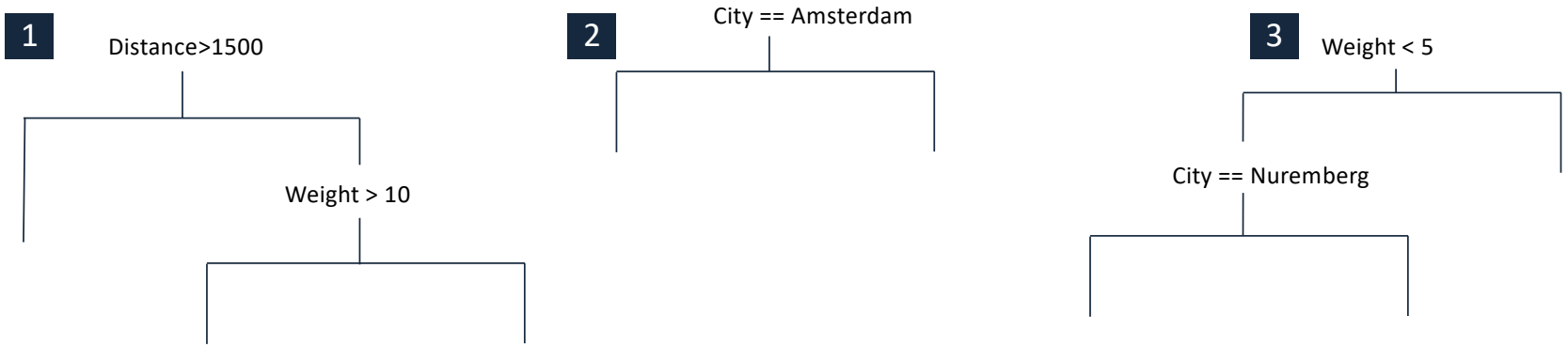
Random Forest



Boosted Trees

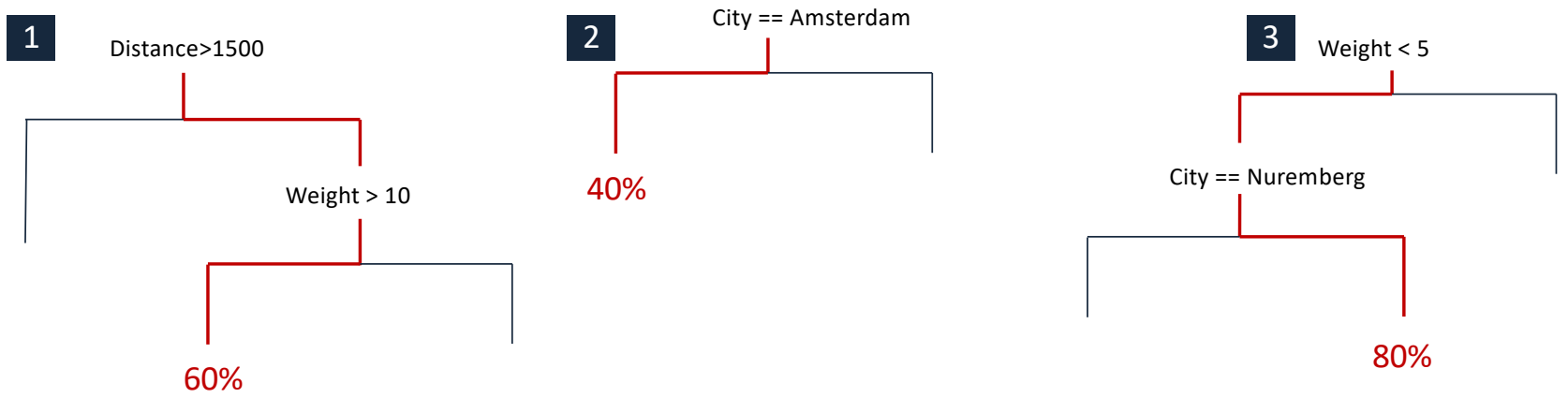
Random Forest

Question: Why should we only build one tree?



Used features:	Distance, Weight	City	Weight, City

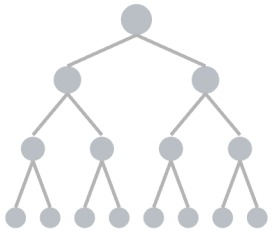
Random Forest



Prediction late: $\frac{60\%+40\%+80\%}{3} = 60\%$

Ensemble Learning

Decision Tree

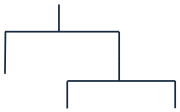


Random Forest

Boosted Trees

Gradient Boosted Trees

(1) Calculate 1. Tree

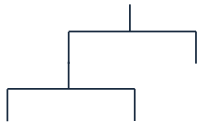


(2) Calculate prediction errors

(3) Use Errors as target for 2. Tree

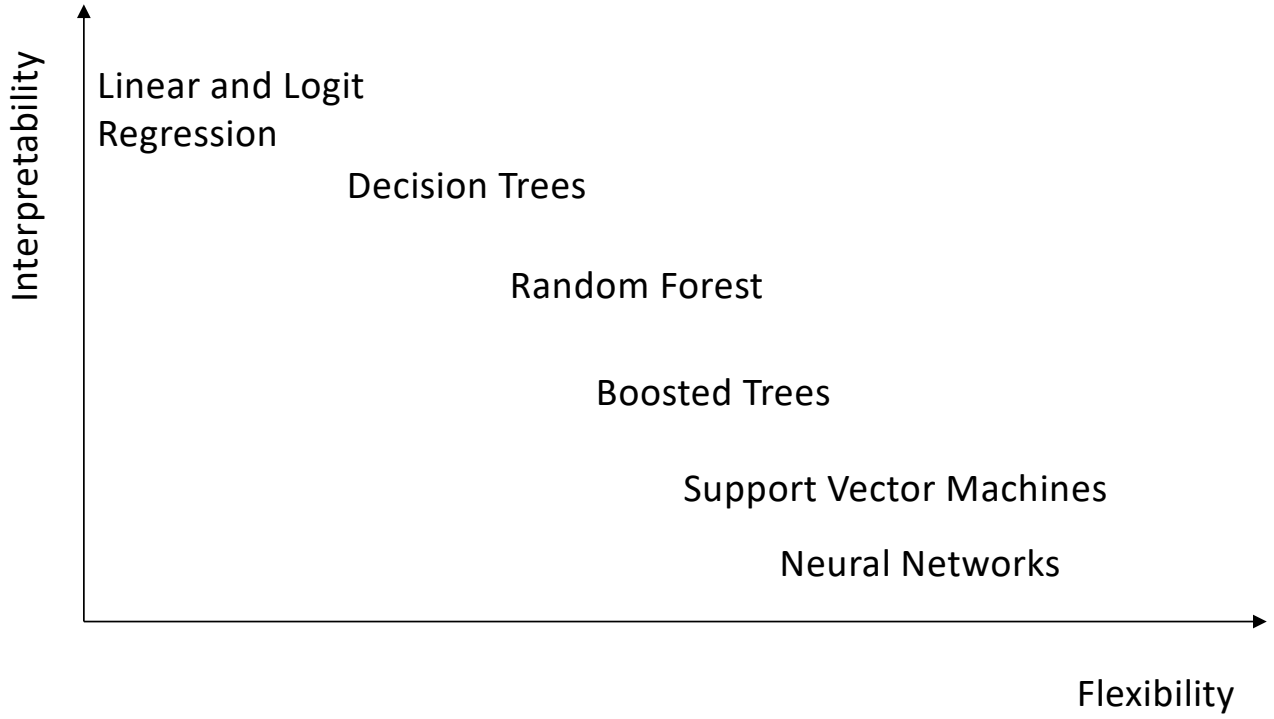
(4) Update predictions by calculating:
*Prediction 1. Tree + learning rate * Prediction 2. Tree*

(5) Use updated errors as target for 3. Tree



(6) Update predictions by calculating:
Prediction 1. Tree +
*learning rate * Prediction 2. Tree +*
*learning rate * Prediction 3. Tree*

Interpretability Vs Flexbility Trade-off



Source: James et al (2023), p. 24.

Agenda

Business Analytics

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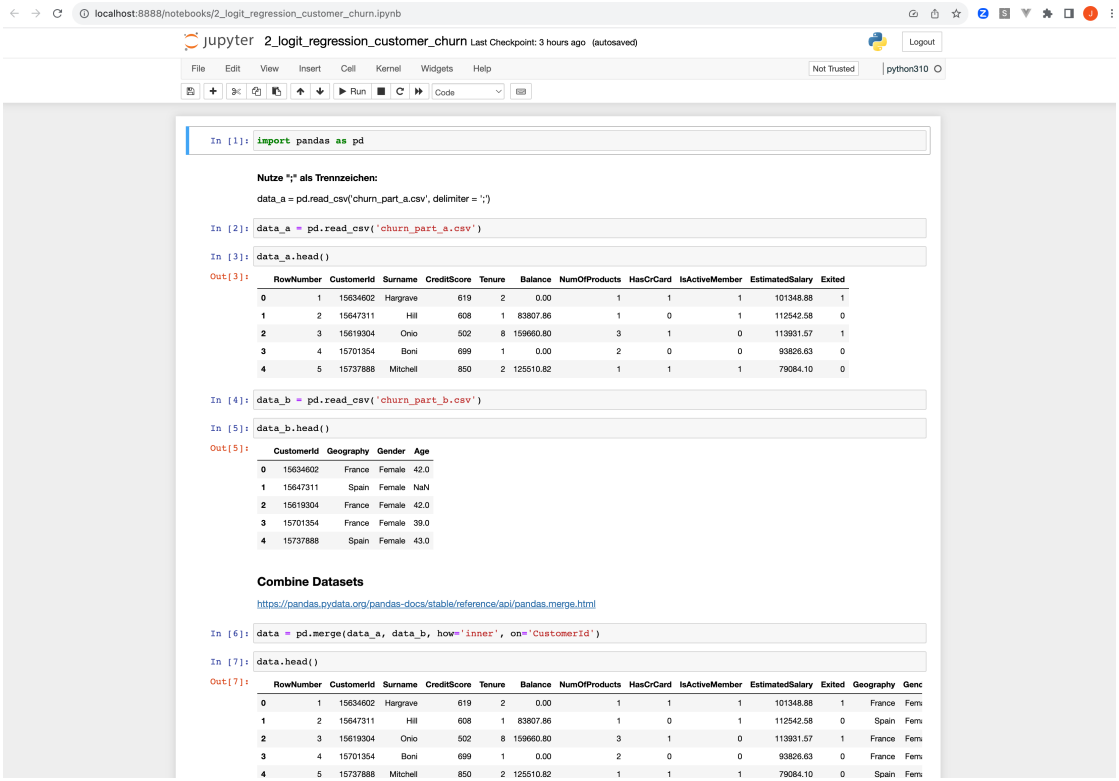
Python - IDEs

Jupyter Notebooks



localhost:8888/notebooks/2_logit_regression_customer_churn.ipynb

jupyter 2_logit_regression_customer_churn Last Checkpoint: 3 hours ago (autosaved)

Logout

File Edit View Insert Cell Kernel Widgets Help

Not Trusted python310

Run Code

In [1]:
```
import pandas as pd
```

Nutze ";" als Trennzeichen:

data_a = pd.read_csv('churn_part_a.csv', delimiter = ';')

In [2]:
```
data_a = pd.read_csv('churn_part_a.csv')
```

In [3]:
```
data_a.head()
```

Out[3]:

	RowNumber	CustomerId	Surname	CreditScore	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	1	15634602	Hargrave	619	2	0.00	1	1	1	101348.88	1
1	2	15647311	Hill	608	1	83807.86	1	0	1	112542.58	0
2	3	15619304	Onio	502	8	159660.80	3	1	0	113931.57	1
3	4	15701354	Boni	699	1	0.00	2	0	0	93826.63	0
4	5	15737888	Mitchell	850	2	125510.82	1	1	1	79084.10	0

In [4]:
```
data_b = pd.read_csv('churn_part_b.csv')
```

In [5]:
```
data_b.head()
```

Out[5]:

	CustomerId	Geography	Gender	Age
0	15634602	France	Female	42.0
1	15647311	Spain	Female	NaN
2	15619304	France	Female	42.0
3	15701354	France	Female	39.0
4	15737888	Spain	Female	43.0

Combine Datasets

https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.merge.html

In [6]:
```
data = pd.merge(data_a, data_b, how='inner', on='CustomerId')
```

In [7]:
```
data.head()
```

Out[7]:

	RowNumber	CustomerId	Surname	CreditScore	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited	Geography	Genc
0	1	15634602	Hargrave	619	2	0.00	1	1	1	101348.88	1	France	Fem
1	2	15647311	Hill	608	1	83807.86	1	0	1	112542.58	0	Spain	Fem
2	3	15619304	Onio	502	8	159660.80	3	1	0	113931.57	1	France	Fem
3	4	15701354	Boni	699	1	0.00	2	0	0	93826.63	0	France	Fem
4	5	15737888	Mitchell	850	2	125510.82	1	1	1	79084.10	0	Spain	Fem

Datastructures in Python

List:

```
["Müller AG", "Smith Ltd", “International Ldt"]
```

Dictionary:

```
{"id": 1, "name": "Müller AG", "city": "Hamburg"}
```

List of Dictionaries:

```
[
 {"id": 1, "name": "Müller AG", "city": "Hamburg"},
 {"id": 2, "name": "Smith Ltd", "city": "London"}
]
```

Pandas Dataframe

	ID	Name	category
0	1	ElectraTech Supplies	Testing and Measurement Equipment
1	2	CircuitSolutions Inc.	Components and Parts Providers
2	3	PowerGrid Electronics	Electronics Manufacturing Tools and Equipment
3	4	Quantum Connectors	Connectivity and Communication Gear
4	5	MegaVolt Tech Distributors	Connectivity and Communication Gear

Getting Started with Pandas

```
# Importing pandas
import pandas as pd

# Reading an excel file
data = pd.read_excel(data.xlsx')

# Getting first 5 rows of data
data.head()

# Getting all column names
data.columns

# Get datatypes of column
data.dtypes
```

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Evaluating the Quality of a Model for a Regression Problem

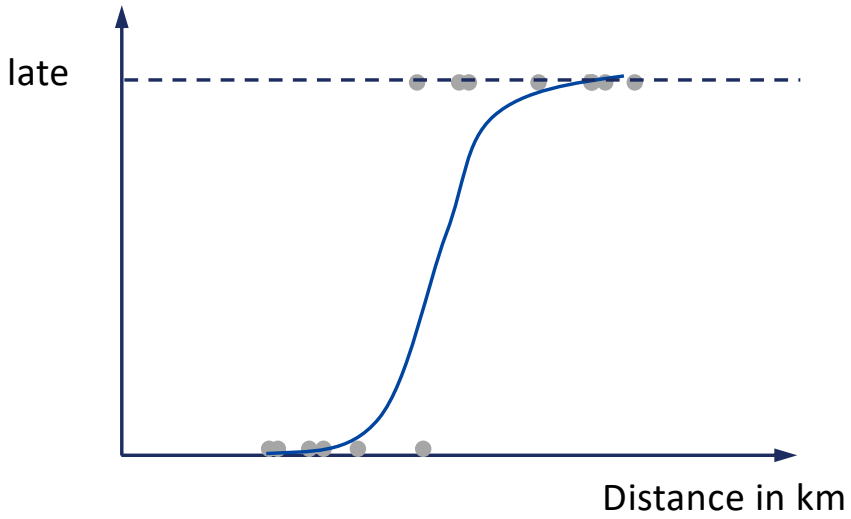
Observed (y_i)	Prediction ($\hat{y}_i$)
2	3
5	7
10	8

$$Mean\ Squared\ Error = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

$$Mean\ Absolute\ Error = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

Evaluating the Quality of a Model for a Classification Problem

Order	Confirmed Date	Distance in km	Actual Late	Prediction Model
#1	2024-06-14	502	True	90%
#2	2024-07-16	205	False	60%
#3	2024-07-14	275	False	33%



Confusion Matrix

		Actual condition: Positive (AP)	Actual condition: Negative (AN)
Predicted condition	**Positive (PP)**	True positive (TP)	False positive (FP)
	Negative (PN)	False negative (FN)	True negative (TN)

Confusion Matrix

Order	Probability (late)	Predicted (>=50%)	Actual
#1	95%	Late	Late
#2	90%	Late	In time
#3	85%	Late	Late
#4	80%	Late	Late
#5	70%	Late	In time
#6	60%	Late	Late
#7	40%	In time	In time
#8	30%	In time	In time
#9	20%	In time	Late
#10	10%	In time	In time

Predicted condition	Actual condition: Positive (AP)	Actual condition: Negative (AN)
Positive (PP)		
Negative (PN)		

Performance Measures Based on the Confusion Matrix

Actual condition

Predicted condition		Positive (AP)	Negative (AN)
	Positive (PP)	True positive (TP)	False positive (FP)
	Negative (PN)	False negative (FN)	True negative (TN)

Measure	Question	Formula
Accuracy	What percentage of the model's predictions were correct?	$\frac{TP + TN}{TP + TN + FP + FN}$
Precision	Out of all the positive predictions, how many were actually correct?	$\frac{TP}{TP + FP}$
True Positive Rate / Recall / Sensitivity	Of all the actual positive instances, how many did the model correctly identify?	$\frac{TP}{TP + FN}$
True Negative Rate / Specificity	Of all the actual negative instances, how many did the model correctly identify?	$\frac{TN}{TN + FP}$

Confusion Matrix

		Actual condition: Positive (AP)	Actual condition: Negative (AN)
Predicted condition	Positive (PP)	4 (TP)	2 (FP)
	Negative (PN)	1 (FN)	3 (TN)

Measure	Formula	Result
Accuracy	$\frac{TP + TN}{TP + TN + FP + FN}$	
Precision	$\frac{TP}{TP + FP}$	
True Positive Rate / Recall / Sensitivity	$\frac{TP}{TP + FN}$	
False Positive Rate / Specificity	$\frac{TN}{TN + FP}$	

Confusion Matrix

Order	Probability (late)	Predicted (>=80%)	Actual
#1	95%	Late	Late
#2	90%	Late	In time
#3	85%	Late	Late
#4	80%	Late	Late
#5	70%	**In time**	In time
#6	60%	**In time**	Late
#7	40%	In time	In time
#8	30%	In time	In time
#9	20%	In time	Late
#10	10%	In time	In time

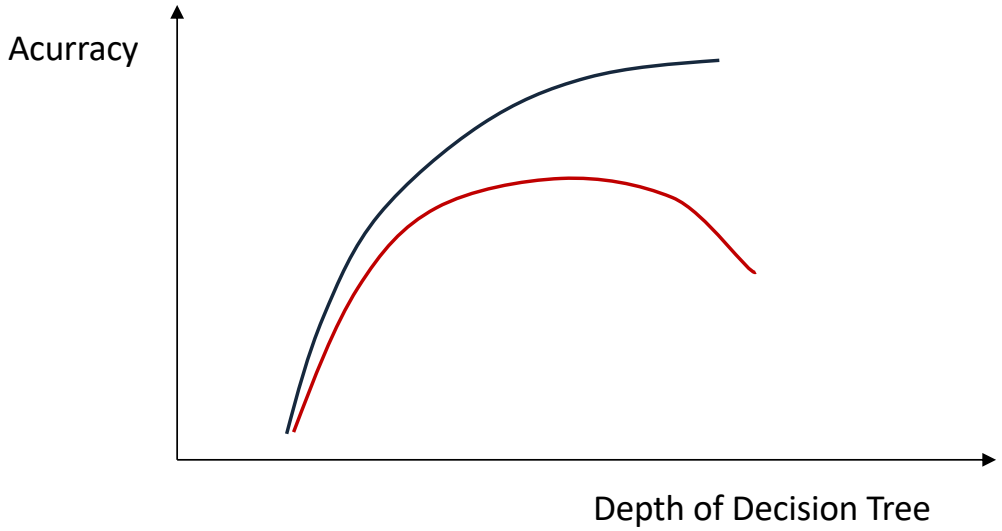
Predicted condition		Actual condition: Positive (AP)	Actual condition: Negative (AN)
	Positive (PP)	3 (TP)	1 (FP)
	Negative (PN)	2 (FN)	4 (TN)

F-1 Score Is the Harmonic Mean Between Precision and Recall

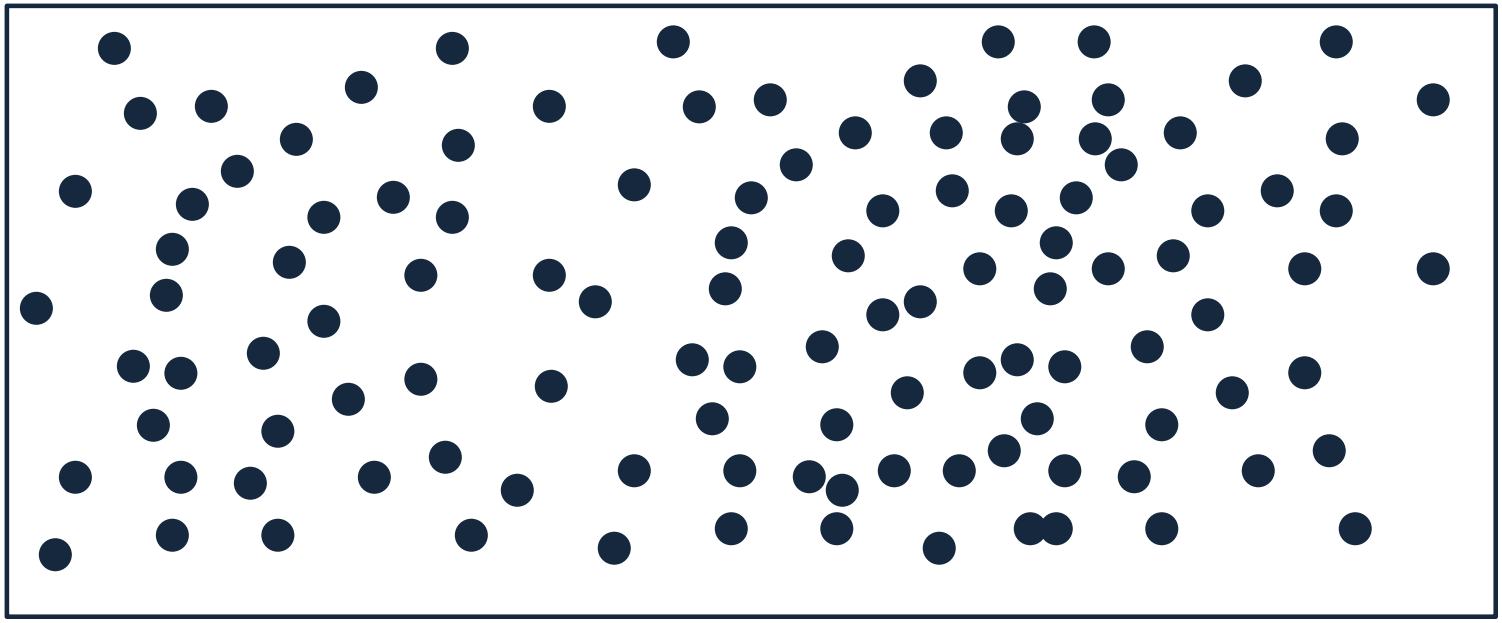
Threshold	Precision	Recall	F1 Score (Harmonic Mean of Precision and Recall)*
0.90	50%	20%	28.6%
0.80	75%	60%	66.7%
0.60	66.7%	80%	72.7%
0.50	66.7%	80%	72.7%
0.20	56%	100%	72.7%

$$* F1 - Score = \frac{2}{\frac{1}{Precision} + \frac{1}{Recall}}$$

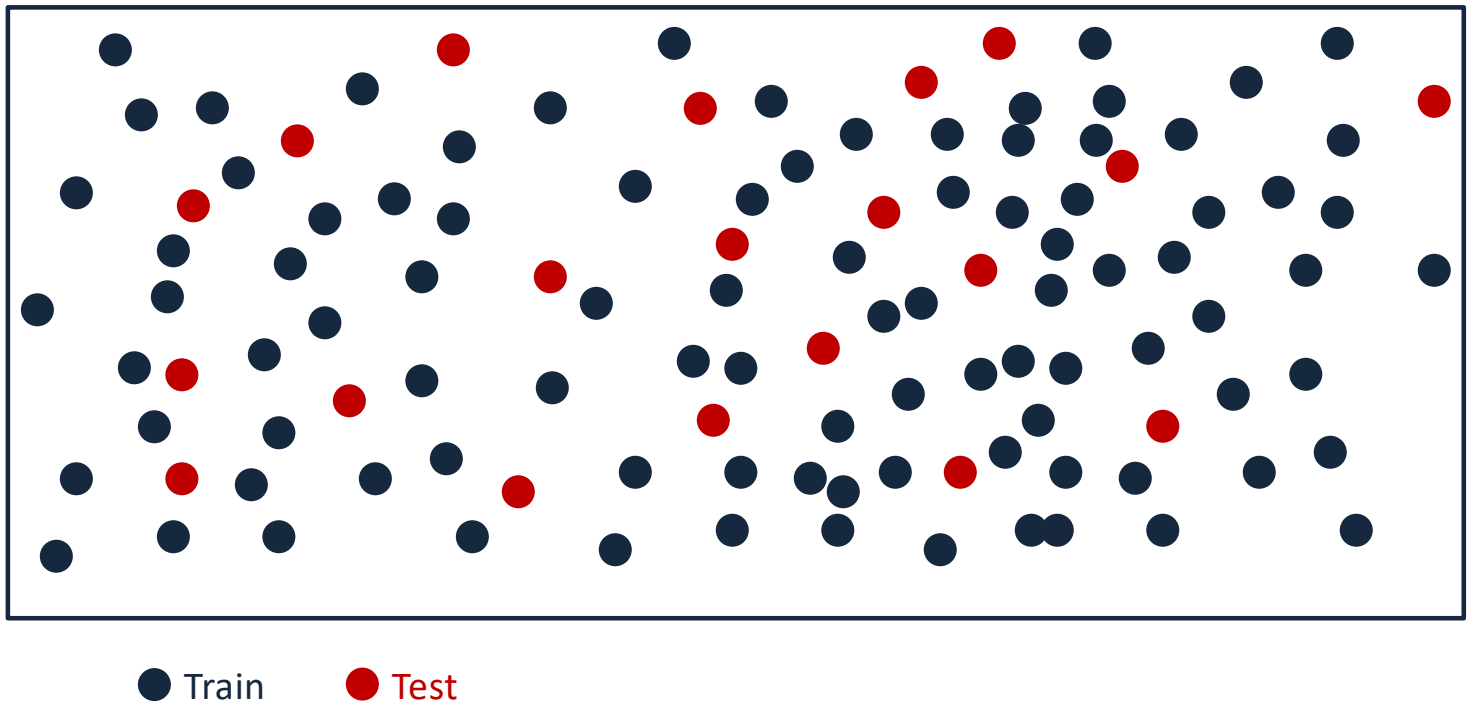
Train Vs. Test Data



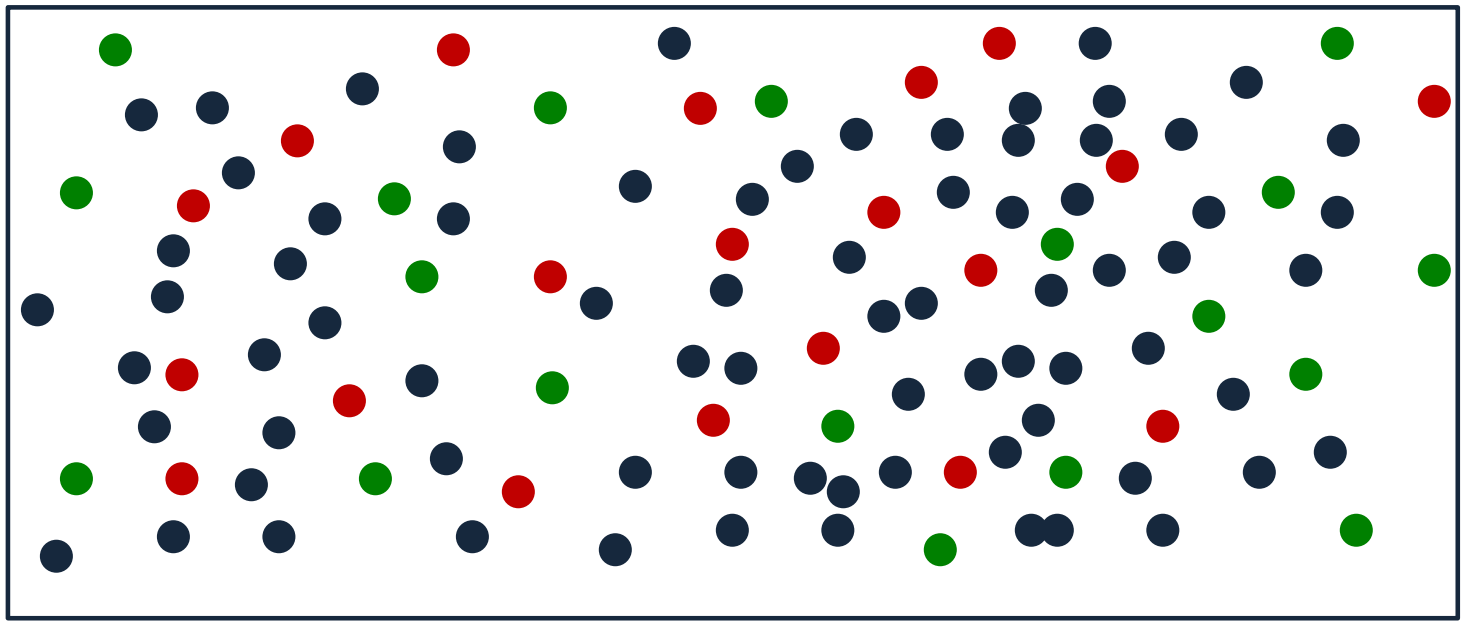
Train Vs. Test Data



Train Vs. Test Data

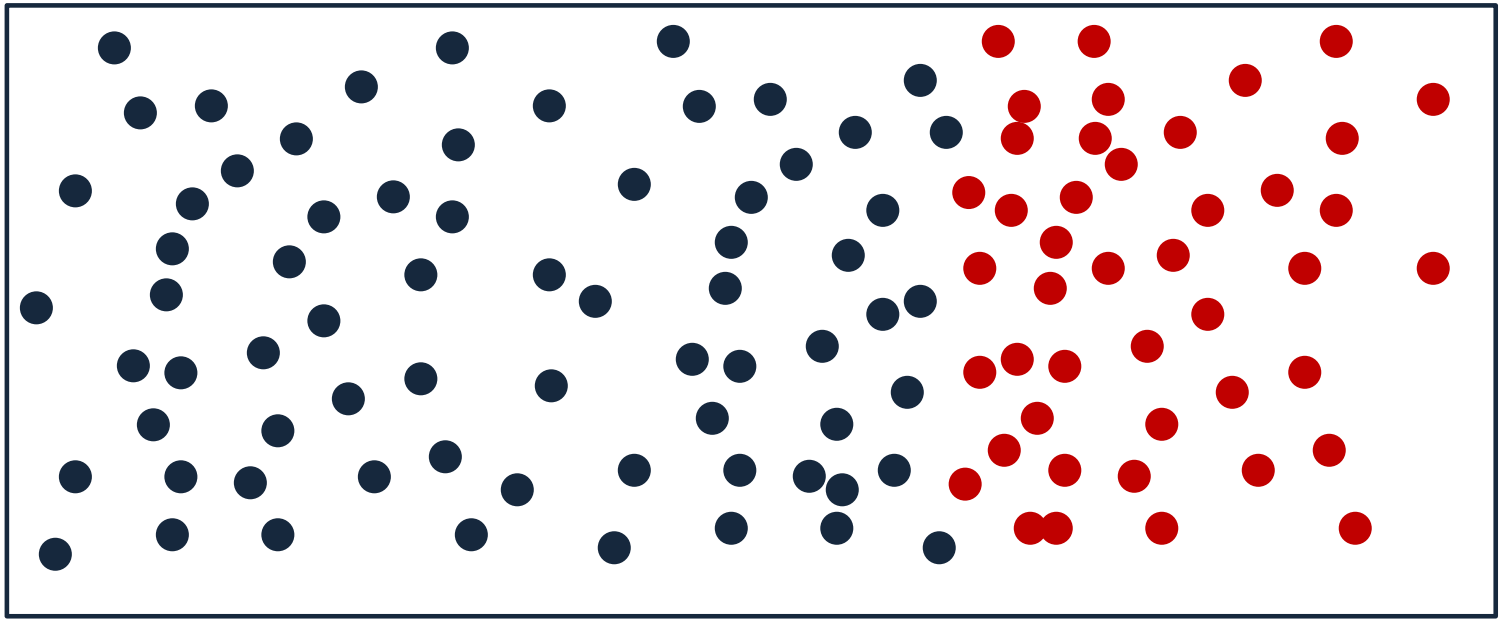


Cross-validation



Step	Train	Test
1	Group 1 & 2	Group 3
2	Group 1 & 3	Group 2
3	Group 2 & 3	Group 1

Splitting Time Series Data



Train (Observations < 1.1.2024 Test (Observations >= 1.1.2024)

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Categorical Variables

Order	Customer Country
#1	France
#2	Germany
#3	Italy
#4	France

Order	Customer Country Numeric
#1	1
#2	2
#3	3
#4	1

Using One-hot Encoding for Categorical Variables

Order	Customer Country
#1	France
#2	Germany
#3	Italy
#4	France

Order	s_France	s_Germany	s_Italy
#1	1	0	0
#2	0	1	0
#3	0	0	1
#4	1	0	0

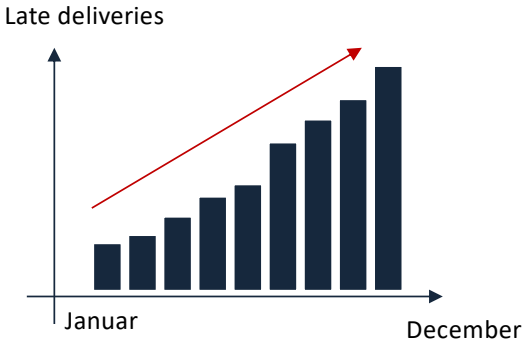
```
pandas.get_dummies(data["customer_state"], prefix="s")
```

Handling Date Information

Order	Month
#1	August
#2	September
#3	December
#4	January

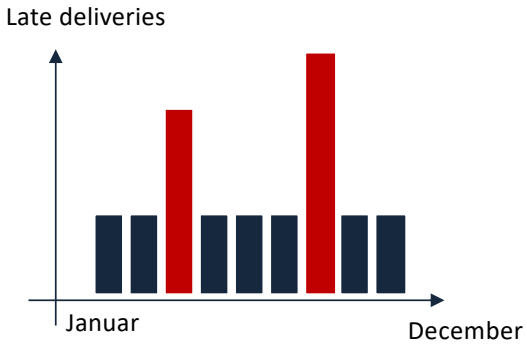
Option 1:

Order	Month Numeric
#1	8
#2	9
#3	12
#4	1



Option 2:

Order	January	…	December
#1	0	…	0
#2	0	…	0
#3	0	…	1
#4	0	…	0



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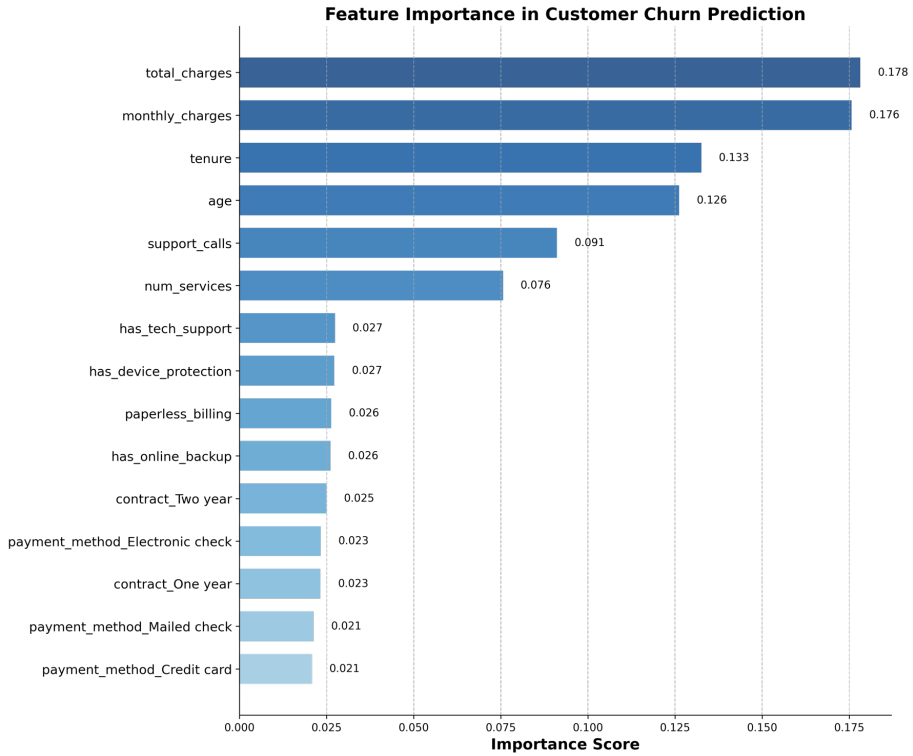
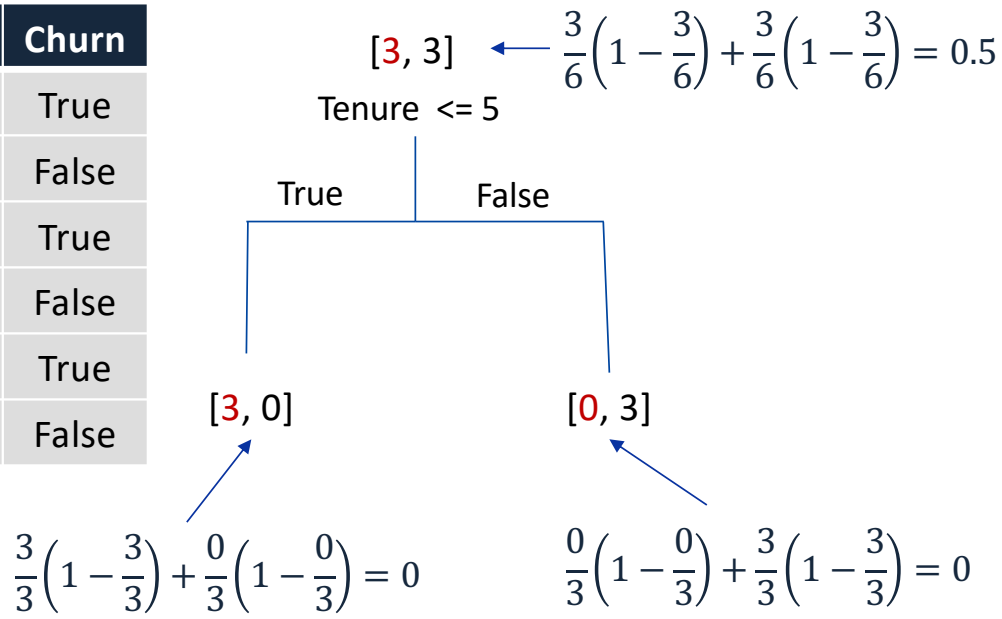
FEATURE IMPORTANCE

Feature Importance



Understanding Feature Importance

Age	Tenure	Churn
25	2	True
35	12	False
28	3	True
54	24	False
48	6	True
32	18	False

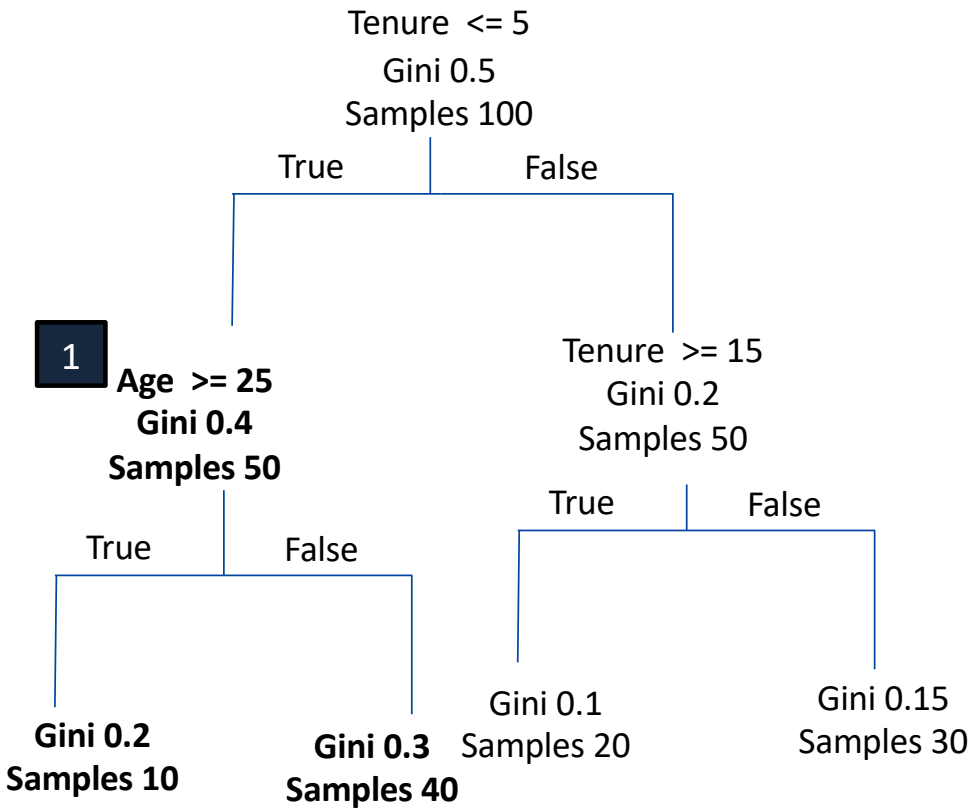


$$Weighted\ Gini = \frac{3}{6}0 + \frac{3}{6}0 = 0.0$$

$$Improvement = 0.5 - \ 0 = 0.5$$

- Repeat this for all nodes in which the features is used
- Weight the Improvement of each node with the samples in that node relative to the total samples

Understanding Feature Importance: Feature Age



Feature Age

1

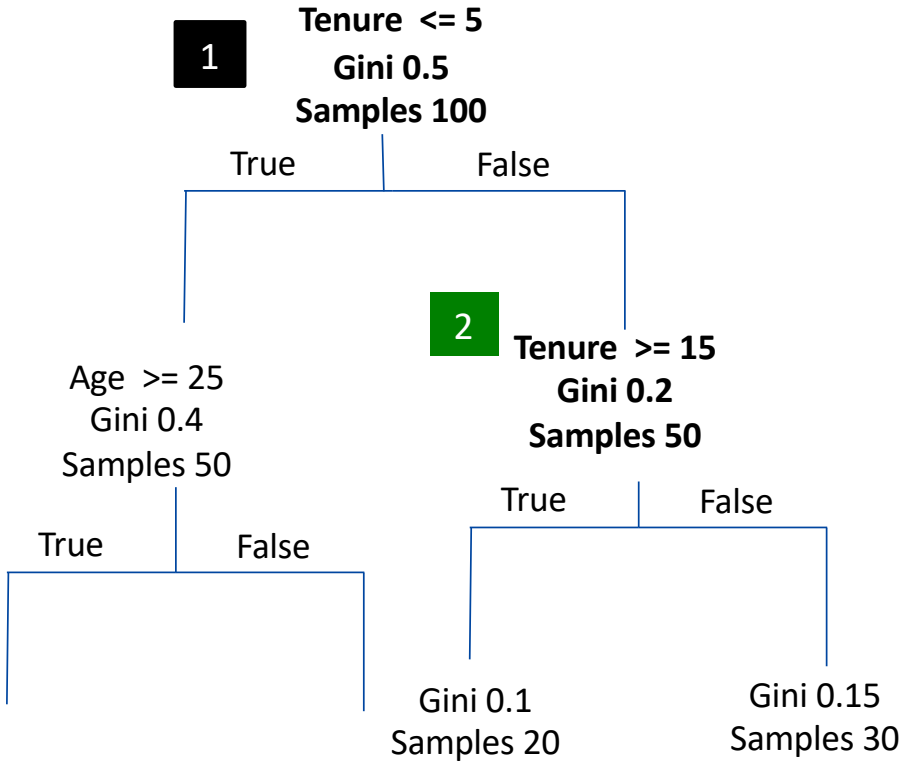
$$Weighted\ Gini = \frac{10}{50}0.2 + \frac{40}{50}0.3 = 0.28$$

$$Improvement = 0.4 - 0.28 = 0.12$$

$$Weightes\ Improvement = \frac{50}{100}0.12 = 0.06$$

$$\boldsymbol{Feature\ Importance = 0.06 = 0.06}$$

Understanding Feature Importance: Feature Tenure



1

$$Weighted\ Gini = \frac{50}{100}0.4 + \frac{50}{100}0.2 = 0.3$$

$$Improvement = 0.5 - 0.3 = 0.2$$

$$Weightes\ Improvement = \frac{100}{100}0.2 = 0.2$$

2

$$Weighted\ Gini = \frac{20}{50}0.1 + \frac{30}{50}0.15 = 0.13$$

$$Improvement = 0.2 - 0.13 = 0.07$$

$$Weightes\ Improvement = \frac{50}{100}0.07 = 0.035$$

$$\boldsymbol{Feature\ Importance = 0.2 + 0.035 = 0.235}$$

SHAPLEY (SHAPLEY ADDITIVE EXPLANATIONS) VALUES

Shapley (shapley Additive Explanations) Values

Scenario:

Assume the following scenario: You've trained a machine learning model to predict apartment prices. For a certain apartment, it predicts €300,000, and you need to explain this prediction.

The apartment:

- has an area of 50 m,
- is located on the 2nd floor,
- has a park nearby,
- Cats are banned

The average prediction for all apartments is €310,000.

Our goal is to explain how each of these feature values contributed to the prediction. How much has each feature value contributed to the prediction compared to the average prediction?

Baseline	**310.000**
Area 50	- 10.000
2nd floor	+ 1.500
Park nearby	+ 4.000
Cats are banned	- 4.500
Prediction	**300.000**

Source: Molnar, C. (2025)

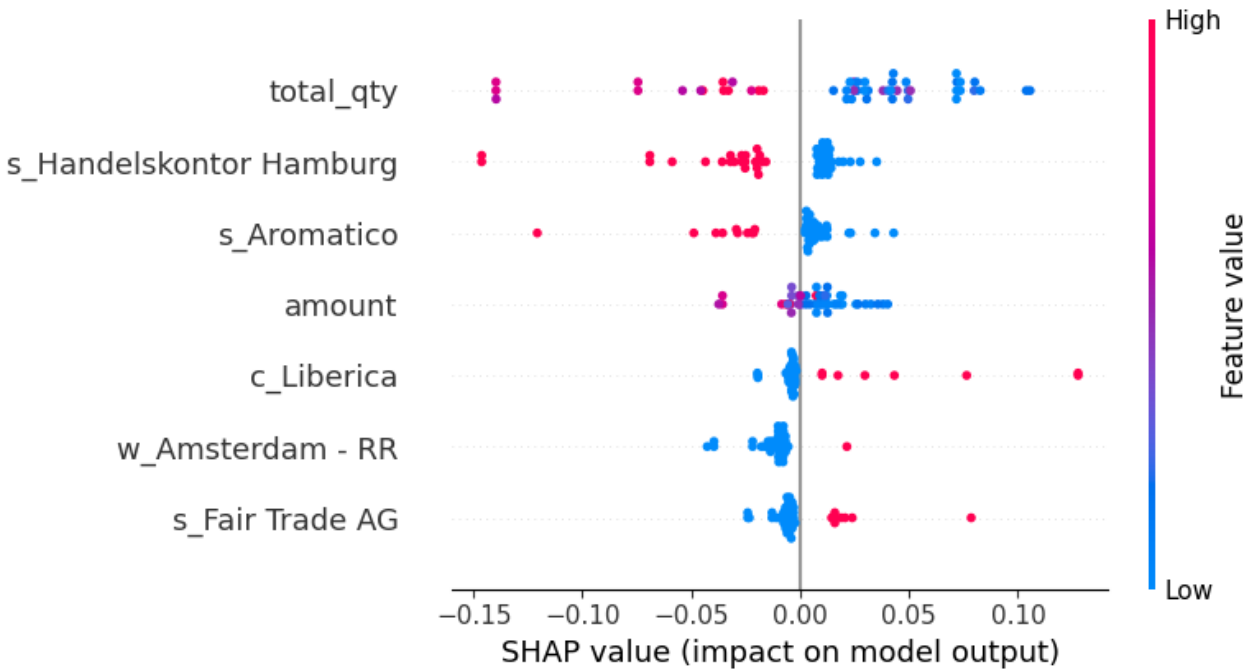
Shapley (shapley Additive Explanations) Values: “cats Are Banned” Feature

Coalitions	Prediction (Cat banned)	Prediction (Cat not banned)	Difference
{} (empty coalition)	310,000	312,000	-2,000
{park-nearby}	315,000	320,000	-5,000
{area-50}	325,000	330,000	-5,000
{floor-2nd}	312,000	317,000	-5,000
{park-nearby,area-50}	328,000	338,000	-10,000
{park-nearby,floor-2nd}	317,000	322,000	-5,000
{area-50,floor-2nd}	329,000	330,000	-1,000
{park-nearby,area-50,floor-2nd}	332,000	335,000	-3,000
Average			**-4.500**

Shapley (shapley Additive Explanations) Values: “cats Are Banned” Feature

Coalitions	Prediction (Cat banned)	Prediction (Cat not banned)	Difference
{} (empty coalition)	310,000	312,000	-2,000
{park-nearby}	315,000	320,000	-5,000
{area-50}	325,000	330,000	-5,000
{floor-2nd}	312,000	317,000	-5,000
{park-nearby,area-50}	328,000	338,000	-10,000
{park-nearby,floor-2nd}	317,000	322,000	-5,000
{area-50,floor-2nd}	**329,000**	**330,000**	**-1,000**
{park-nearby,area-50,floor-2nd}	332,000	335,000	-3,000
Average			**-4.500**

Shapley Values



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- Source: Lamarre, E., Smaje, K., & Zemmel, R. (2023). Rewired: the McKinsey guide to outcompeting in the age of digital and AI.

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