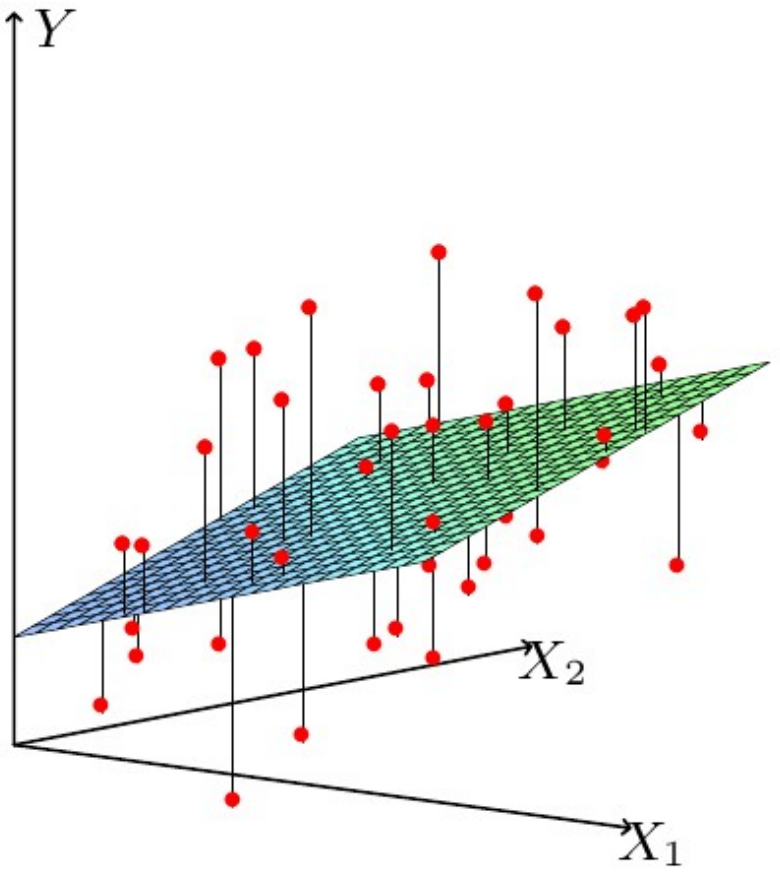
# Skúška

- Nezabudnite odovzdať svoje projekty **do 7.1.2025**
- Posledná domáca úloha **7.1.2025**
- **Písomná skúška:** ukážkový príklad písomky do konca týždňa
  40% známky, na úspešné absolvovanie aspoň polovicu bodov zo skúšky
  riadne termíny 10.1. a 16.1., opravné termíny po dohode
  žiadne ďalšie termíny po 11.2.
  **prihlasovanie / odhlasovanie najneskôr 2 dni pred skúškou**
- Môžete si doniesť **ťahák** – 2 listy A4 popísané čímkoľvek z oboch strán
- **Pred uzavretím známky vás môžeme požiadať o ústnu konzultáciu / demo vášho projektu!**

# Course Summary

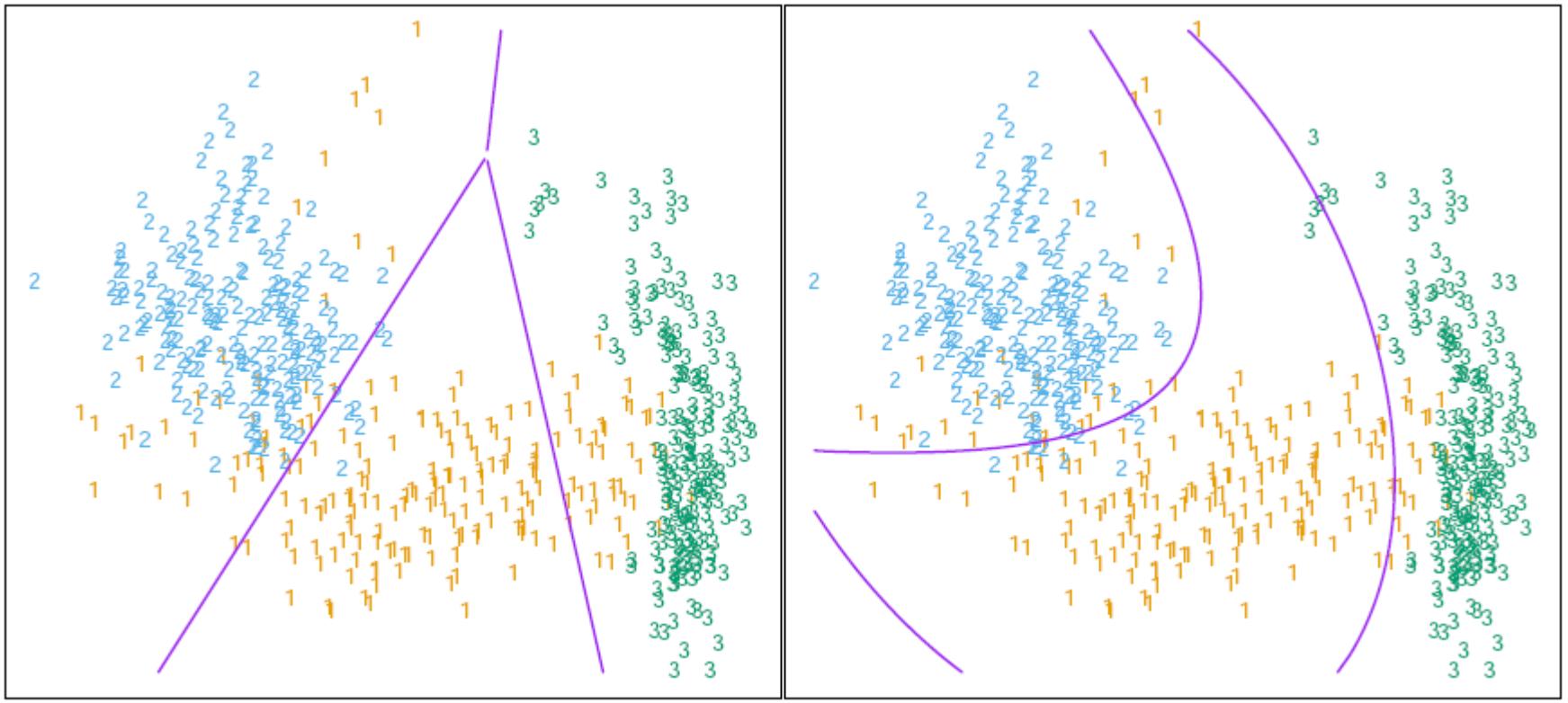
- **Supervised learning**
  - regression, classification
- **Unsupervised learning**
  - clustering, dimensionality reduction
- **Machine learning theory**
  - bias and variance, PAC learning, VC dimension
- **On-line learning and reinforcement learning**

# Regression




- Linear regression
- Solving normal equations in O(n^3)
- Gradient descent
- Expansion of underlying vector space through non-linear transformation => generalized linear regression

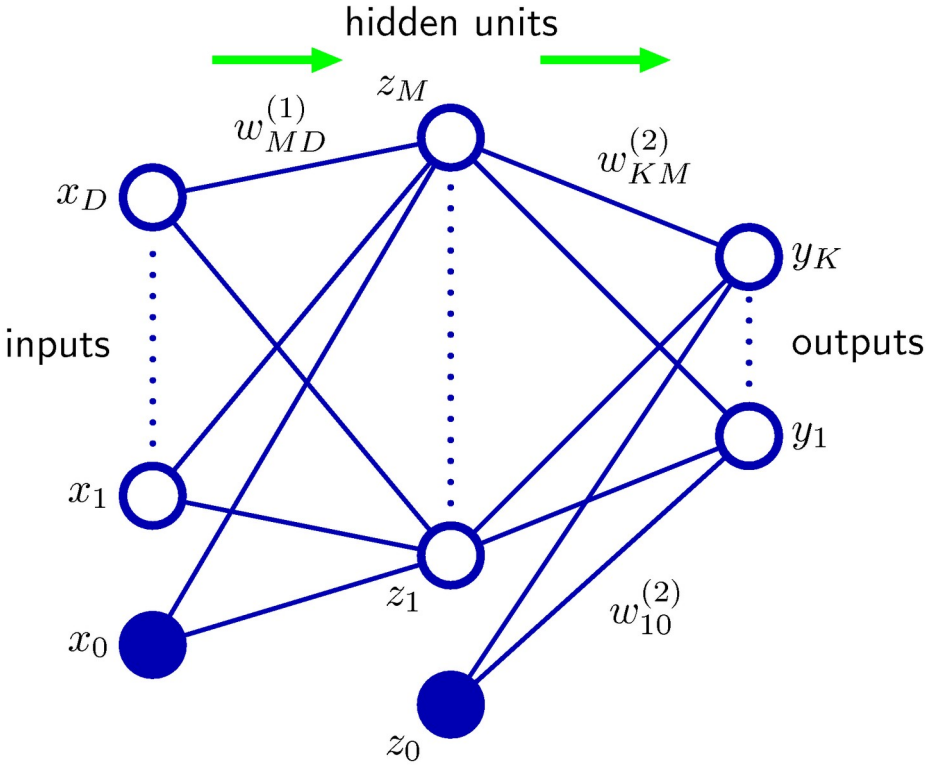
# Classification



Linear classification

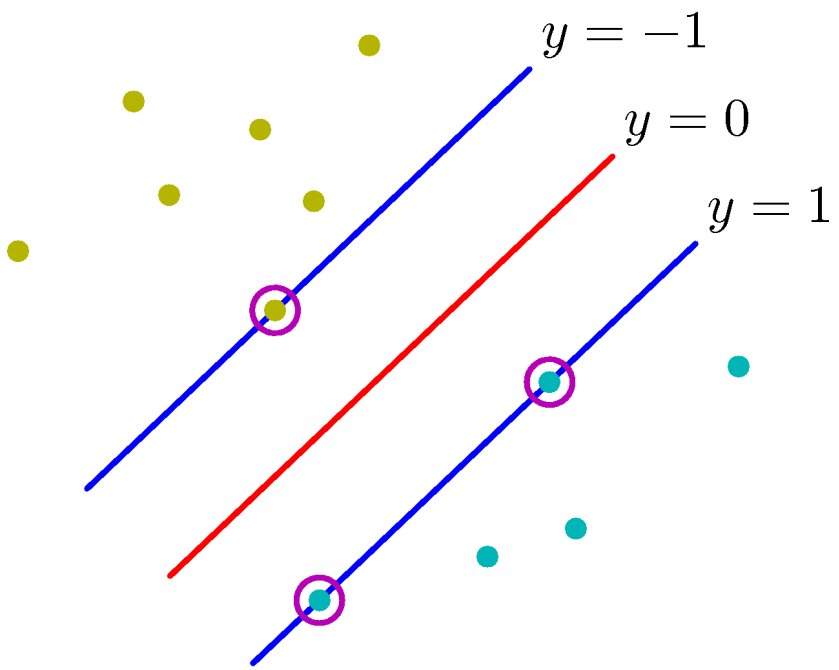
Using non-linear expansions

# Neural Networks



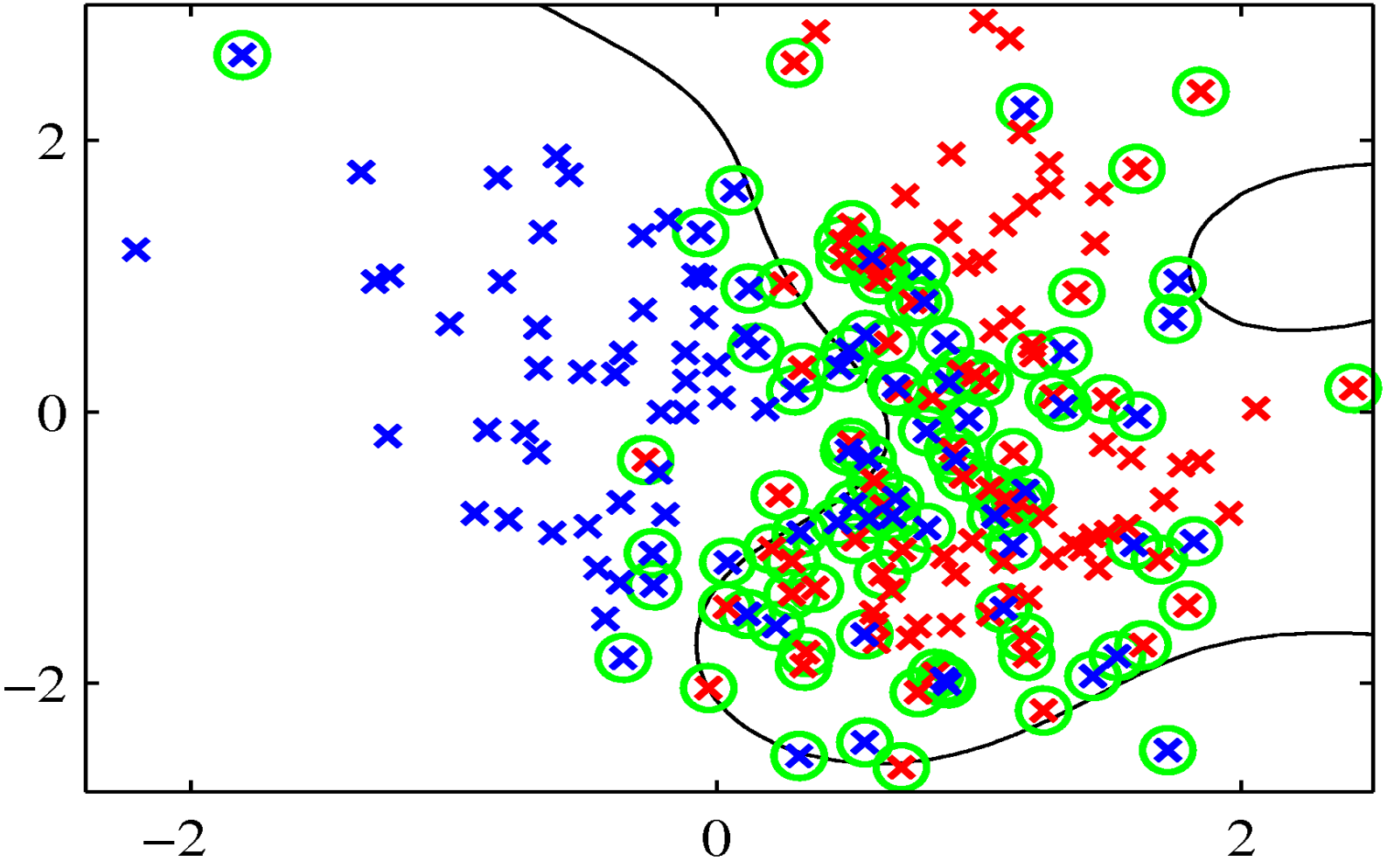

- Each unit (“neuron”) - linear combination followed by non-linear transformation
- Gradient descent (so called “back propagation”)

# Support Vector Machines

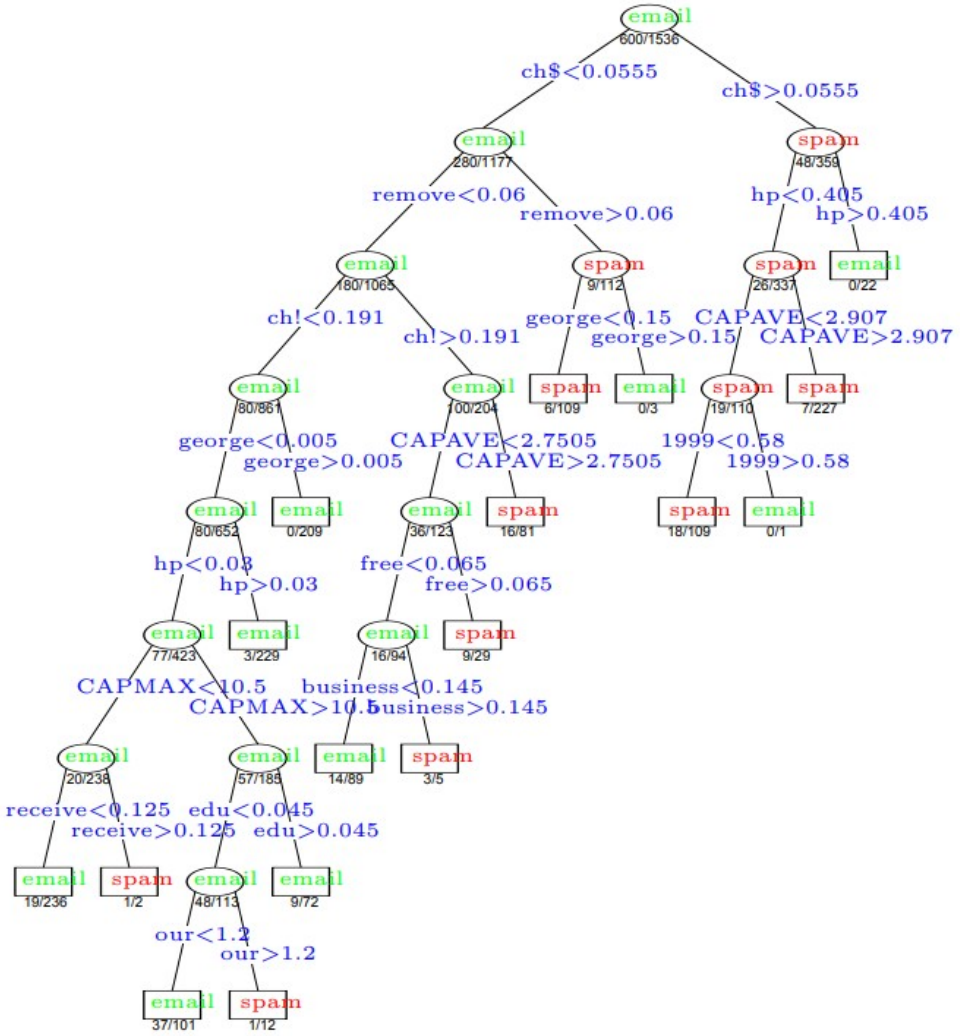



- Linear classifier maximizing margin
- Quadratic programming, dual programs
- Kernel trick: expansion into infinite dimensional vector space
  K(x,y) – dot product in the expanded space (intuition: similarity measure)

# Support Vector Machines

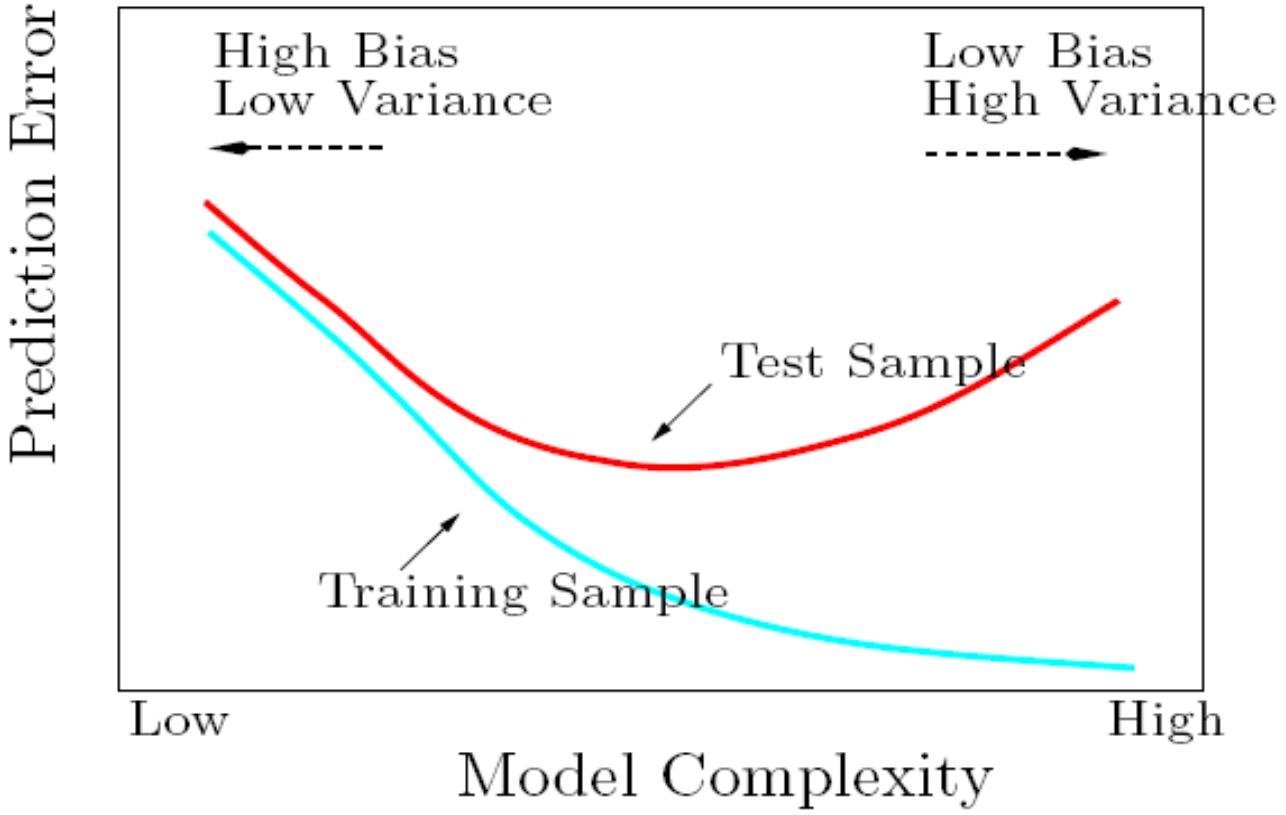


# Decision Trees and Random Forests




- ID3 algorithm for building trees (based on entropy measure)
- Stopping criteria
- Bagging – ensemble of complex classifiers
- Boosting – ensemble of simple classifiers

# Bias and Variance



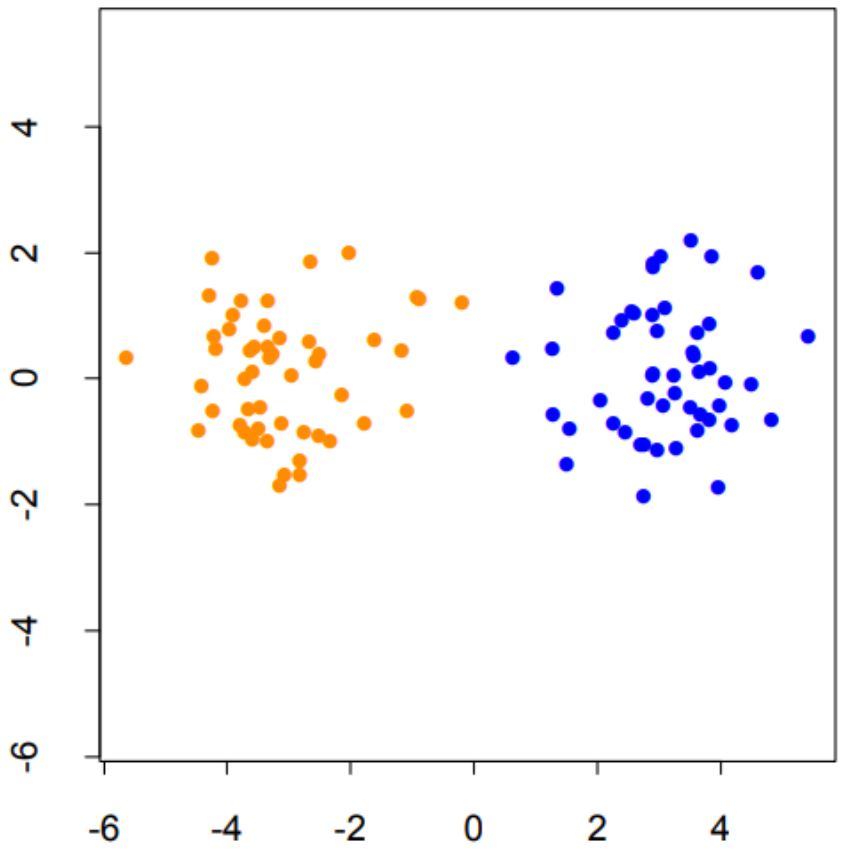
# PAC Learning (Probably Approximately Correct)

- How many training data points do we need to train a classifier?
- For large enough t,
  **training and testing error**
  **with high probability (>1-δ)**
  **will not differ much (<ε)**
- PAC learning theory provides bounds on t for specific H, ε and δ

# PAC learning - bounds

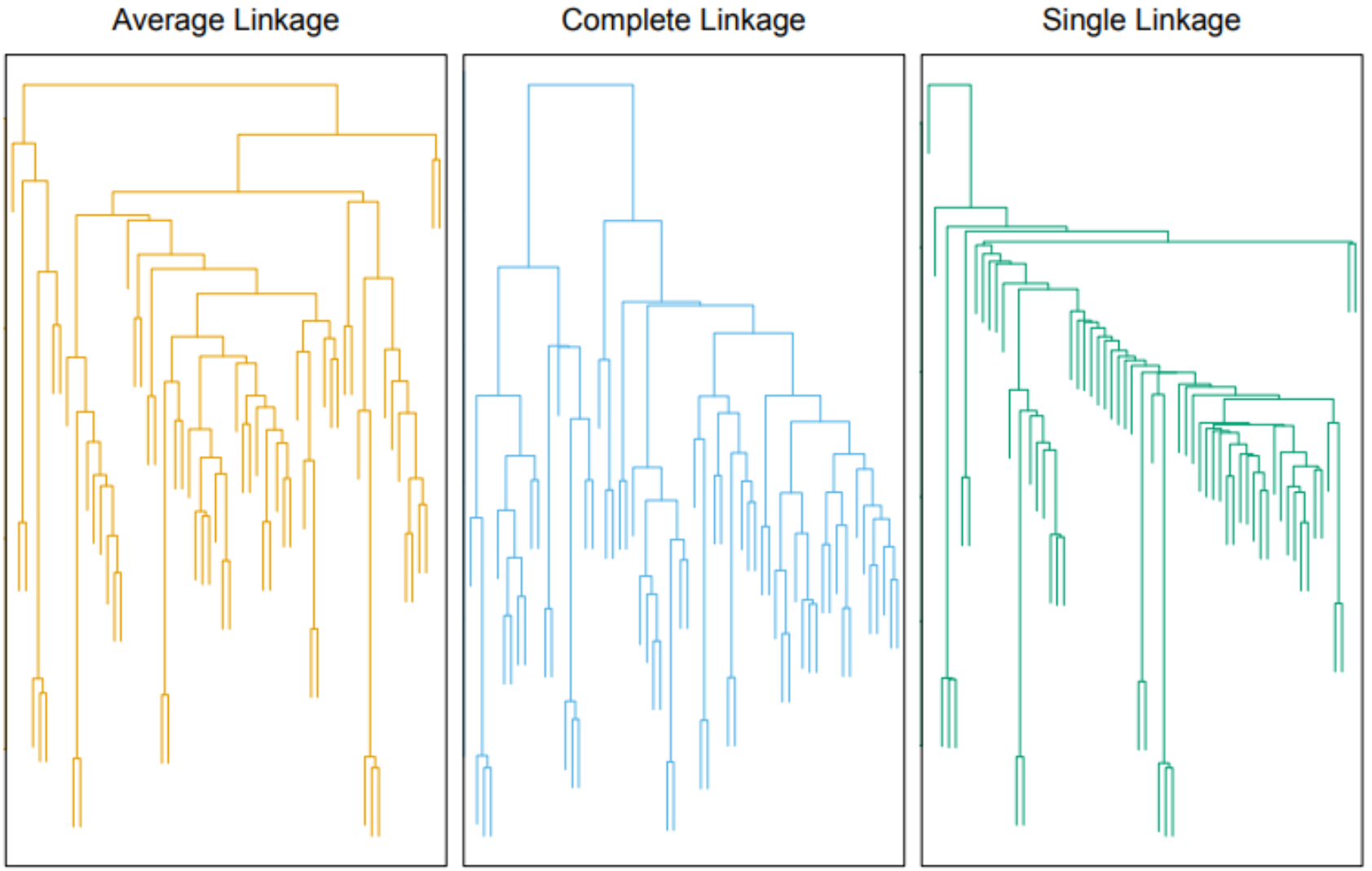
- **Finite hypothesis space:**
  $t=O(\log |H|)$
- **Infinite hypothesis space:**
  - Vapnik-Červonenkis (VC) dimension d
    (t grow linearly with d)
    Neural networks: $d=\Theta(W.\log n)$
    (W – # weights, n – # sigmoids )
  - SVM: $t=O(1/r^2 \log^2 1/r)$
    (r – margin size)

# Clustering

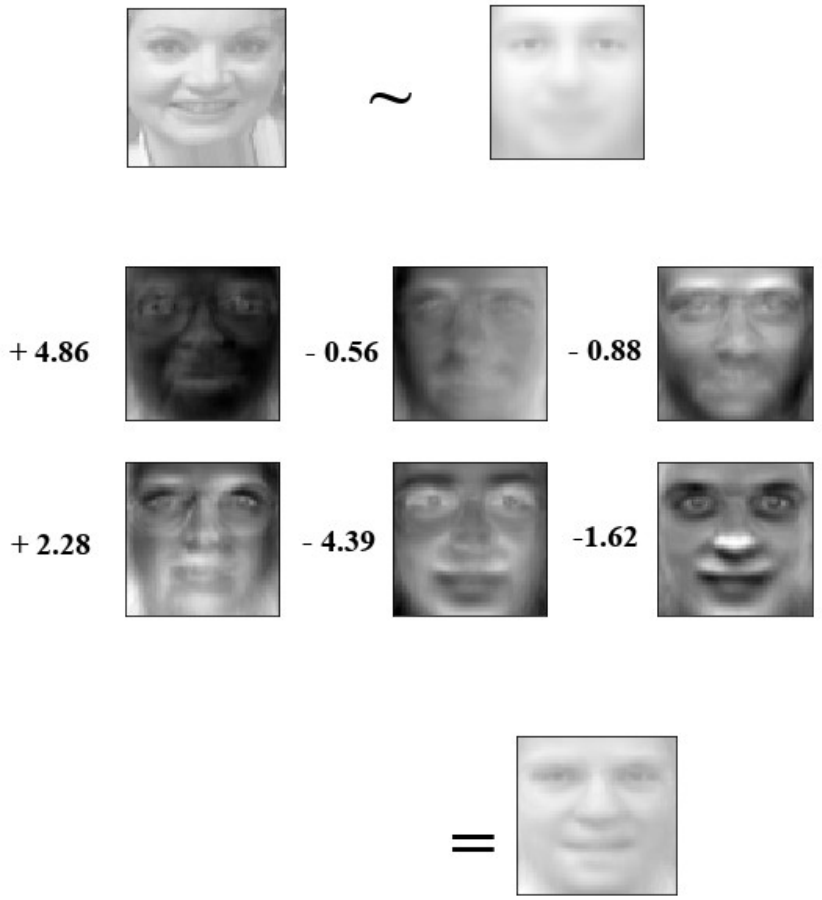



- K-means and k-medoids clustering
- Iterative methods to find a good solution
- Beware: slow!

# Hierarchical clustering



# Dimensionality reduction




- Principal Component Analysis (PCA)
- Kernel trick (again)
- Multi-dimensional scaling (i.e. t-SNE)

# Mathematical Methods

- Matrix algebra, solving systems of linear equations
- Eigenvectors and eigenvalues
- Partial derivatives, Lagrange multipliers
- Numeral mathematics: Gradient descent
- Optimization: linear and quadratic programming, duality
- Analytical geometry
- Vector spaces

# (Ne)súvisiace predmety

**Leto 2022:**

- 2-INF-188: Moderné techniky ML (Boža)
- 2-AIN-132: Neurónové siete (Farkaš)
- 2-AIN-235: Algoritmy UI v robotike (Petrovič)
- 2-AIN-288: Rozpoznávanie reči (2023)

**Zima 2022:**

- 1-BIN-301: Metódy v bioinformatike (Vinař, Brejová)
- 2-AIN-268: Neur. siete pre počítačové videnie (Černeková)
- 2-PMS-129: Stochastické optimalizačné metódy (Harman)