



Lecture Slides for

INTRODUCTION TO

Machine Learning

2nd Edition

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Why “Learn” ?

- Machine learning is programming computers to optimize a performance criterion using example data or past experience.
- Learning is used when:
 - Human expertise does not exist (navigating on Mars),
 - Human expertise is too expensive
 - Humans are unable to explain their expertise (speech recognition)
 - Solution changes in time (routing on a computer network)
 - Solution needs to be adapted to particular cases (user biometrics)

What We Talk About When We Talk About “Learning”

- Learning general models from a data of particular examples
- Data is cheap and abundant (data warehouses, data marts); knowledge is expensive and scarce.
- Example in retail: Customer transactions to consumer behavior:
*People who bought “Blink” also bought “Outliers”
(www.amazon.com)*
- Build a model that is *a good and useful approximation* to the data.

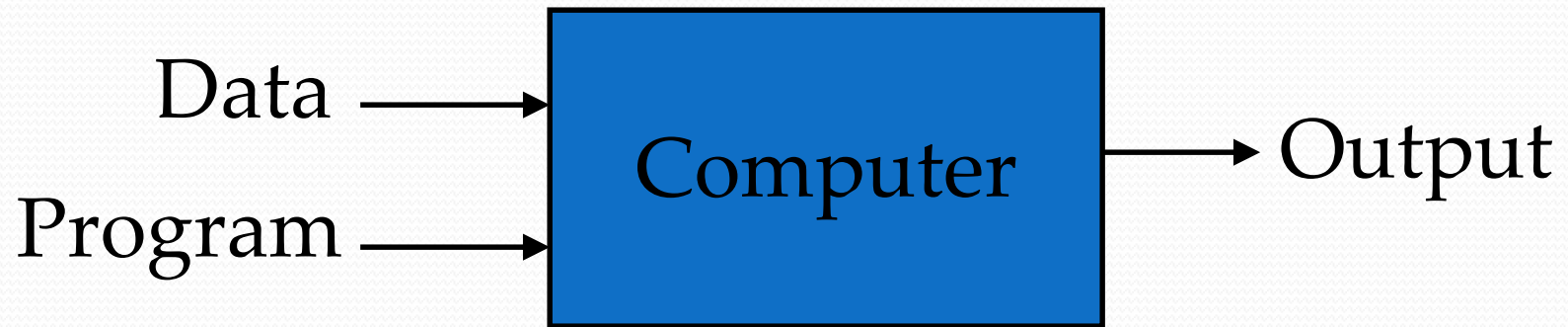
Data Mining

- Retail: Market basket analysis, Customer relationship management (CRM)
- Finance: Credit scoring, fraud detection
- Manufacturing: Control, robotics, troubleshooting
- Medicine: Medical diagnosis
- Telecommunications: Spam filters, intrusion detection
- Web mining: Search engines, recommendations, similarity detection
- NLP: Automatic translations
- ...

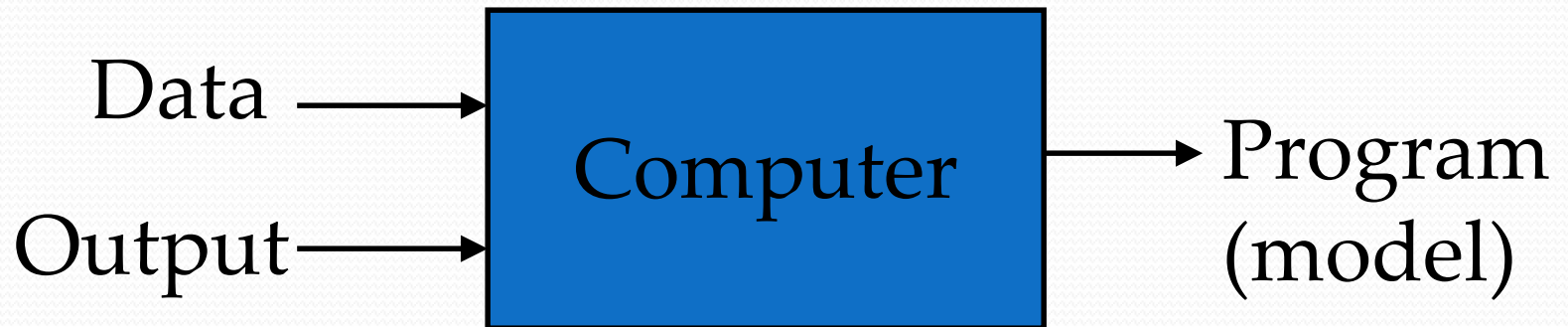
What is Machine Learning?

- Optimize a performance criterion using example data or past experience.
- Role of Statistics: Inference from a sample
- Role of Computer science: Efficient algorithms to
 - Solve the optimization problem
 - Representing and evaluating the model for inference

Traditional Programming



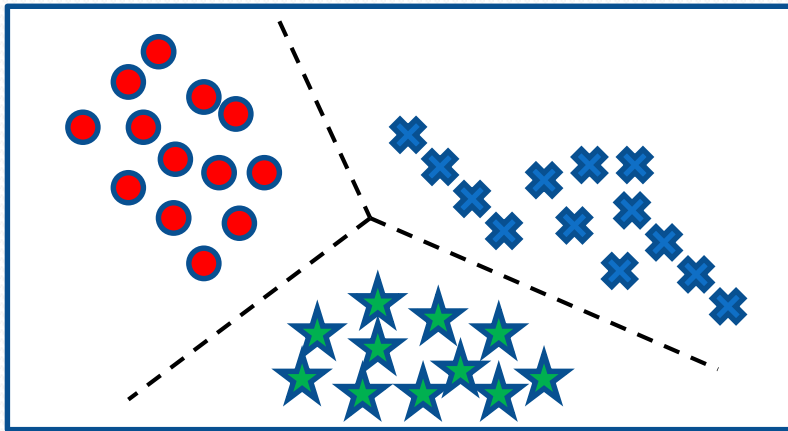
(Supervised) machine Learning



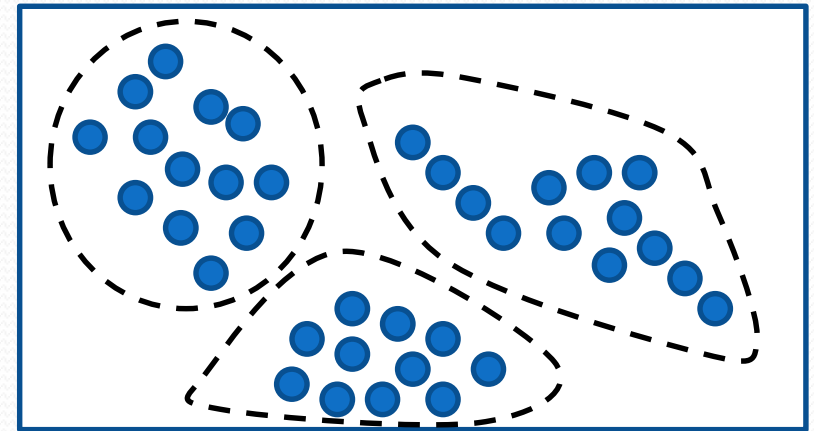
Applications

- Association
- Supervised Learning
 - Classification
 - Regression
- Unsupervised Learning
- Reinforcement Learning

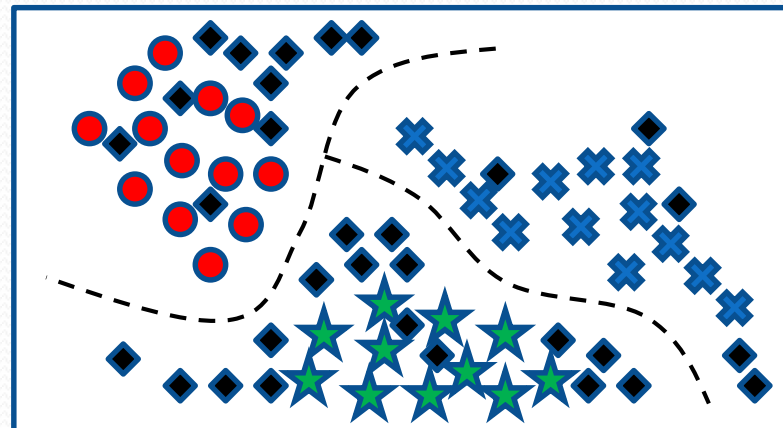
Algorithms



Supervised
learning



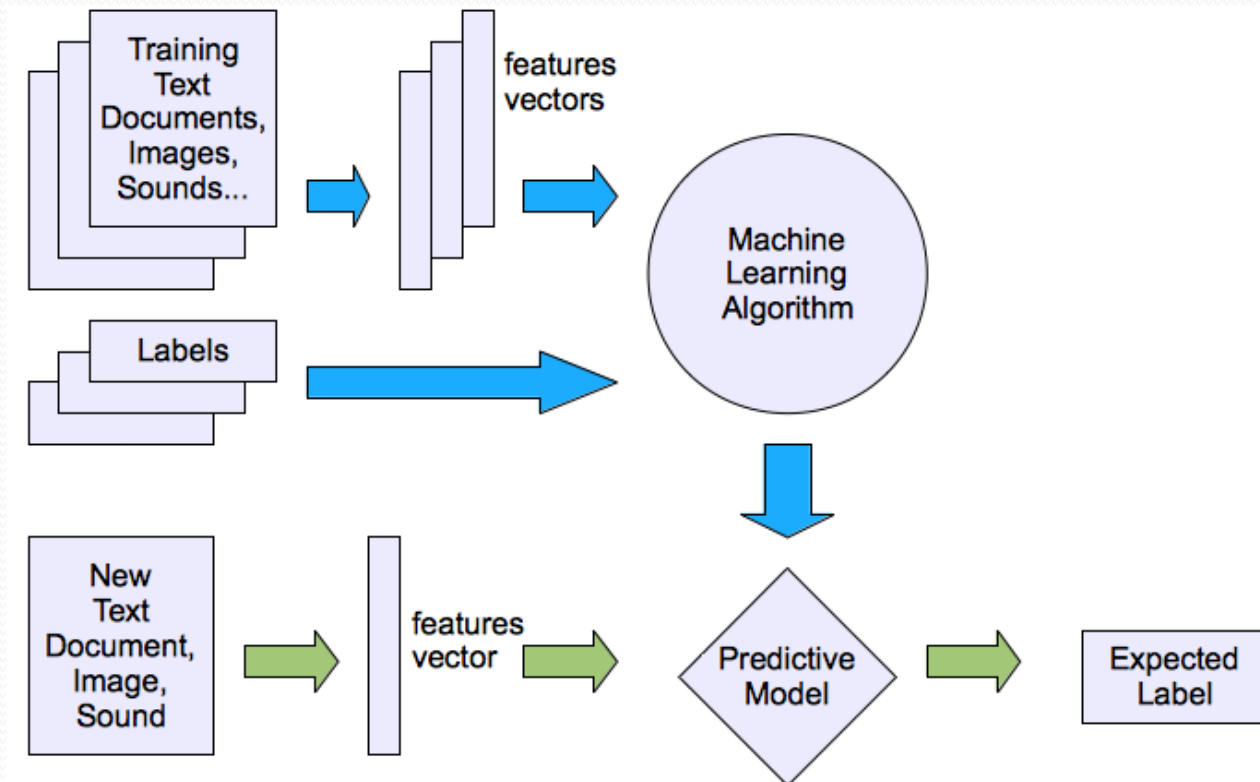
Unsupervised
learning



Semi-supervised learning

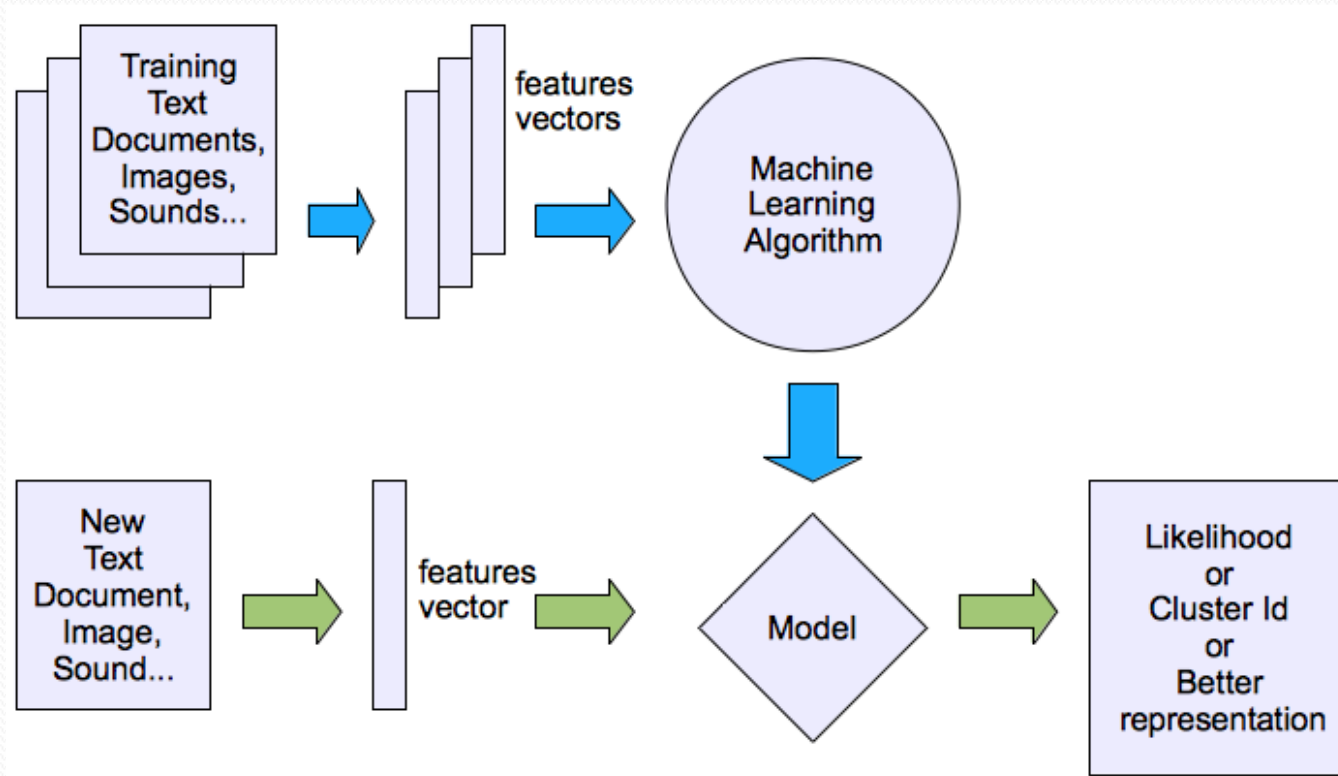
Machine learning structure

- Supervised learning



Machine learning structure

- Unsupervised learning



Learning Associations

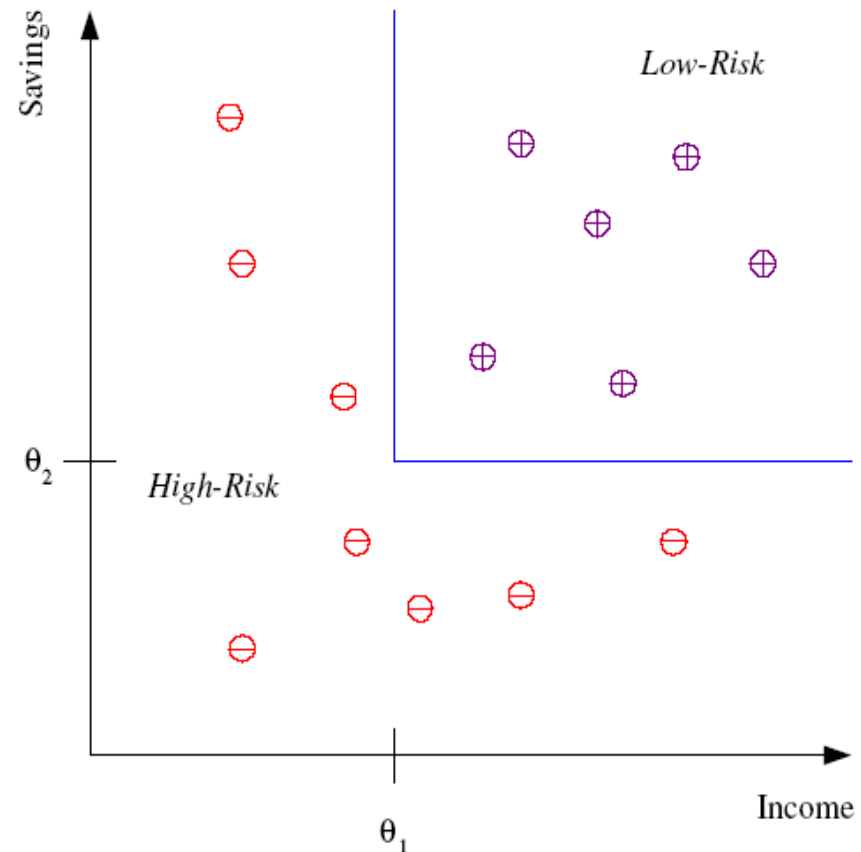
- Basket analysis:

$P(Y | X)$ probability that somebody who buys X also buys Y where X and Y are products/services.

Example: $P(\text{chips} | \text{beer}) = 0.7$

Classification

- Example: Credit scoring
- Differentiating between **low-risk** and **high-risk** customers from their *income* and *savings*



Discriminant: IF *income* $> \theta_1$ AND *savings* $> \theta_2$
THEN **low-risk** ELSE **high-risk**

Regression

- Example: Price of a used car

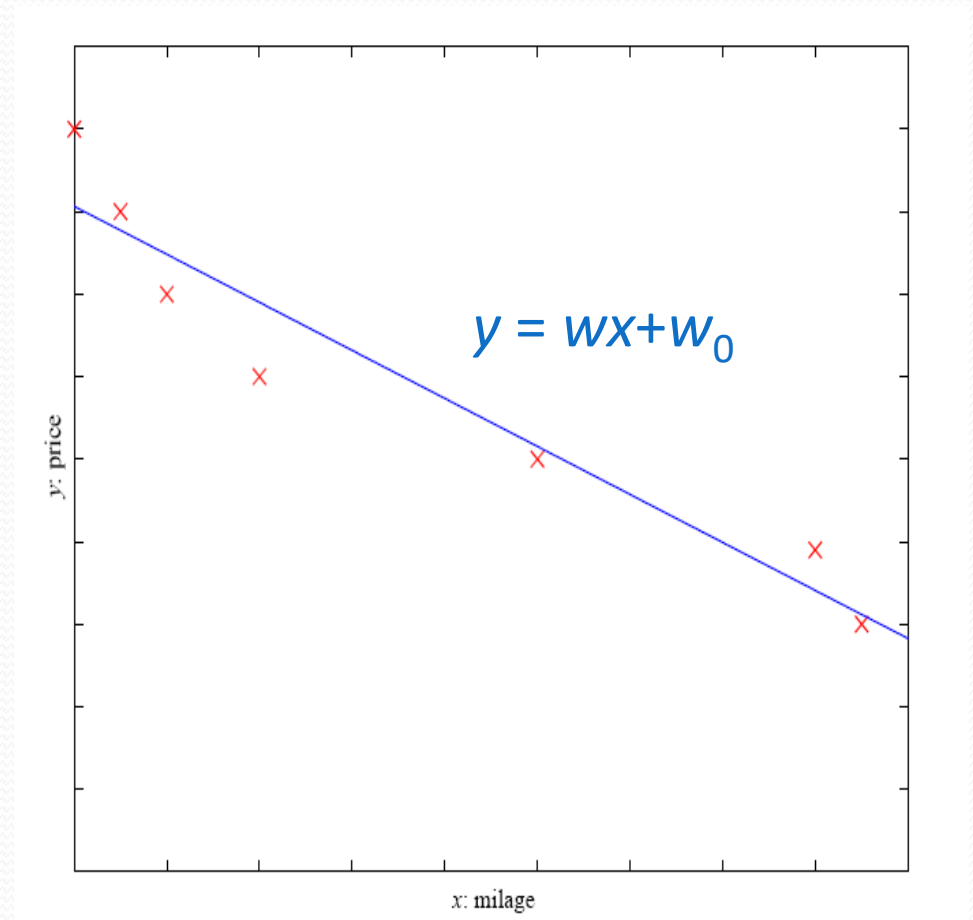
• x : car attributes

y : price

$$y = g(x \mid \theta)$$

$g(\)$ model,

θ parameters



Supervised Learning: Uses

- Prediction of future cases: Use the rule to predict the output for future inputs
- Knowledge extraction: The rule is easy to understand
- Compression: The rule is simpler than the data it explains
- Outlier detection: Exceptions that are not covered by the rule, e.g., fraud

Unsupervised Learning

- Learning “what normally happens”
- No output
- Clustering: Grouping similar instances
- Example applications
 - Customer segmentation in CRM
 - Image compression: Color quantization
 - Bioinformatics: Learning motifs

Reinforcement Learning

- Learning a policy: A sequence of outputs
- No supervised output but delayed reward
- Credit assignment problem
- Game playing
- Robot in a maze
- Multiple agents, partial observability, ...

Resources: Datasets

- UCI Repository: <http://www.ics.uci.edu/~mlearn/MLRepository.html>
- Delve: <http://www.cs.utoronto.ca/~delve/>
- Kaggle challenges: <https://www.kaggle.com/>

Resources: Journals

- Journal of Machine Learning Research www.jmlr.org
- Machine Learning
- Neural Computation
- Neural Networks
- IEEE Transactions on Neural Networks
- IEEE Transactions on Pattern Analysis and Machine Intelligence
- ...

Resources: Conferences

- International Conference on Machine Learning (ICML)
- European Conference on Machine Learning (ECML)
- Neural Information Processing Systems (NIPS)
- Uncertainty in Artificial Intelligence (UAI)
- Computational Learning Theory (COLT)
- International Conference on Artificial Neural Networks (ICANN)
- International Conference on AI & Statistics (AISTATS)
- International Conference on Pattern Recognition (ICPR)
- ACM Recommender Systems (RecSys)
- ...

Supervised Learning

- Input:
 - Explaining features (data)
 - Target variable (label)
- Output:
 - Function $f(\text{data} \rightarrow \text{label})$

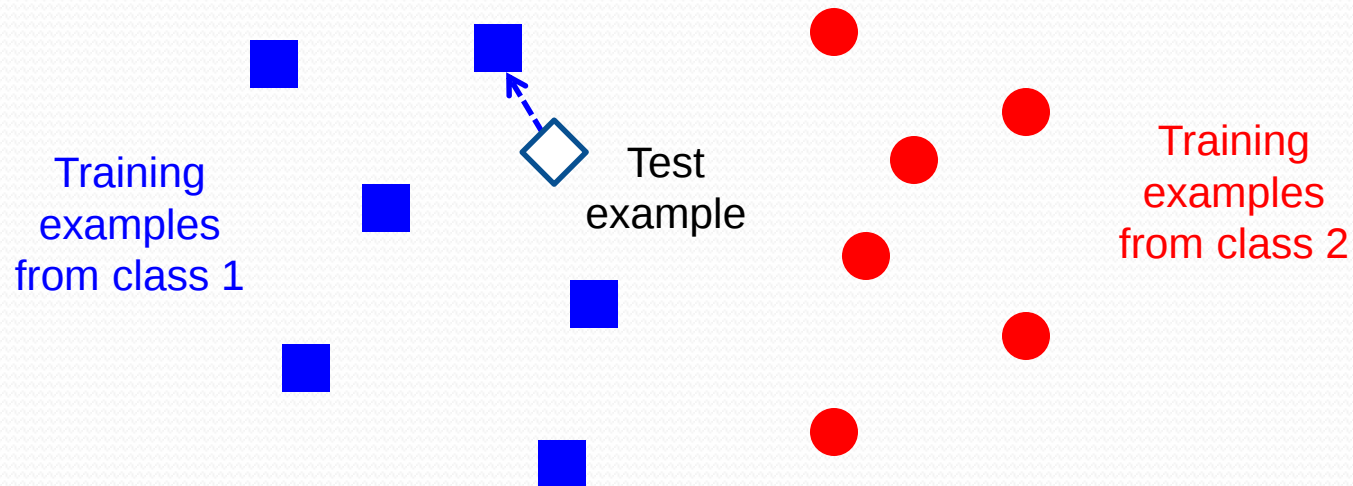
Supervised Learning - Examples

- Regression: income prediction
 - Data: Age, gender, location, education, profession,...
 - Target: income
- Classification: spam detection
 - Data: Length, from, to, metadata, text representation
 - Target: spam or not
- Multiclass classification: bank transactions labeling
 - Data: Payment ammount, target account details, text repr.
 - Target: Expense category

Supervised Learning

- Two basic approaches
 - Linear Regression
 - Nearest Neighbor Method

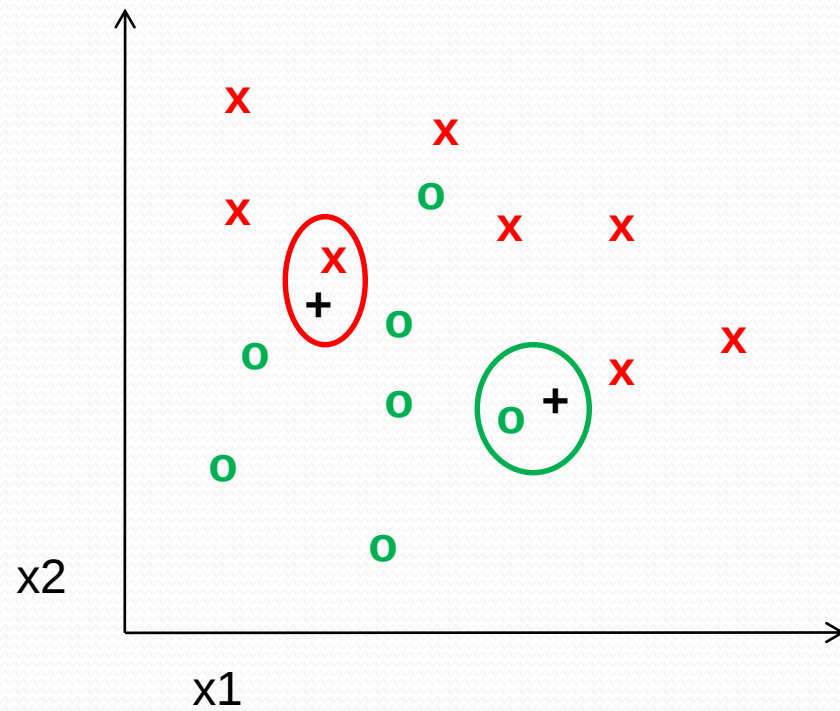
Classifiers: Nearest neighbor



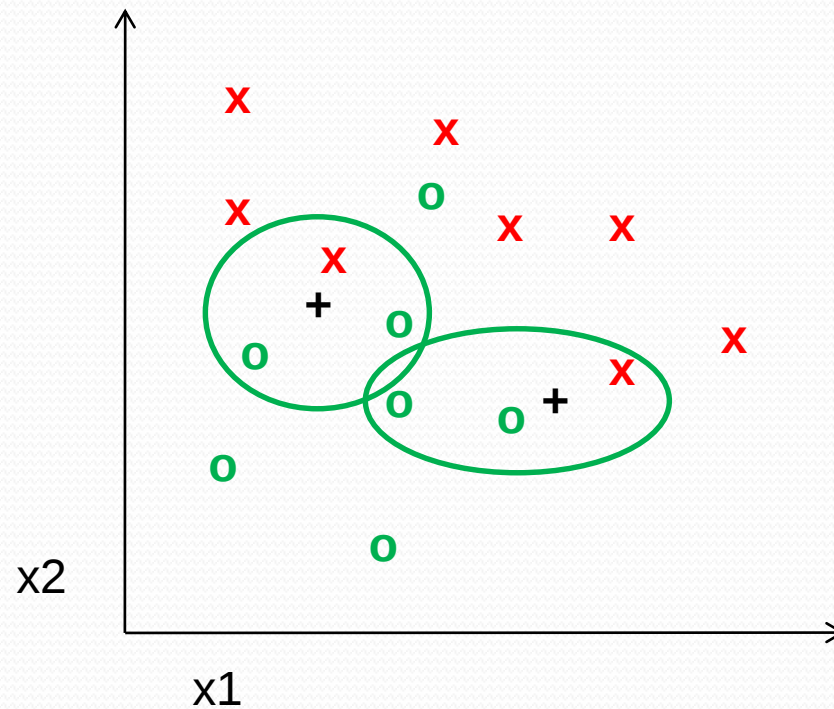
$f(\mathbf{x}) = \text{label of the training example nearest to } \mathbf{x}$

- All we need is a distance function for our inputs
- No training required!

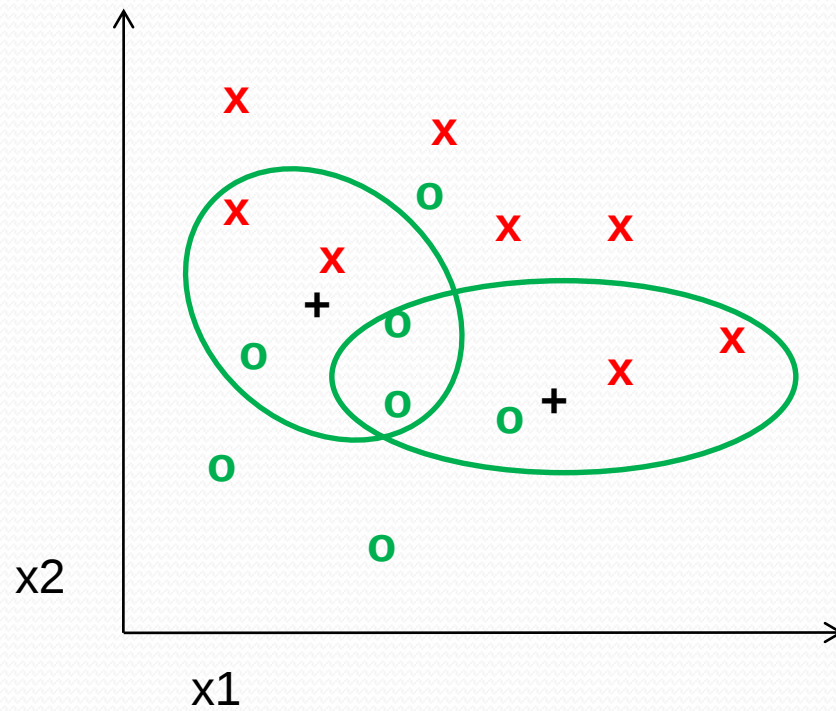
1-nearest neighbor



3-nearest neighbor



5-nearest neighbor



Using K-NN

- Simple, a good one to try first
- With infinite examples, 1-NN provably has error that is at most twice Bayes optimal error
- You need to define a distance metric among objects!

K-NN Algorithm

- „Training“
 - Just store data and labels
- Classify new example O
 - Obtain K closest neighbors to the O (*may be time consuming*)
 - Use majority vote of neighbors to define label of O

Linear Regression – Least Squares

- Target attribute is a linear combination of source data
 - Up to a certain noise with normal distribution

$$y_i = \beta_0 1 + \beta_1 x_{i1} + \cdots + \beta_p x_{ip} + \varepsilon_i = \mathbf{x}_i^\top \boldsymbol{\beta} + \varepsilon_i, \quad i = 1, \dots, n,$$

- How to estimate $\boldsymbol{\beta}$?

- Minimize the residual square error

$$S(b) = \sum_{i=1}^n (y_i - x_i^\top b)^2 = (y - Xb)^\top (y - Xb),$$

- Derive by b, set = 0

$$\hat{\boldsymbol{\beta}} = \operatorname{argmin}_{b \in \mathbb{R}^p} S(b) = \left(\frac{1}{n} \sum_{i=1}^n x_i x_i^\top \right)^{-1} \cdot \frac{1}{n} \sum_{i=1}^n x_i y_i$$

$$\hat{\boldsymbol{\beta}} = (X^\top X)^{-1} X^\top y.$$

Úkol č.3

- Predikce žánrů knih (multi-label klasifikace)
 - Vyjděte z předchozího úkolu s knihami, načtěte prvních 1000 řádků datasetu. Pro knihy na řádcích 0-100 chcete predikovat jejich žánry na základě znalostí z ostatních knih.
 - Použijte k -NN algoritmus a vhodně definovanou podobnost na knihách. Vyzkoušejte vícero variant k , případně různé podobnostní metriky.
 - Pro každou testovanou knihu vyhodnoťte výslednou predikci jako Jaccardovu podobnost skutečných a predikovaných žánrů ($A \cap B / A \cup B$). Zkuste do konce hodiny dosáhnout co nejlepší průměrné Jaccard sim.
- Otázky na zamyšlení:
 - Jaký počet žánrů predikovat?
 - Jaký je efekt k v k -NN?
 - Jaké jsou nevýhody k -NN?

More on KNN

- A Complete Guide to K-Nearest-Neighbors with Applications in Python and R: <https://kevinzakka.github.io/2016/07/13/k-nearest-neighbor/>
(nice tutorial with further references)
- Hubness aware k-NN:
<https://www.sciencedirect.com/science/article/pii/S0950705115002282>
(deal with „bad hubs“ in k-NN)
- Optimality of k-NN (if sufficient data is available):
<http://cseweb.ucsd.edu/~elkan/151/nearestn.pdf>
- Curse of dimensionality (why we do not have sufficient data):
https://en.wikipedia.org/wiki/Curse_of_dimensionality

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https://en.wikipedia.org/wiki/Curse_of_dimensionality,
<https://math.stackexchange.com/questions/346775/confusion-related-to-curse-of-dimensionality-in-k-nearest-neighbor>