CORVINUS UNIVERSITY of BUDAPEST

Machine Learning in Practice I

Antal Jakovac, 2025

About the course

- Course Title: "Machine Learning in Practice I"
- instructor: antal.jakovac@uni-corvinus.hu
- course objectives
  - why and when to use Machine Learning (ML)
  - data handling methods
  - core ML models before deep learning
  - how to build an ML project

About the course

- about the course
  - evaluation: written exams (together with exercises)
  - learning material: course slides, books, podcasts, etc.
  - books:
    - An Introduction to Statistical Learning
      (G.James , D. Witten , T. Hastie , R. Tibshirani, https://www.statlearning.com/)
    - Designing machine learning systems (Chip Huyen)
  - github repository: https://github.com/ajakovac/ML-in-Practice-I

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    - Design
  - github rep

```
#git clone project from command line
git clone https://github.com/ajakovac/ML-in-Practice-I.git
cd ML-in-Practice-I
#read the README.md file and follow instructions
```

- Introduction to Machine Learning
- Data Preprocessing & Feature Engineering
- Tree-Based Methods
- Ensemble Methods (Bagging, Random Forests, Boosting)
- Instance-Based Learning — k-Nearest Neighbors
- Probabilistic Models — Naive Bayes & Gaussian Mixtures
- Linear Models for Regression
- Linear Models for Classification
- Support Vector Machines (SVMs)
- Dimensionality Reduction
- Examples from audio and computer vision

Introduction

Introduction

- why do we need Artificial Intelligence (Machine Learning)?

	observation	modelling	computation	conclude/action
historic times	human	human	human	human
machines	**machine**	human	human	human
computers	**machine**	human	**machine**	human
AI	**machine**	**machine**	**machine**	human

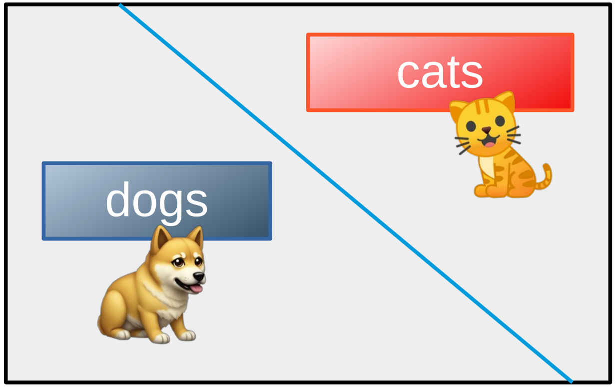
- task of AI is not to solve an actual problem, but solve modelling
- we do not know the model it uses → it can be smarter than us!

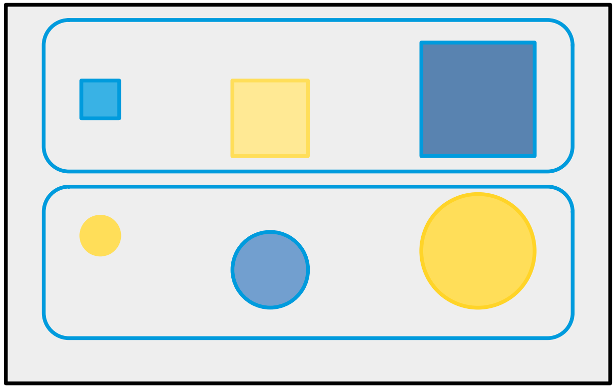
Introduction

- Traditional Programming vs. ML
  - traditional: data + rules → output
  - ML: data + output → rules
- when to use ML?
  - Automation of complex tasks → heuristics
  - Adaptability
  - Performance on large data
  - Real-world examples (email spam, face detection, recommendation systems)

Introduction

- Types of ML; traditionally
  - supervised:
    - show data + labels → learns the assignment
    - examples: classification, regression
  - unsupervised:
    - find patterns in unlabeled data
    - not unique → context, magnitude
    - examples: clustering, dimensionality reduction
  - reinforcement:
    - learn by interacting with the environment
    - not covered in this course





Introduction

- Types of ML; other points of view
  - task-driven (System I)
    - define a task (classification, prediction, control)
    - show examples of good (eventually bad) solutions
    - train models to optimize for success on that task
    - includes most supervised/reinforcement learning examples
  - data-driven (System II)
    - reveal structures by showing similar data
    - does not need explicit labelling
    - LLM’s, autoencoders, similarity learning
    - recently popular (self-supervised learning, foundation models, and retrieval-based systems)

Introduction

- Typical ML tasks
  - classification
    - face, dog breeds, bird songs classification
    - spam detection, disease diagnosis, sentiment analysis
    - lot of labeled data
  - regression (price prediction, weather forecasting, energy demand)
  - clustering (customer segmentation, document grouping, biological cell types)
  - compression (PCA, visualization, autoencoders, embeddings)

Introduction

- Typical ML tasks
  - decision making (robotics, game playing, resource allocation, monitoring)
  - generation (text, translation, image, data, molecular structure, code)
  - outlier analysis (email spam, suspicious customer, fraud detection, etc.)
  - recommendation systems (movies, jobs, code completion, etc.)
  - ranking/retrieval (search engines, document/data retrieval)

Introduction

- somewhat overlapping areas; e.g. chemical plant monitoring system
  - anomaly detection
  - classification
  - time-series forecasting
  - reinforcement learning (control), recommendation systems

Introduction

- ML algorithms (pre-deep neural networks)
  - Linear regression, logistic probability
  - Bayesian analysis, probability theory
  - Support Vector Machines
  - Decision Trees, ensemble methods
  - k-nearest neighbour method
  - Principal Component Analysis
  - Extreme Learning Machine
- majority of ML applications in production are not DNN!

Introduction

Tools

- language: Python
- packages:
  - numpy: numerical computing
  - scipy, scikit-learn: classical ML tools
  - pandas: data manipulation
  - matplotlib, seaborn: visualization

Introduction

Tools

- Python virtual environment:

```
> python -m venv .venv
```

- activate environment:
  - Linux/Windows WSL:

    ```
    > source .venv/bin/activate
    ```

  - Windows PowerShell:

    ```
    > .venv\Scripts\Activate
    ```

- Install necessary packages within the environment

```
> pip install matplotlib numpy scipy scikit-learn pandas seaborn ipykernel
```

- automation:

```
> pip freeze > requirements.txt
> pip install -r requirements.txt
```

Introduction

Tools for code development

- notebook services: Jupyter, Google Colab
- advanced editors: Visual Studio Code or similar
- Linux-like environment in Windows: WSL
- docker: containerize your work – like a standalone machine
- communication: API endpoints (Python fastAPI or Flask)

Typical ML workflow

Introduction

- Typical ML workflow
  1) Problem definition
  2) Data collection
  3) Data cleaning & preprocessing
  4) Feature engineering
  5) Model selection
  6) Training & validation
  7) Evaluation
  8) Deployment & monitoring

Introduction

- Typical ML workflow
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- what is the problem we want to solve? (classification, regression, clustering, …)
- is ML an adequate tool?
- what does success look like? (accuracy? low error? business impact?)
- what are the domain constraints and goals (e.g. medicine data availability, privacy → practical, ethical or technical limits)
- example: predict customer churn or classify handwritten digits

Introduction

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- enough data
- sampling methods → diverse data
- labelled data (if supervised)
- example: downloading a CSV of housing prices or collecting user logs

Introduction

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- missing values, duplicates, outliers
- normalize, scale, encode categorical features
- convert raw inputs into usable formats
- example: fill missing ages with median; scale prices to [0,1]

Introduction

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  1) Problem definition
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  8) Deployment & monitoring

- create meaningful input features
- transform or combine raw attributes
- select or construct new features based on domain knowledge
- example: from date of birth → compute age; combine “city” and “job type”

Introduction

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- choose a suitable algorithm (e.g. linear regression; SVM; RF; k-NN)
- consider interpretability, complexity, training time
- example: try logistic regression first for classification, then maybe a random forest, or a deep neural network

Introduction

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- split data into training and validation sets (and possibly test)
- train on one part, validate on another
- tune hyperparameters (e.g., via cross-validation)
- example: train a model on 80% of the data, validate on 20%

Introduction

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Use metrics appropriate for the task:

- classification: accuracy, precision, recall, F1
- regression: MSE, MAE, R^2
- plot confusion matrices, ROC curves, residuals
- example: check precision/recall on spam classification

Introduction

- Typical ML workflow
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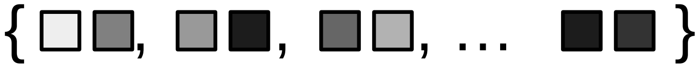
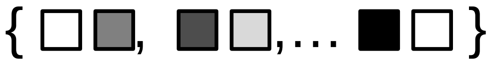
- integrate the model into production (web app, API, etc.)
- monitor for drift, performance degradation
- retrain if needed (based on new data or feedback)
- example: host model on a server and track prediction accuracy over time

Logics of Intelligence

Logics of Intelligence

- Consider a world W consisting of 2 pixels
  
- W also has two visible states A and B. We observe that
  - A → 
  - B → 
- **Step1**: problem definition: tell the state from the pixels
  → classification task

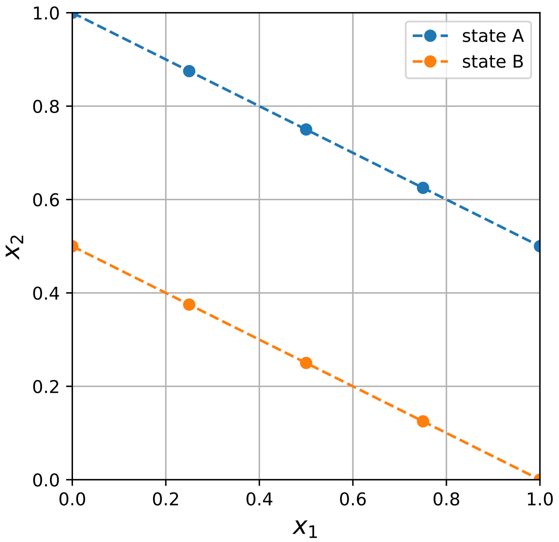
- **Step2-3**: Data collection, cleaning, preprocessing
- in our case: observation → numerics
- the pixels are black-and-white → brightness is a number in [0,1]
  - black: 0
  - white: 1
  - grey: somewhere in between
- 2 pixels mean 2 numbers (x_1, x_2)
- *usually Step2-3 is rather tedious…*

- **Step4-5-6**: feature engineering, model selection, training (in practice these are separate steps)
- Let us plot the point pairs corresponding to state A and B
  - the points lie in subspaces (lines)
  - within state A and B

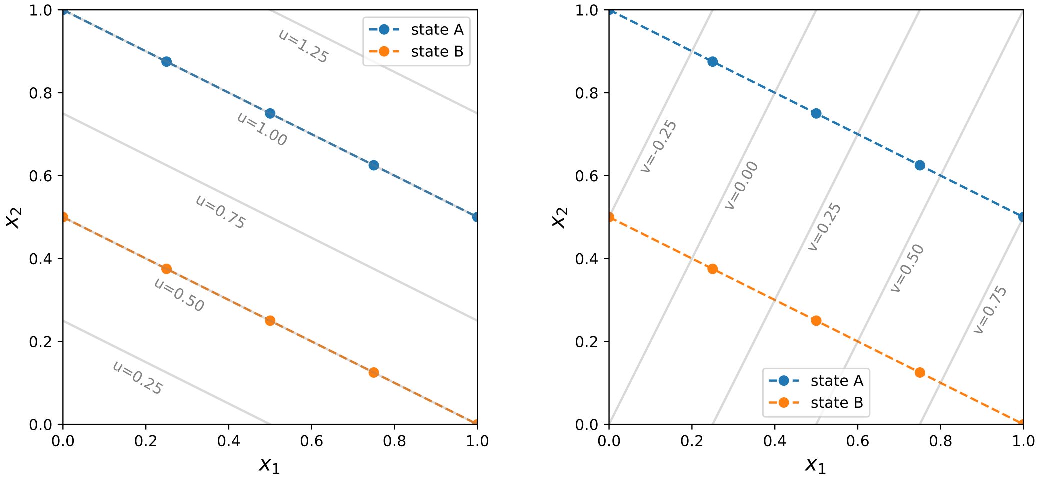
$$\frac{x_1}{2}+x_2=\begin{cases}1 & \text{for state } A\\ 0 & \text{for state } B\end{cases}$$

  - worth to introduce new coordinates (features)

$$u=\frac{x_1}{2}+x_2,\ \ v=x_1-\frac{x_2}{2}$$

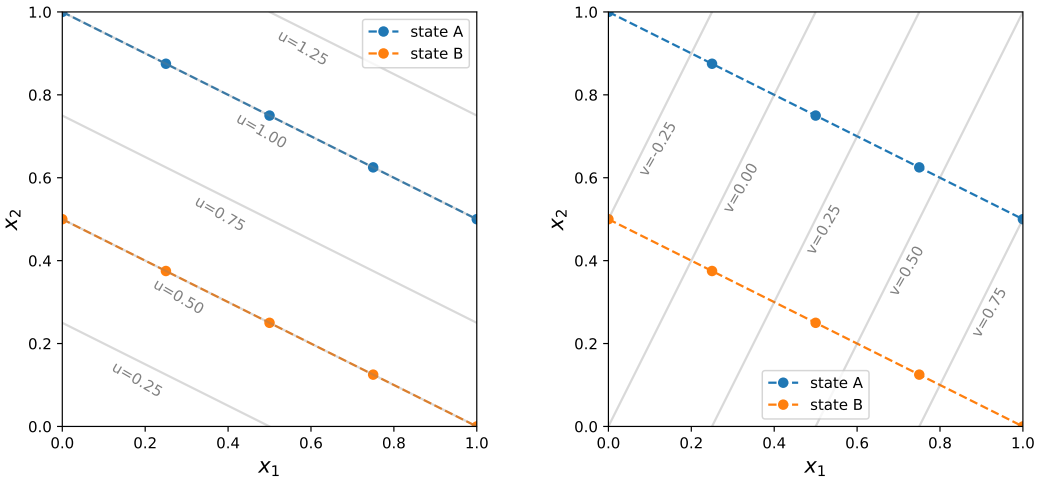


- **Step4-5-6**: feature engineering, model selection, training
- with the new coordinates $x_1 = \frac{2u}{5} + \frac{4v}{5}, \; x_2 = \frac{4u}{5} - \frac{2v}{5}$
- constant u – aligned with states; constant v – changes within a given state



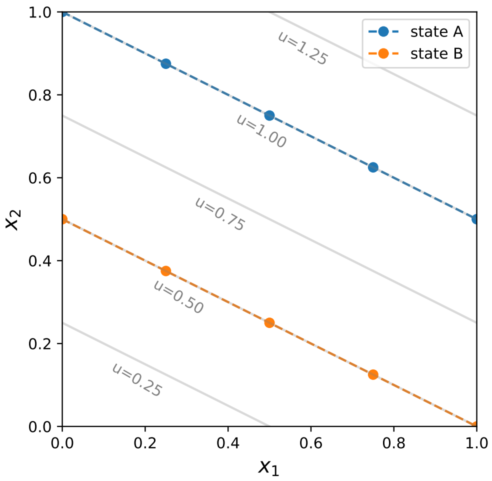
Logics of Intelligence

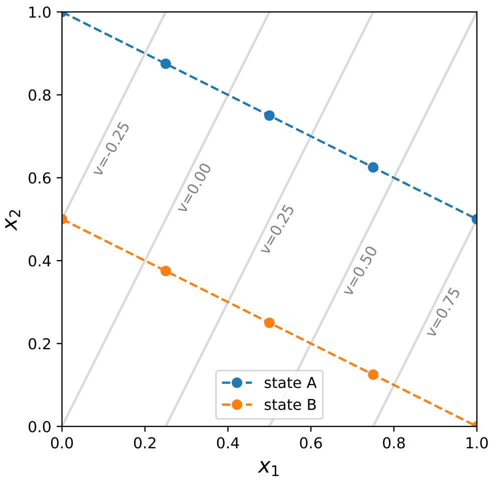
- **Step4-5-6**: feature engineering, model selection, training
- To tell apart state A and B we need only the value of u!
  - u = 1.0 state A
  - u = 0.5 state B
  - otherwise neither
- solves classification task



Logics of Intelligence

- **Step4-5-6**: feature engineering, model selection, training
- To describe a instance belonging to a state we need just v!
  - state A: v in [-0.5,0.75]
  - state B: v in [-0.25,1]
- solves compression, dimensional reduction





Logics of Intelligence

- **Step4-5-6**: feature engineering, model selection, training
- a perfect **feature selection** provides a **coordinate system** best aligned with the equivalence classes of the data
  - there are coordinates that are constant on each data class, and have different values on different classes (*relevant/selective coordinates* – good for classification)
  - there are coordinates that change within a given data class (*descriptive/irrelevant coordinates* – good for compression)
- **task of all model building is to find (approximately) these coordinates/features**

Logics of Intelligence

- **Step4-5-6**: feature engineering, model selection, training
- in practice we separate the task of coordination
  - **feature selection**: original features, simple combinations
  - **model selection**: single out a parametrizable functional space to combine the features (distance, linear- or nonlinear combinations)
  - **training**: determine the free parameters of the model that fits the data the best

Logics of Intelligence

- **Step4-5-6**: feature engineering, model selection, training
- **mind vs data?**
  - data/models importance ratio → data are central importance in real world applications
  - are data enough? do we possess the necessary knowledge?
  - present approach: data engineering is the most important, few fundamental research (cf. LeCun vs Wang in Meta)

Logics of Intelligence

- **Step7:** evaluation
- try to estimate how well the original task was solved
  - class reconstruction accuracy
  - robustness, proclivity for failures
  - treatment of outliers
  - business benefits

Logics of Intelligence

- **Step8:** deployment and monitoring
- in a real-life application the ML code is used as a product
- requires continuous monitoring
  - data/environment may change
  - new classes appear
  - errors may occur

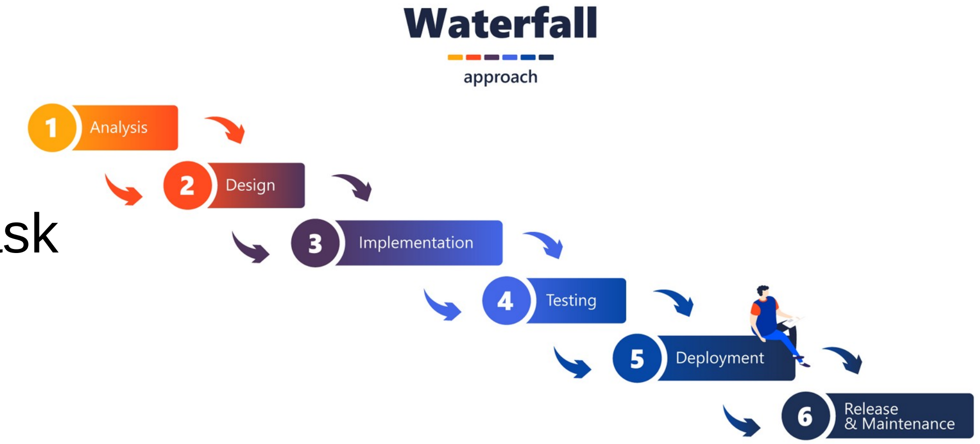
takehome message: Task of the intelligence is to

find the **relevant features** and **adapt** their values to the task

Organizing ML projects

Organizing ML projects

- two popular workflow schemes today: **waterfall** vs. **agile**
- **waterfall** workflow:

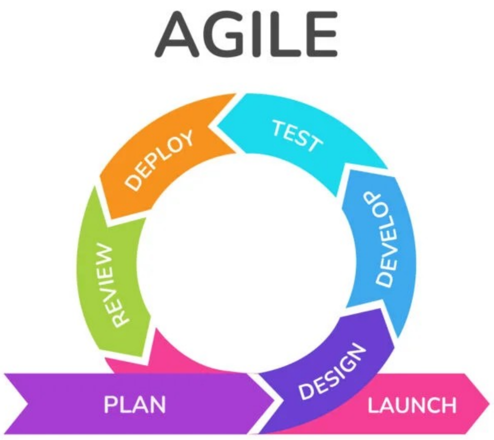


  - clear documentation of the task
  - predictable timeline
  - inflexible
  - late discovery of errors
- **good for well-defined projects** (like bridge building)

Organizing ML projects

- **agile** workflow: (agile manifesto, description)
  - individuals > processes
    - collaborative vs rigid teams
  - working model > detailed documentation
    - Minimal Viable Product MVP
    - improvement

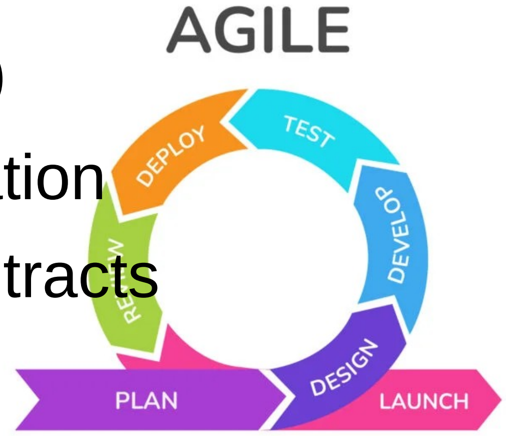
“If you’re not embarrassed by the first version of your product, you’ve launched too late.”
— Reid Hoffman, founder of LinkedIn



Goal: **Solve transportation**
- MVP: Skateboard 🛹
- Next: Bicycle 🚲
- Then: Motorcycle 🏍️
- Finally: Car 🚗

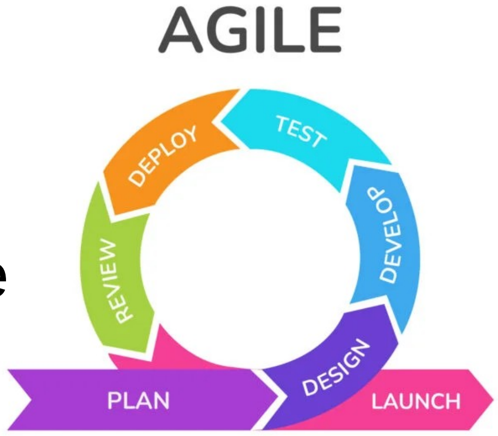
Organizing ML projects

- **agile** workflow: (agile manifesto, description)
  - customer collaboration > contract negotiation
    - customer needs even over signed contracts
  - responding to change > following a plan
    - original ideas/original task estimates may fail
    - continuous adaptation
  - launch a “good enough” product



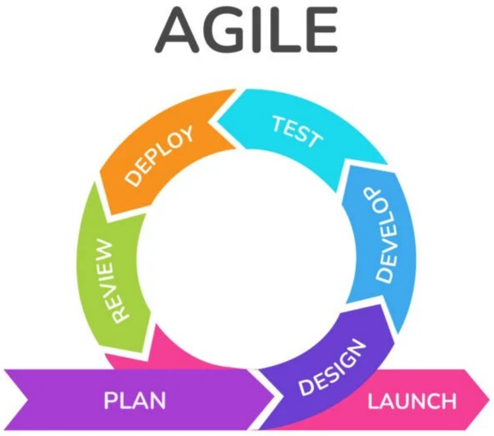
Organizing ML projects

- **agile** workflow: (agile manifesto, description)
  - pros:
    - flexible, self-improving, communicative
    - customer-centric
  - cons:
    - over-emphasized meetings (“agile theater”)
    - over-controlled
    - less predictable



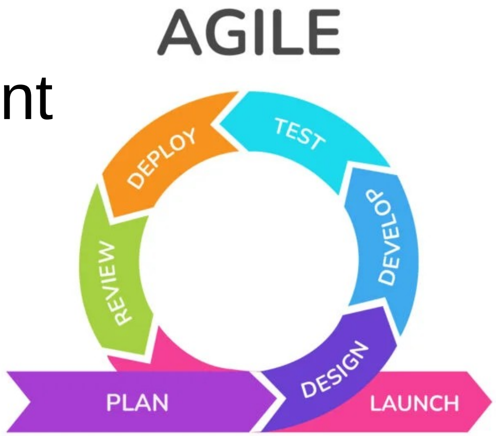
Organizing ML projects

- **agile** workflow: (agile manifesto, description)
  - loops, sprints
  - user interface/user experience (UI/UX)
  - CI/CD, CI/CD pipelines
    continuous integration, continuous deployment
  - Kanban/Jira: project development visualization (backlog, to do, in progress, testing, done)



Organizing ML projects

- typical small group agile project
  - define the goal (user stories), create a backlog (list of tasks)
  - make repo (github), branches
  - make MVP, backend API, frontend, testbed
  - get MVP working, deploy to test environment
  - collect feedback (team + users)
  - refine tasks, and directions to proceed



Organizing ML projects

Structure of a professional ML organization

- 🌐 Business side
  - client/stakeholder: business requirements (e.g., “reduce equipment downtime,” “recommend better products”)
  - Business Analyst / Product Manager (translates business goals into ML problems, acts as the bridge between client and technical teams)
  - Project/ Product Manager (budgeting, timelines, and resource allocation, Coordinates with business analysts and technical leads to estimate cost)

Organizing ML projects

Production level ML organization

- 🧠 Data/model experts
  - data engineer: build and maintain data pipelines → data collection, cleaning, validating, transformation (ETL/ELT), storing (database, data lake), monitoring
  - ML engineer/data scientist
    - feature generation
    - design, train, and fine-tune ML models
    - explores and experiments with data, build prototypes
    - performance evaluation

Organizing ML projects

Production level ML organization

- 🏗️ Software & Infrastructure
  - software architect: designs overall system, service planning, integration with other services, APIs, databases
  - software developer (coder): implements algorithms, frontend-backend
  - DevOps/MLOps engineer:
    - automates deployment, monitoring, scaling of ML models
    - works with Docker, Kubernetes, CI/CD pipelines, cloud platforms.
    - ensures the ML system is reproducible, reliable, and easy to maintain.

Organizing ML projects

Production level ML organization

- 🛡️ Operations, Monitoring & Safety
  - QA / Test Engineer: tests software and ML pipelines (unit tests, integration tests, stress tests), ensures reliability before release
  - Monitoring & Reliability Engineer: monitors system health after deployment.; tracks data drift, performance degradation, unusual patterns
  - Security Engineer: ensures compliance with data privacy, protects against adversarial attacks, model leaks.

Organizing ML projects

🎭 The Full Pipeline in a Story (user story)

- Client says: “I need early warnings for dangers in a chemical plant.”
- Business Analyst refines: “This means anomaly detection on sensor signals.”
- Data Engineer sets up pipelines to collect sensor data.
- Data Scientist explores, builds a prototype anomaly detector.
- ML Engineer optimizes the model for latency and accuracy.

🎭 The Full Pipeline in a Story (user story)

- Software Architect decides how it fits into the production system.
- Developers implement the service around the model.
- DevOps/MLOps deploys it to the cloud with monitoring.
- QA & Monitoring check performance and flag issues.
- Security Engineer ensures compliance and robustness.

Programming code structure

Code structure

How to organize a (ML) code?

- points of view:
  - effective code development (also in teams)
  - scalability
  - extensibility
  - easy maintenance

monolith code structure

Original approach: monolith program structure

- UI, business logic, data access in one code
- coding logic*: input data* → *transformation* → *resulting data*
- best fits for imperative/procedural languages (like C, Fortran)
  - program state: mutable variables
  - program is a chain of commands, changing the state
- natural approach → original programming style

monolith code structure

```
y = 3 #global state variable

def function(x):
    x +=y
    y+=1 #changes y tacitly
    return x
```

problems:

- hard to trace bugs or change code:
  - variable change appear in different functions
  - frequently hidden state change in procedures
  - in a large code intractable structure
- functions are specific → not reusable
- experience: monolith codes become unmaintainable *(software complexity crisis in the 1970s–80s)*
- still used for starting a project (MVP)

programming paradigms

different type of solutions:

- object oriented programming
  - data and the corresponding procedures are bundled: ”objects” of the world
  - abstraction:
    hierarchy of classes
  - inheritance: classes are reusable
  - examples: C++, Java

```
class MyClass:
        def __init__(self, state):
                self.state = state

        #change of state is a class method
        def rotate(self, angle):
                self.state → self.state’(angle)
                return self
```

programming paradigms

- functional programming
  - stateless programs, unmutable variables
  - functions give back new objects
    (pure functions)
  - based on mathematical logic (λ-calculus)
    e.g. λx. x+1 and their application, e.g. (λx. x+1) 5 → 6
  - basic elemental functions: see next page

```
counter=0
def impure():
	counter+=1 #side effect
	return counter
def pure(x):
	return x+1 #no side effect
```

programming paradigms

- basic elemental functions
  - map: `map (λx. x*2) [1,2,3] → [2,4,6]`
  - reduce/fold: `fold (+) 0 [1,2,3] → 6`
  - filter: `filter even [1,2,3,4] → [2,4]`
  - zip: `zip [‘a’,’b’,’c’] [1,2,3] → [(‘a’,1),(‘b’,2),(‘c’,3)]`
  - compose: `(compose f g) x → f(g(x))`
- examples: Haskell, Lisp, F#
- not popular in the original form, but lot of elements are applied

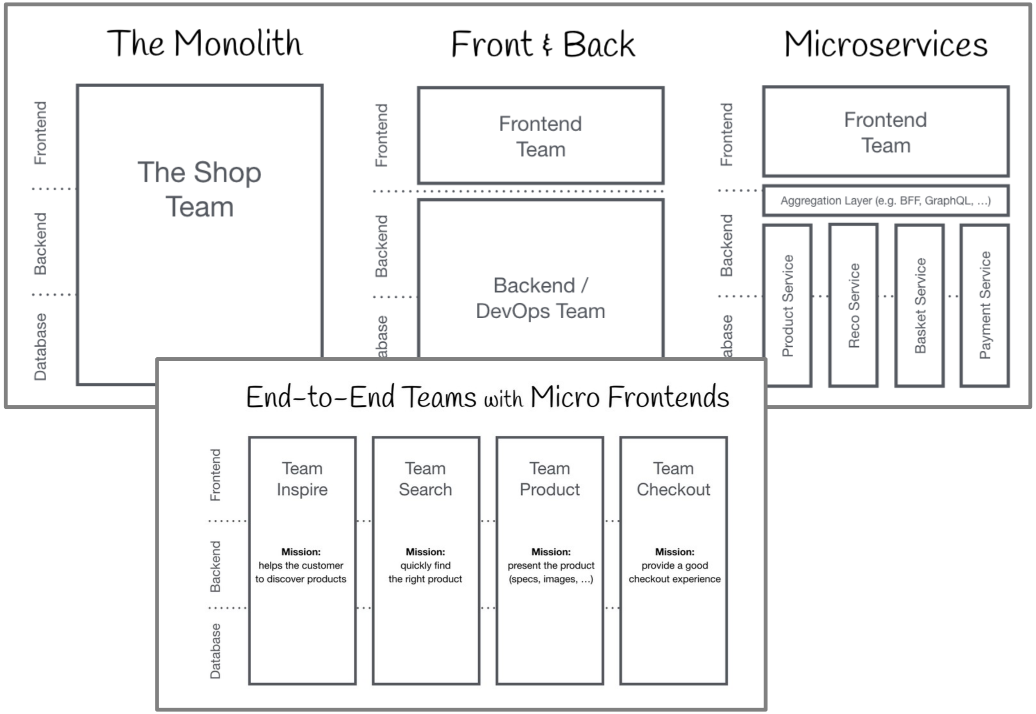
programming paradigms

- mixed (multi-paradigm) languages:
  - allow all kind of programming style
  - examples: Python, JavaScript, Rust, Swift,
  - e.g. Python has map, filter, reduce, based on lists.
  - Python supports OOP, classes, inheritance, etc.

architectures

Other way of deviating from monolithic imperative coding

- monolithic structure
- frontend+backend
- microservices
- micro frontend structure
  (c.f. https://micro-frontends.org/)



backend + frontend

Backend + frontend

- rise of web (1990s) browsers became universal clients
- specialized tools for browser programming
(like HTML, CSS, JavaScript)
- task solving (backend) + visualization (frontend) separately
  - develop separately, different languages, tools
  - scale BE and FE separately
  - needs interface management → see next page

backend + frontend

- functions designed for intra-code communication, can not be applied any more
- inter-service communication standards:
  - APIs (application programming interface → synchronous)
  - queues (message buffer → asynchronous)

backend + frontend

- APIs – call server functions (endpoints)
  - needs continuously running background processes (web server process), listening to input channels (ports)
  - endpoints: well defined input and output formats, usually in json
  - communication → REST API: get, put/patch, post, delete
  - in Python: Flask, fastAPI
  - can be asynchronous, too

```
#fastAPI snippet
from fastapi import FastAPI
app = FastAPI()
@app.get("/")
def read_root():
    return {"message": "Hello ✨"}
-----------------------------
#start service
uvicorn main:app
-----------------------------
#call service
open http://127.0.0.1:8000, or
curl http://127.0.0.1:8000/
results {"message": "Hello ✨"}
```

backend + frontend

- queues: async send message
  - message broker runs in background, it stores messages
  - worker processes deliver messages for subscribers/consumers
  - data plain text or json
  - metadata + payload
  - in Python: queue + threading

```
#queue application example
import queue
q = queue.Queue()

#put data to queue
q.put(item)

#read data from queue
item = q.get()
#... process data ...
q.task_done()
```

microservices

Microservices + frontend

- good scaling properties (e.g. web users) → requiring independence of elementary tasks became popular
- lot independent, narrowly scoped (micro) services
  - separate development (languages, tools, teams), deployment
  - separate scaling
  - resilience: bugs are confined, not affect the whole system
- examples Netflix, Amazon → hype in 2010s

microservices

- new challenge: how to organize a lot of services
- microservice management: docker, Kubernetes

```
#example Dockerfile
FROM python:3.12-slim
WORKDIR /app
COPY main.py .
RUN pip install fastapi uvicorn
CMD ["uvicorn", "main:app", "--host", "0.0.0.0", "--port", "8000"]
```

```
#example docker-compose.yml
services:
  service1:
    build: ./service1
    container_name: service1
    ports:
      - "8001:8000"

  service2:
    build: ./service2
    container_name: service2
    ports:
      - "8002:8000"
------------------------------------------------
docker-compose up --build
```

microservices

- new challenge: how to organize a lot of services
- CI/CD pipelines:
  - continuous improvement
  - continuous deployment
  - team communication
- example: github

microservices

- new challenge: how to organize a lot of services
- CI/CD pipelines:
  - continuous improvement
  - continuous deployment
  - team communication
- example: github

```yaml
#example .github/workflows/ci.yml
name: CI
on:
  push: branches: ["main"]
  pull_request: branches: ["main"]
jobs:
  build-and-test:
    runs-on: ubuntu-latest
    steps:
      - name: Checkout code
        uses: actions/checkout@v4
      - name: Set up Python
        uses: actions/setup-python@v5
        with:
          python-version: "3.12"
      - name: Install dependencies
        run: |
          python -m pip install --upgrade pip
          pip install -r requirements.txt
          pip install pytest
```

microservices

- new challenge: how to organize a lot of services
- CI/CD pipelines:
  - continuous imp
  - continuous deployment
  - team communication
- example: github

```
#practical example: git clone project

git clone https://github.com/ajakovac/ML-in-Practice-I.git
cd ML-in-Practice-I
```

microservices

- despite all advantages microservices have drawbacks
  - operational complexity → manage hundreds of services
  - network calls → latency, performance issues
  - interprocess debugging is hard

microservices

- Current trends (2020s → now)
  - modular monolith applications
  - microservices where they make sense
  - functions-as-a-service (FaaS)
    - in cloud services like AWS, Azure, Google cloud
    - locally they seem like functions
    - behave like services when deployed
    - run on demand

microservices

- Current trend
  - modular m
  - microserv
  - functions-
    - in clou
    - locally
    - behave
    - run on

```
#example in AWS
#lambda_function.py
def lambda_handler(event, context):
        name = event.get("name", "my_name")
        return { "statusCode": 200,
                    "body": f"Hello, {name}! ✨"}
-------------------------------------------
zip function.zip lambda_function.py
aws lambda create-function \
  --function-name helloLambda \
  --runtime python3.12 \
  --role arn:aws:iam::<YOUR_ACCOUNT_ID>:role/lambda-ex-role \
  --handler lambda_function.lambda_handler \
  --zip-file fileb://function.zip
--------------------------------------------------
curl -X POST \
    -H "Content-Type: application/json" \
    -d '{"name": "MLcourse"}' \
    https://abcd1234.execute-api.us-east-1.amazonaws.com/default/hello
```

ML Code structure

Code infrastructure → software architecture

- use few necessary microservices → clear task definition
- use lambda for simple services
- containerize microservices → portability, environmental stability
- use container management → docker (Kubernetes)
- use CI/CD management → github or similar

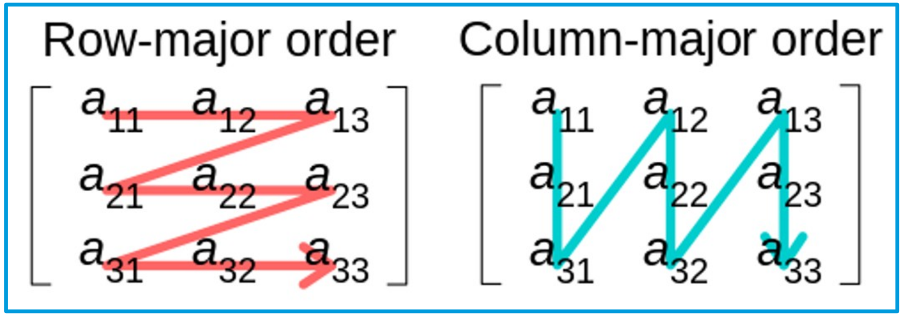
Data management

Data management

data sources:

- user input (text, image, video, etc.) – often not well formed, errors
- system generated (logs, measurements, predictions) – well formed data, easy-to-use
- own data, own clients (first-party), other companies, their own clients (second-party), other companies not own clients (third-party – e.g. internet usage, traffic, etc)

Data management



data formats

- CSV (comma separated values)
  - text, human readable
  - tabular, row-major
  - fast to get data belonging to the same example
- Parquette
  - binary – more compact, but not human readable
  - tabular, column major
  - fast to get data belonging to the same feature

Data management

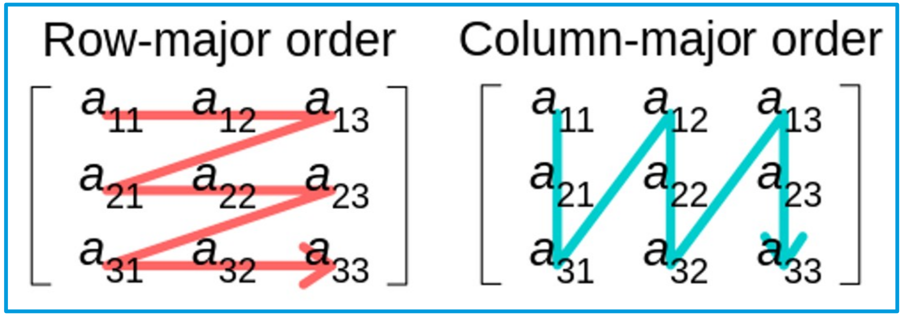
data formats

- CSV (comma
  - text, human
  - tabular, row
  - fast to get c
- Parquette
  - binary – mo
  - tabular, colu
  - fast to get c

```
#example books.csv
title,author,publisher,year
The Hobbit,J.R.R. Tolkien,George Allen & Unwin,1937
The Fellowship of the Ring,J.R.R. Tolkien,George Allen & Unwin,1954
Nineteen Eighty-Four,George Orwell,Secker & Warburg,1949
Brave New World,Aldous Huxley,Chatto & Windus,1932
The Catcher in the Rye,J.D. Salinger,"Little, Brown and Company",1951
----------------------------------------
#read data using pandas
import pandas as pd
df = pd.read_csv("books.csv")
print(df)
----------------------------------------
#output
                        title          author                 publisher  year
0                  The Hobbit  J.R.R. Tolkien      George Allen & Unwin  1937
1  The Fellowship of the Ring  J.R.R. Tolkien      George Allen & Unwin  1954
2        Nineteen Eighty-Four   George Orwell          Secker & Warburg  1949
3             Brave New World   Aldous Huxley           Chatto & Windus  1932
4      The Catcher in the Rye   J.D. Salinger  Little, Brown and Company  1951
```

er

data formats



- CSV (comma separated values)
  - text, human readable
  - tabular, row-major
  - fast to get data belonging to the same example
- Parquette
  - binary – mor
  - tabular, colu
  - fast to get da

```
#store in parquette – needs fastparquet to be installed
df.to_parquet("books.parquet", engine="fastparquet", index=False)
--------------------------
#store in parquette – needs fastparquet to be installed
df_parquet = pd.read_parquet("books.parquet", engine="fastparquet")
```

Data management

data formats:

- JSON (JavaScript Object Notation) → today's standard
  - hierarchical structure
  - text, human readable
  - key-value pairs
  - in Python: dict
  - supported by all languages

Data management

data formats:

- JSON (JavaS
  - hierarchical
  - text, human
  - key-value p
  - in Python: d
  - supported b

```
#example books.json
[
  {
    "title": "The Hobbit",
    "author": "J.R.R. Tolkien",
    "publisher": "George Allen & Unwin",
    "year": 1937
  },
  {
    "title": "The Fellowship of the Ring",
    "author": "J.R.R. Tolkien",
    "publisher": "George Allen & Unwin",
    "year": 1954
  },…
]
-------------------------------------------
#read with pandas
df = pd.read_json("books.json")
```

Data management

data models:

- for more complicated data, and if queries are required, storing data in simple files is not enough
- instead: databases with dedicated database handlers
  - relational (e.g. Sqlite)
  - nonrelational (e.g. Redis, Mongo)

Data management

data models:

- relational
  - tabular logic: main tables, subtables for standardization, index tables for faster query
  - strict schemas
  - query language for data retrieval → SQL (structured query language): declarative, specify the result, not the algorithm
  - **pros**: simple logic, widely used
  - **cons**: abundant schema systems, lots of superficial data, tedious to introduce new features, complicated table structure

Data management

data models:

- relational
  - tabular logi… …r faster query…
  - strict schem…
  - query langu… declarative,…
  - **pros**: simpl…
  - **cons**: abun… introduce n…

```
#example sqlite application – built in Python package
import sqlite3
#create/connect database
conn = sqlite3.connect("Data/books.db")
cur = conn.cursor()
#create tables
cur.execute("""
CREATE TABLE IF NOT EXISTS publishers (
    id INTEGER PRIMARY KEY AUTOINCREMENT,
    name TEXT NOT NULL
)
""")
cur.execute("""
CREATE TABLE IF NOT EXISTS books (
    id INTEGER PRIMARY KEY AUTOINCREMENT,
    title TEXT NOT NULL,
    author TEXT NOT NULL,
    year INTEGER,
    publisher_id INTEGER,
    FOREIGN KEY (publisher_id) REFERENCES publishers(id)
)
""")
```

Data management

data models:

- relational
  - tabular logi... ...or faster query...
  - strict schem...
  - query langu... declarative,...
  - **pros**: simpl...
  - **cons**: abun... introduce n...

```
#insert a publisher
cur.execute("INSERT INTO publishers (name) VALUES (?)", ("George Allen &
Unwin",))
publisher_id = cur.lastrowid
# Insert a book linked to that publisher
cur.execute("INSERT INTO books (title, author, year, publisher_id) VALUES
(?, ?, ?, ?)",("The Hobbit", "J.R.R. Tolkien", 1937, publisher_id))
#commit changes
conn.commit()
----------------------------------------------
# Query join
cur.execute("""
SELECT b.title, b.author, p.name AS publisher
FROM books b
JOIN publishers p ON b.publisher_id = p.id
""")
print(cur.fetchall())
conn.close()
-----------------------------------------------
#output
[('The Hobbit', 'J.R.R. Tolkien', 'George Allen & Unwin')]
```

Data management

data models:

- NoSQL: no SQL → not only SQL
  - pros: no schemas → flexibility, scalability, treat of unstructured data
  - cons: storage capacity, performance trade-offs, data chaos
  - document stores: data are stored as a JSON (string)
    - query can be a more difficult task
    - examples: mongoDB, CouchDB – create own index tables for effectivity
  - key-value pairs: for fast query (example: RedisDB, DynamoDB)
  - graph databases: concentrate on relations (nodes and edges) (Examples: Neo4j, Amazon Neptune, ArangoDB)

Data management

data models:

- NoSQL: no S
  - pros: no sc
  - cons: stora
  - document s
    - query ca
    - examples
  - key-value p
  - graph datab
    (Examples: N

```
#install mongodb-image and pymongo
docker run -d --name mongodb -p 27017:27017 -v ~/my_data/mongo:/data/db mongo:7.0
pip install pymongo
-----------------------------------------
#runs a service in the background – start/stop it
docker start/stop mongodb
----------------------
#install mongodb and pymongo
from pymongo import MongoClient

# 1. Connect to local MongoDB
client = MongoClient("mongodb://localhost:27017/")

# 2. Create (or use existing) database
db = client["library"]

# 3. Create collections
publishers = db["publishers"]
books = db["books"]

# 4. Clear old data (for demo purposes)
publishers.delete_many({})
books.delete_many({})
```

Data management

data

- N

```
# 5. Insert publishers
pub_allen = publishers.insert_one({"name": "George Allen & Unwin"}).inserted_id
pub_secker = publishers.insert_one({"name": "Secker & Warburg"}).inserted_id
pub_chatto = publishers.insert_one({"name": "Chatto & Windus"}).inserted_id
pub_little = publishers.insert_one({"name": "Little, Brown and Company"}).inserted_id

# 6. Insert books with publisher references
books.insert_many([
    {"title": "The Hobbit", "author": "J.R.R. Tolkien", "year": 1937, "publisher_id": pub_allen},
    {"title": "The Fellowship of the Ring", "author": "J.R.R. Tolkien", "year": 1954, "publisher_id": pub_allen},
    {"title": "Nineteen Eighty-Four", "author": "George Orwell", "year": 1949, "publisher_id": pub_secker},
    {"title": "Brave New World", "author": "Aldous Huxley", "year": 1932, "publisher_id": pub_chatto},
    {"title": "The Catcher in the Rye", "author": "J.D. Salinger", "year": 1951, "publisher_id": pub_little},
])

# 7. Query: find all books and join publisher info manually
for book in books.find():
    publisher = publishers.find_one({"_id": book["publisher_id"]})
    print(f"{book['title']} by {book['author']} "
          f"was published by {publisher['name']} in {book['year']}.")
```

Data management

data storage:

- data warehouse:
  - stores historical data → structured, cleaned, integrated
  - optimized for analysis, reporting → few but very large, complex queries
  - ETL (extract, transform, load)
  - OLAP (online analytic processing)
  - examples: historical sales data, stock price data
  - solutions: Amazon Redshift, Google BigQuery

Data management

data storage:

- database:
  - stores current, operational data.
  - used for day-to-day transactions (insert, update, delete).
  - optimized for fast read/write, many small simple queries
  - example: an e-commerce database storing users, orders, payments
  - OLTP (Online Transaction Processing)
  - solutions: MySQL, PostgreSQL, Oracle DB, MongoDB, DynamoDB

Data management

data storage:

- data lake:
  - stores data in raw form → future-proof
  - application goal not needed to be specify
  - cheap and scalable storage (HDFS, Amazon S3, Azure Data Lake Storage, Google Cloud Storage)
  - schema-on-read solutions (ELT, extract, load, transform) → processing engines (Kafka, TensorFlow, Athena)
  - example: log storage, IoT data storage

Data management

data sampling: collecting all data usually not feasible

- nonprobability sampling → focus on data collection; prone to selection bias
  - convenience sampling: take all what is available
  - snowball sampling: start with a small set, and follow its descendants
  - judgement sampling: experts say what to collect
  - quota sampling: collect the same number of data from different areas (like age groups)
  - example of bias: psychology experiments (university students), sentiment analysis (wordy people), medical data (unsuccessful treatments)

Data management

data sampling:

- probability sampling → needs a data model → biased?
  - stratified sampling: collect the same amount of data per class
  - weighted sampling: take into account data scaled with probability
    - in choice: class A 25%, class B 75% → consider A samples 3 times
    - in training: give weight for underrepresented classes (see later)
  - reservoir sampling: keep the first k sample, and replace it randomly
  - importance sampling

$$E_P[x] = \sum_x x\ P(x) = \sum_x x\ P\frac{(x)}{Q}(x)\,Q(x) = E_Q\left[x\,P\frac{(x)}{Q}(x)\right]$$

Data management

data augmentation:

- if there are not enough data, or not representative enough, we can transform data to generate new ones (symmetries)
  - rotation, scaling
  - perturbation, noising
  - texture or style change
- data generation: simulations in artificial environment (e.g. self-driving cars)

Data management

labelling:

- for classification we should collect examples in different classes
- problems:
  - how unambiguous are the labels? → multi-label classes
  - how precise are the labels? → no database is 100% correct!
  - what to do with missing labels? → label functions, semi-supervised, etc.
- hand labelled data, naturally labelled data (context is given), automatically generated data

Monitoring and evaluation

Monitoring and evaluation

How can we assess the success of the ML results?

- not unique! depends on the problem on hand
  - example: percentage of correctly classified images
  - if the probability of belonging to class A is 99%, then the simple method saying that *all* elements belong to A is 99% accurate!
  - clearly not good, if the task is to find the 1% not-A class!

Monitoring and evaluation

- baselines: how accurate are simple methods and other approaches?
  - random baseline: choose class randomly → 1/N probability for balanced
  - zero rule: all belonging to one class → high probability for inbalanced
  - simple heuristic → use a simple proxy (feature)
  - human experts → how well do humans perform?
  - other ML methods

Monitoring and evaluation

- confusion matrix
  - correct classes vs. estimated classes
  - works for multi-class evaluation
  - in probabilistic sense joint probability: $C_{ij} = P(\mathrm{predicted}_i, \mathrm{actual}_j)$

	Actual Yes	Actual No	Predicted Total
Predicted Yes	TP=0.510	FP=0.038	PP=0.548
Predicted No	FN=0.032	TN=0.420	PN=0.452
Actual Total	AP=0.542	AN=0.478	1.0

Monitoring and evaluation

- correctness measures for 2-class evaluation
  - *accuracy*: prob. of choosing the correct class: (TP+TN)
  - *precision*: conditional for Predicted Yes: $P\left(\text{actual}_P \middle| \text{predicted}_P\right) = \frac{TP}{PP}$
  - *recall*: conditional for Actual Yes: $P\left(\text{predicted}_P \middle| \text{actual}_P\right) = \frac{TP}{AP}$
  - *type I error*: probability of false alarm: $P\left(\text{predicted}_P \middle| \text{actual}_N\right) = \frac{FP}{AN}$
  - *type II error*: probability of missing signal: $P\left(\text{predicted}_N \middle| \text{actual}_P\right) = \frac{FN}{AP}$

Monitoring and evaluation

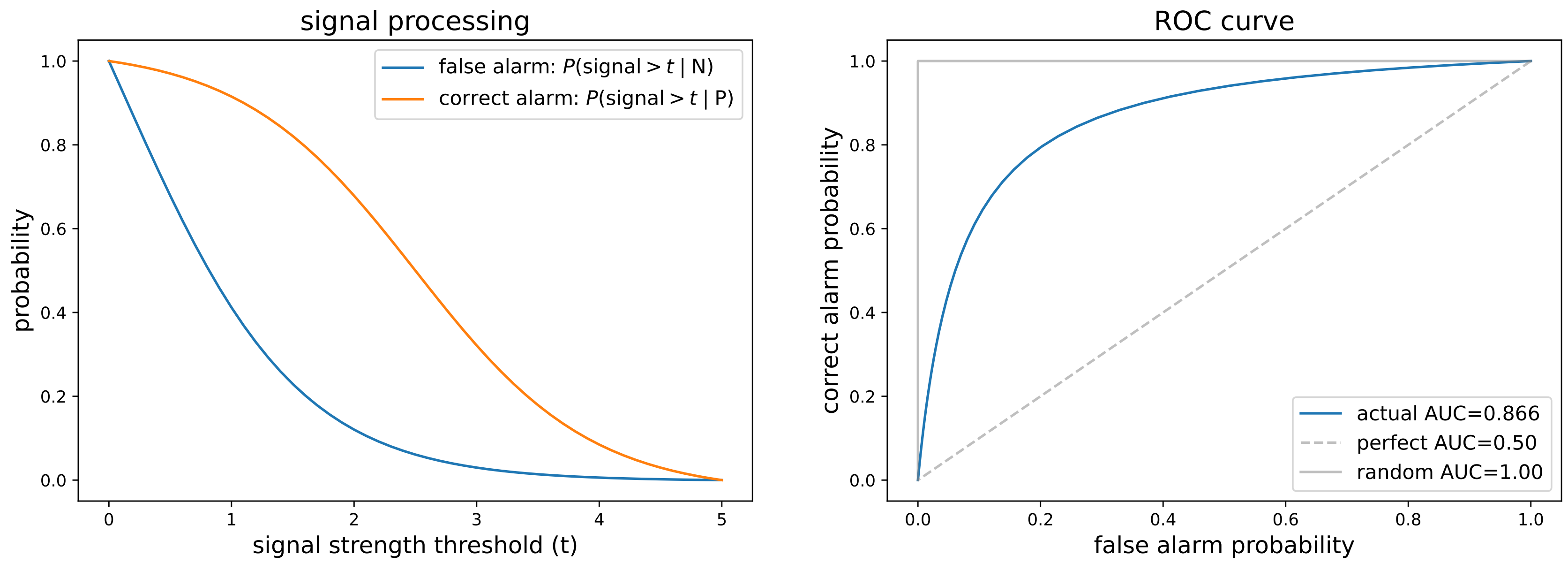
- effect of a threshold on the prediction
  - in lot of cases Yes/No decision comes from comparing a signal with a threshold → e.g. smoke detector signal vs. danger level
  - ROC (receiver operating characteristics)

$$\mathrm{ROC} = \frac{P\left(\mathrm{predicted}_P \middle| \mathrm{actual}_P\right)}{P\left(\mathrm{predicted}_P \middle| \mathrm{actual}_N\right)} = \frac{\mathrm{recall}}{\mathrm{type\ I\ error}}$$

  - AUC: area under curve

Monitoring and evaluation

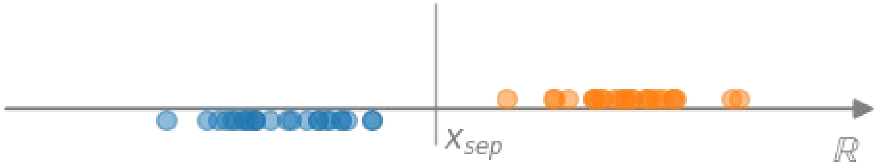
- effect of a threshold on the prediction



Data modelling

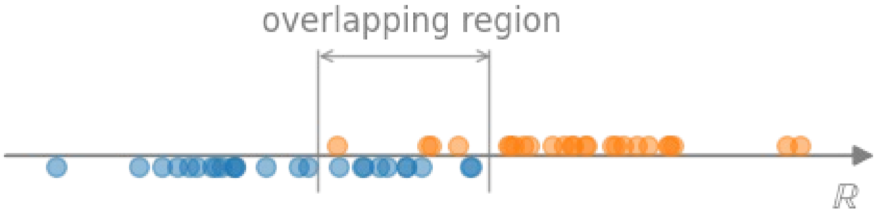
One dimensional dataset

- Simplest basic case: characterization of one-dimensional data
  - data $\rightarrow x \in \mathbb{R}$ (numbers for analytic characterization)
  - most complicated case: union of sections
  - a single section can be characterized by $X \le x \le Y$
- Separation of two 1D sets
  - if the two sets are separated (hard margin) $\left\{ \begin{array}{l} x \in A \Leftrightarrow x < x_{sep} \\ x \in B \Leftrightarrow x > x_{sep} \end{array} \right\}$
  - overlapping case? $\rightarrow$ no perfect solution



One dimensional dataset

- overlapping regions → define an error function to minimize
  - error function for example $$L_p(x_{sep}) = \sum_{x \in \text{overlap}} |x - x_{sep}|^p$$
  - sum up points in the overlapping region
  - meaning of p:
    - p=2 → mean
    - p=1 (“hinge loss”) → median



$$0 = \frac{d}{dx_{sep}} \sum_{i=1}^{N} (x_i - x_{sep})^2 = 2 \sum_{i=1}^{N} (x_{sep} - x_i) \;\Rightarrow\; x_{sep} = \frac{1}{N} \sum_{i=1}^{N} x_i$$

$$\sum_{i=1}^{N} |x_i - x_{sep}| = \sum_{x_i > x_{sep}} (x_i - x_{sep}) + \sum_{x_i < x_{sep}} (x_{sep} - x_i) = (N_< - N_>) x_{sep} + \sum_{x_i > x_{sep}} x_i - \sum_{x_i < x_{sep}} x_i \;\Rightarrow\; N_< = N_>$$

One dimensional dataset

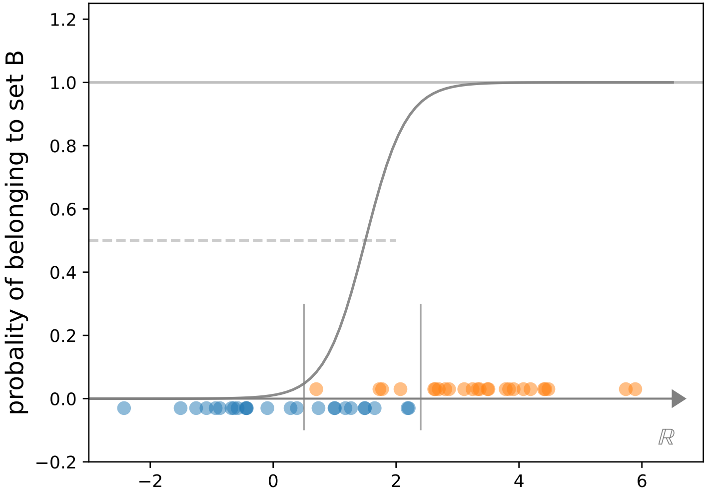
- Another approach: treat the problem as a regression
  - define a function $f:\mathbb{R}\to\mathbb{R}$, that $\begin{Bmatrix} f(x)<0 \Leftrightarrow x\in A \\ f(x)>0 \Leftrightarrow x\in B \end{Bmatrix}$
  - a classification can always be translated to regression
  - simplest: linear relation f(x)=ax+b
  - probabilistic interpretation: $p(x)=\dfrac{e^{f(x)}}{1+e^{f(x)}} \in[0,1], \quad p(0)=0.5$

    logistic map, probability of belonging to class B
  - loss function: $L(a,b)=\sum_x \left(p(x)-I_{x\in B}\right)^2, \quad I_{x\in B}=1 \text{ if } x\in B, \text{ else } 0$

One dimensional dataset

- Another approach: treat the problem as a regression
  - logistic map, probability of belonging to class B

$$p(x)=\frac{e^{ax+b}}{1+e^{ax+b}}$$



One dimensional dataset

Statistical / information theory characterization

- take a sample where $n_A \in A,\ \ n_B \in B,\ \ n = n_A + n_B$
- **entropy**: ~ log of how many ways we can order this set

$$S = \frac{1}{n} \ln \binom{n}{n_A} = \frac{1}{n} \ln \frac{n!}{n_A!\, n_B!}$$

- Stirling formula: $\ln(n!) \approx n \ln n - n \ldots$
- Shannon entropy: $\boxed{S = \ln n - \frac{n_A}{n} \ln n_A - \frac{n_B}{n} \ln n_B = -n \sum_{i=1}^{2} p_i \ln p_i}$ $\quad p_i = \frac{n_i}{n}$

One dimensional dataset

Statistical / information theory characterization

- if we randomly choose A with probability q, and B with (1-q), then what is the probability to get $n_A \in A, \;\; n_B \in B$?
  - choose the first n_A from A, the rest from B + ordering: $P = \binom{n}{n_A} q^{n_A} (1-q)^{n_B}$

$$\ln P = -n\, p_A \ln p_a - n\, p_B \ln p_B + n_A \ln q + n_B \ln(1-q) = n \sum_{i=1}^{2} p_i \ln \frac{q}{p_i}$$

- Kullback-Leibler (KL) divergence: probability to get the sample from a random choice with probability q:
  - "distance" of distributions

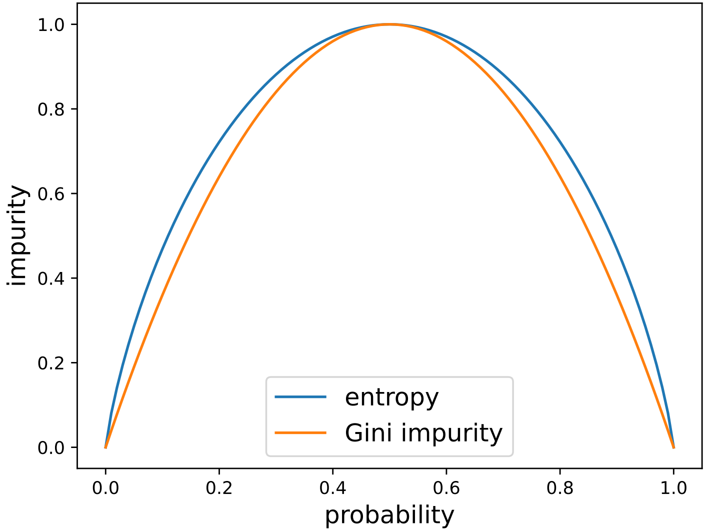
$$\boxed{D(p \| q) = \frac{1}{n} \ln P = \sum_{i=1}^{2} p_i \ln \frac{q}{p_i}}$$

One dimensional dataset

How successful is the separation?

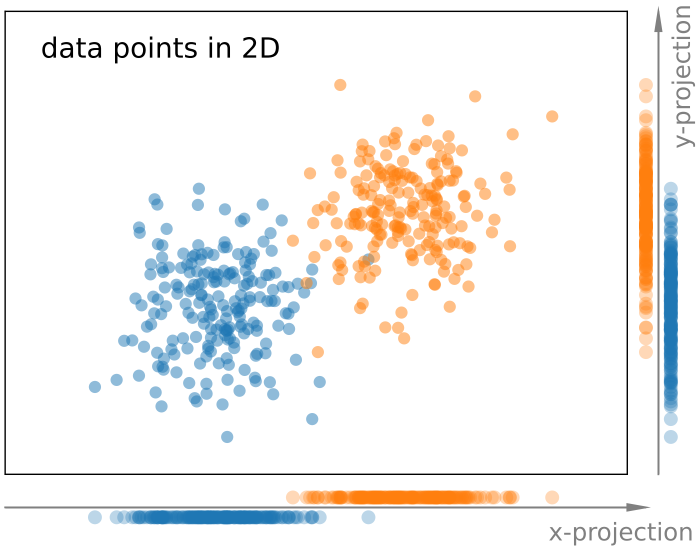
- impurity of a sample: $n_A \in A, \quad n_B \in B \;\Rightarrow\; p = \dfrac{n_A}{n_A + n_B}$
- impurity measure:
  - entropy: $I_H(p) = p \log(p) + (1-p) \log(1-p)$
  - Gini impurity: $I_G(p) = p(1-p)$
- with separation total impurity change

$$\Delta I = I_0 - \left(\frac{n_{\text{left}}}{n} I_{\text{left}} + \frac{n_{\text{right}}}{n} I_{\text{right}}\right)$$



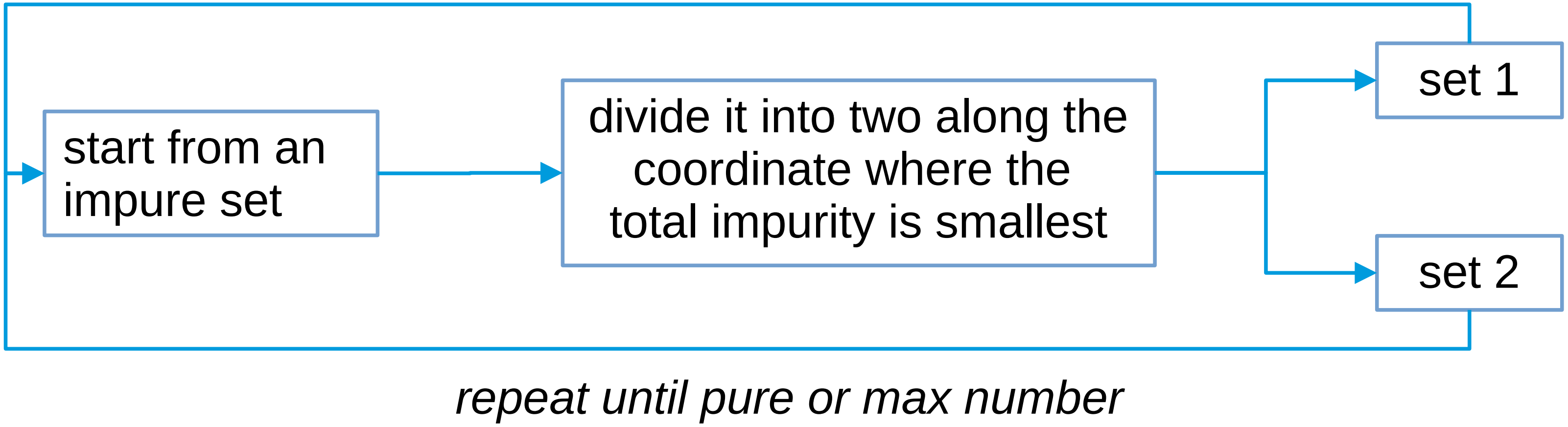
Tree based methods

- The **generalization to multiple dimensions** is not simple
  - in 1D the coordinates are unique
  - in multidimensional case we can optimize the coordination → features
  - simplest case: use original coordinates
  - usually the original coordinates are not equally useful
    (c.f. image → x coord separates more)
  - choose that coordinate that leads to the smallest total impurity!



Tree based methods

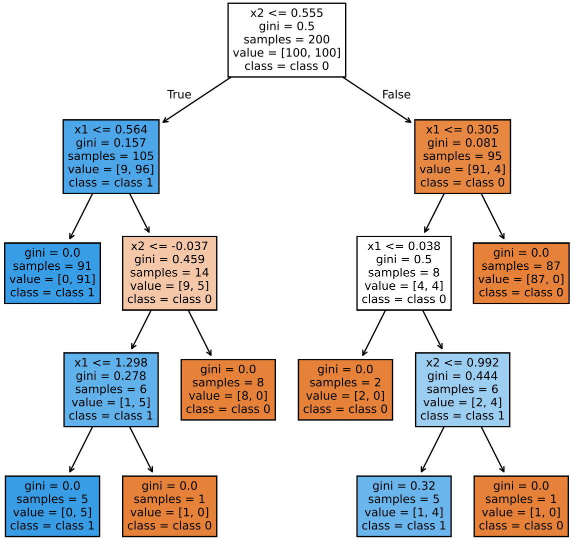
- Decision tree (DT)

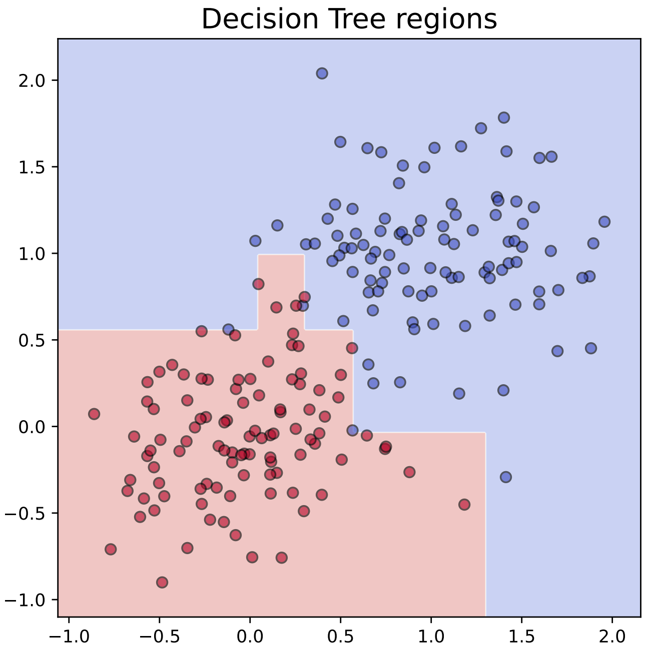


- always converges, but may result in fragmented divisions

Tree based methods

- Decision tree (DT) example
  - two 2D sets
- pros:
  - simple
  - interpretable
- cons:
  - not robust enough
    ($\rightarrow$ *irregular shape)*

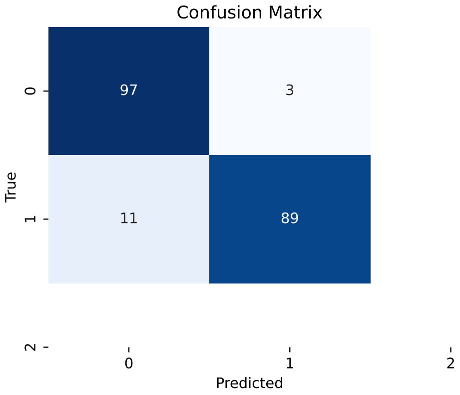


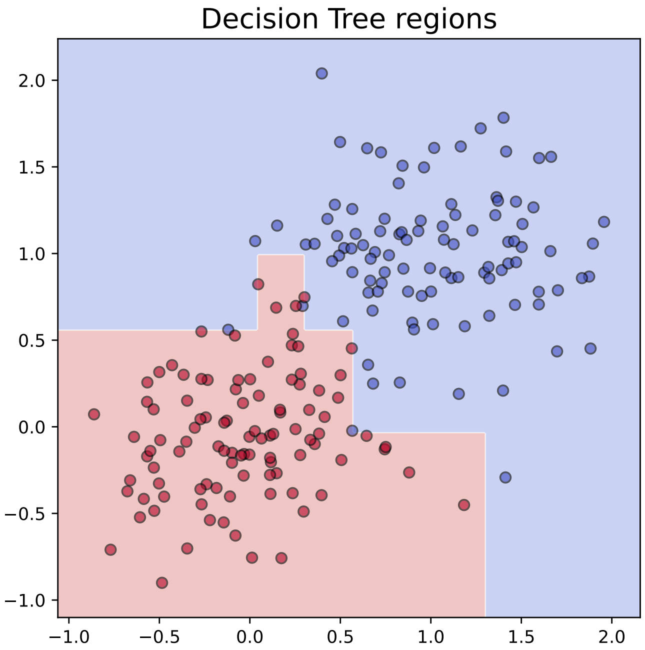


Tree based methods

- Decision tree (DT) example
  - two 2D sets
- pros:
  - simple
  - interpretable
- cons:
  - not robust enough

    (→ irregular shape)
    use fixed depth!





Tree based methods

- Decision tree (DT) technical solution in Python → Google colab

imports

```
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.tree import
DecisionTreeClassifier
from sklearn.tree import plot_tree
from sklearn.metrics import confusion_matrix
```

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2d data generation

```
x = np.random.normal(1, 0.4, size=100)
y = np.random.normal(1, 0.4, size=100)
data1 = np.array([x,y]).T

x = np.random.normal(0, 0.4, size=100)
y = np.random.normal(0, 0.4, size=100)
data2 = np.array([x,y]).T

X = np.concatenate((data1, data2))
y =
np.concatenate((np.zeros(100),np.ones(100)))
```

Tree based methods

Decision tree (DT) technical solution in Python → Google colab

training DT

```
clf =
DecisionTreeClassifier(max_depth=4)
clf.fit(X, y)
```

Ensemble methods

- Decision tree → too specific for a sample
- Possible solution: use an ensemble of trees (“bag” or “forest”)
- ways of improvement
  - bagging (Bootstrap AGGregatING) → bagging, random forest
  - boosting → adaptive boosting, gradient boosting
  - other methods → extra trees, isolated forests, oblique trees