Course Overview and Introduction

Machine Learning

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Sharif University
of Technology

Prerequisites:

- Programming skills
  - Python
- Probability and statistics
- Basic linear algebra

Marking Scheme

- Midterm Exam: 20%
- Final Exam: 30%
- Homeworks (Includes programming assignments): 40%
- Quizzes: 10%
- Class Activity & Exam Bonus: 7.5%
- (1.5 extra points)

Assignments

- 6 Problem sets
  - contain both theoretical and programming assignments

ML Talks

- Invited Talks from Machine Learning & AI Industry
- The Schedule and the Speaker will be announced

References

- Pattern Recognition and Machine Learning, C. Bishop, Springer, 2006.
- Machine Learning, T. Mitchell, MIT Press, 1998.
- Other books:
  - The elements of statistical learning, T. Hastie, R. Tibshirani, J. Friedman, Second Edition, 2008.
  - Machine Learning: A Probabilistic Perspective, K. Murphy, MIT Press, 2012.
  - Richard Sutton and Andrew Barto, Reinforcement Learning: An introduction. MIT Press, Second edition, 2017.
- Recommended Video Lectures:
- Andrew Ng: https://www.youtube.com/watch?v=jGwO_UgTS7I

A Definition of ML

- Tom Mitchell (1998):
  - A computer program is said to learn a **task** from **experience** if its **performance** improves with experience

- Using the observed data to make better decisions
  - Generalizing from the observed data

ML has a wide reach

- Wide applicability
- Very-large-scale complex systems
- Internet (billions of nodes), sensor network (new multi-modal sensing devices), genetics (human genome)
- Huge multi-dimensional data sets
- 20,000 genes x 10,000 drugs x 100 species x ...
- Improved machine learning algorithms
- Improved data capture (Terabytes, Petabytes of data), networking, faster computers
- The New York Times is regularly talks about machine learning!

ML Definition: Example

- Consider an email program that learns how to filter spam according to emails you do or do not mark as spam.

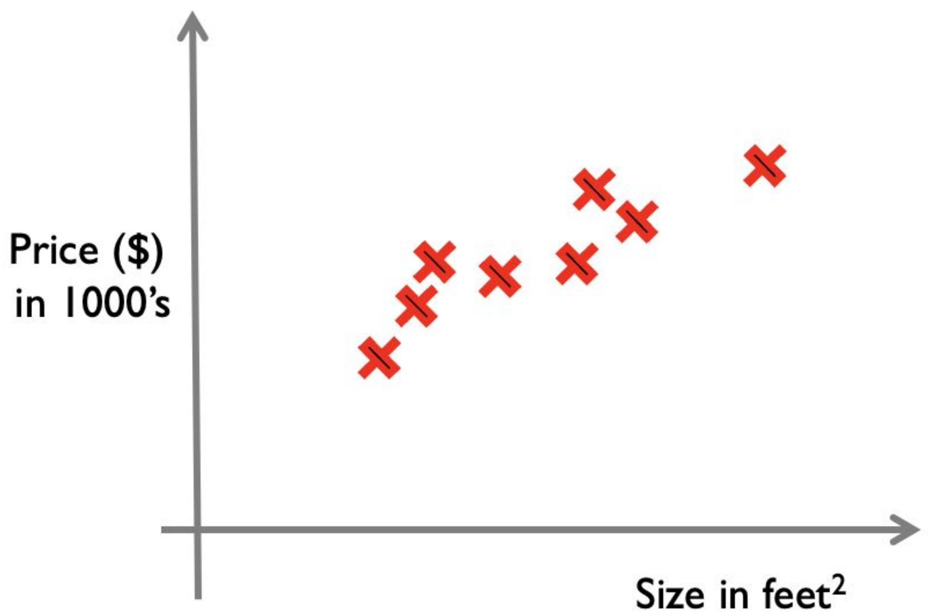
  - Task: Classifying emails as spam or not spam.
  - Experience: Watching you label emails as spam or not spam.
  - Performance: The number (or fraction) of emails correctly classified as spam/not spam.

The essence of machine learning

- A pattern exist
- We do not know it mathematically
- We have data on it

Example: Home Price

- Housing price prediction

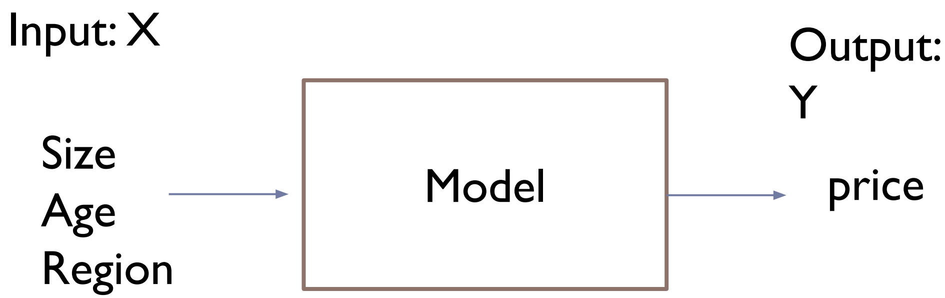


Example: Home Price

- Predicting house price from 3 attributes

	Age (year)	Region	
100	2	5	500
80	25	3	250
…	…	…	…

Example: Home Price



Example: Bank loan

- Applicant form as the input:
  - salary
  - age
  - gender
  - current debt
  - …
- Output: **approving** or **denying** the request

Experience (E) in ML

- Basic premise of learning:
  - "Using a set of observations to uncover an underlying process"

- We have different types of (getting) observations in different types or paradigms of ML methods

Early Paradigms of ML

- <u>Supervised learning</u> (regression, classification)
  - predicting a target variable for which we get to see examples.
- <u>Unsupervised learning</u>
  - revealing structure in the observed data

Data in Supervised Learning

- Data are usually considered as vectors in a d dimensional space
  - Now, we make this assumption for illustrative purpose
    - We will see it is not necessary

Columns:
Features/attributes/dimensions

Rows:
Data/points/instances/examples/samples

Y column:
Target/outcome/response/label

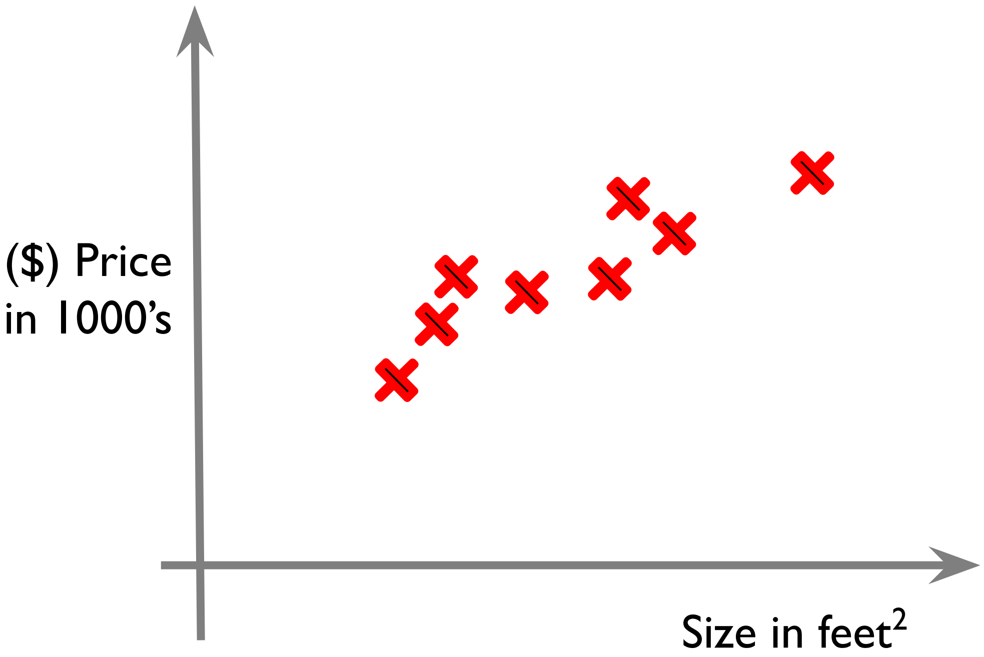
		…			
					Sample 1
					Sample 2
					…
					Sample n-1
					Sample n

Supervised Learning: Regression vs. Classification

- Supervised Learning
  - **Regression**: predict a <u>continuous</u> target variable
    - E.g., $y \in [0,1]$
  - **Classification**: predict a <u>discrete</u> (unordered) target variable
    - E.g.,$y \in \{1,2, \dots, C\}$

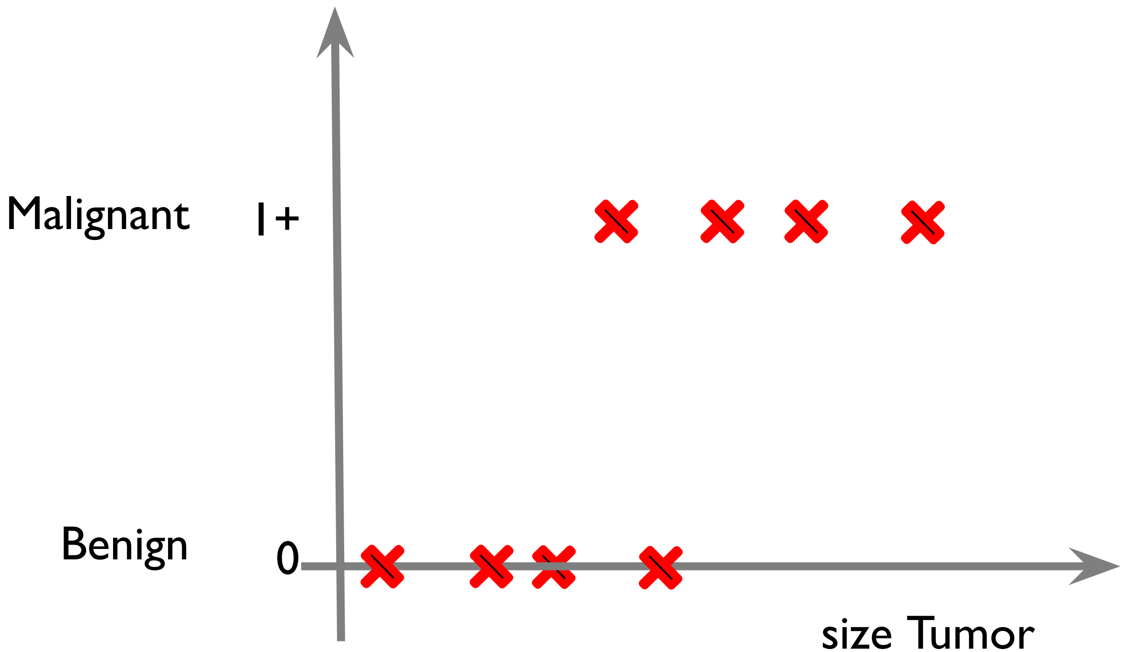
Regression: Example

- Housing price prediction



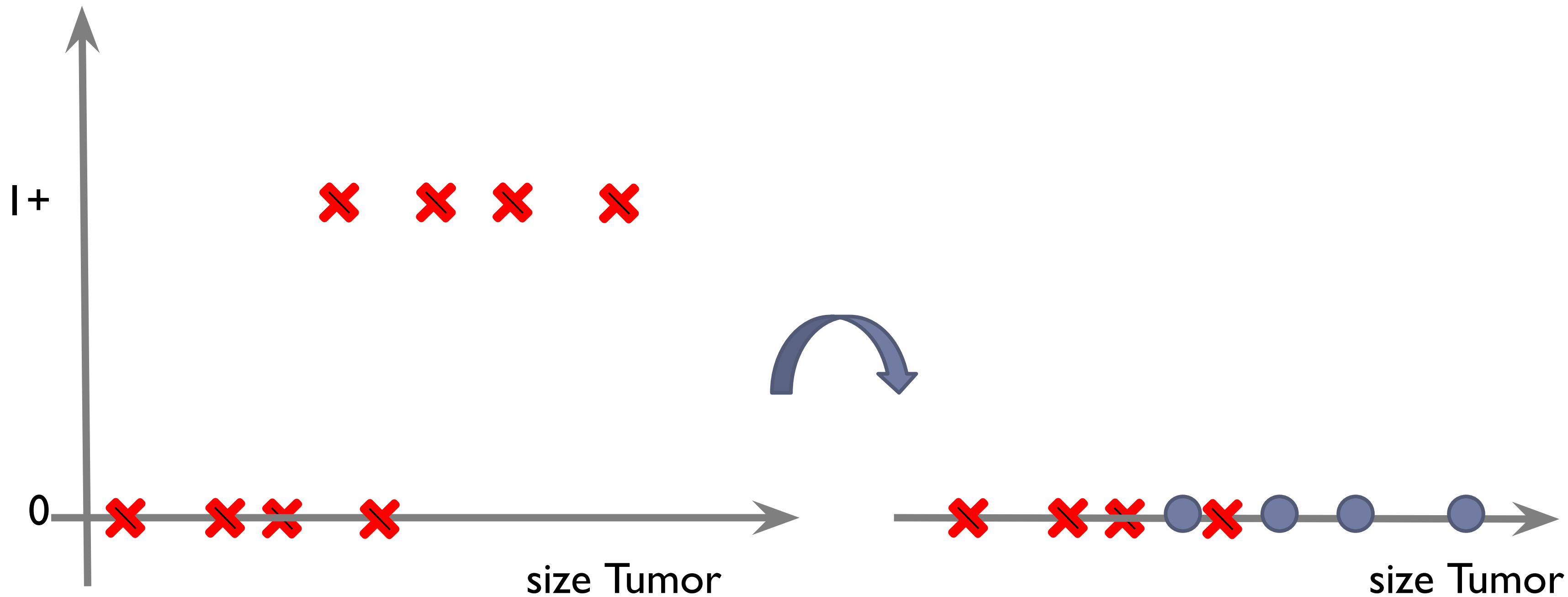
Classification: Example

- Classification of tumors to Benign/Malignant according to attributes

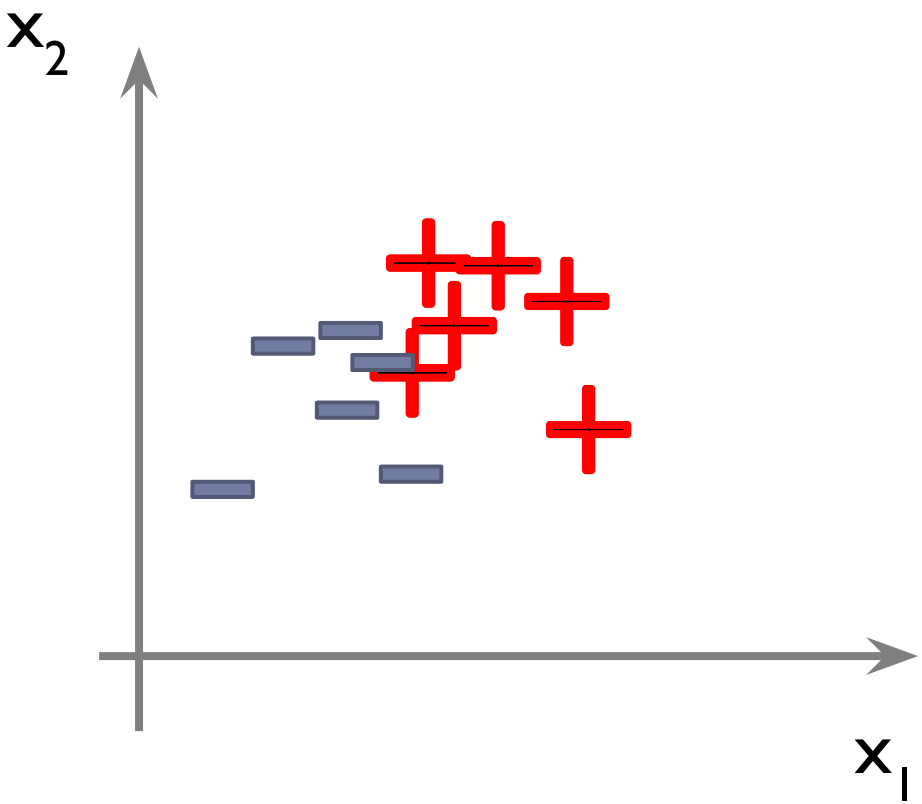


Classification: Example

Classification of tumors to Benign/Malignant according to attributes



Training data: Example

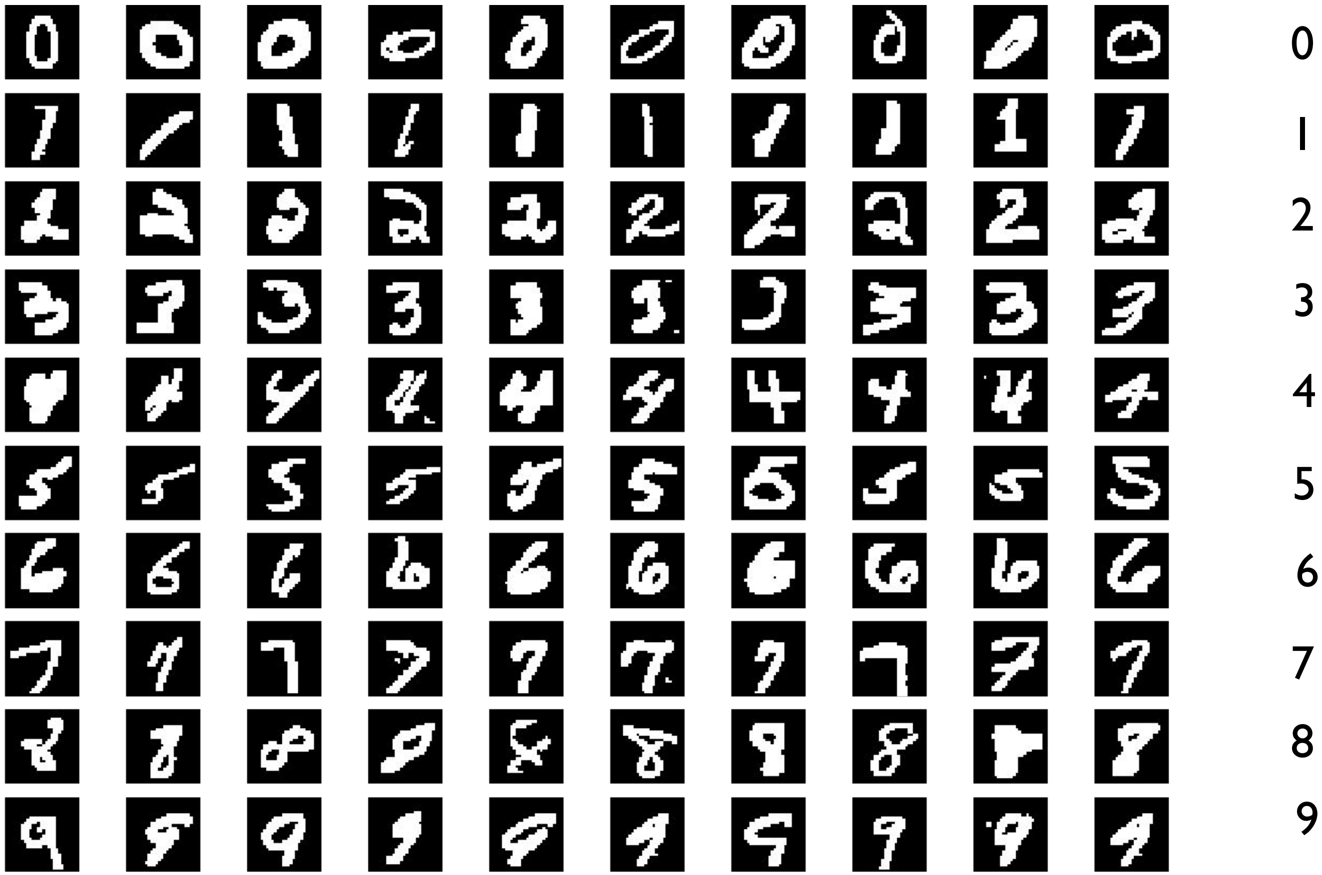


Training data

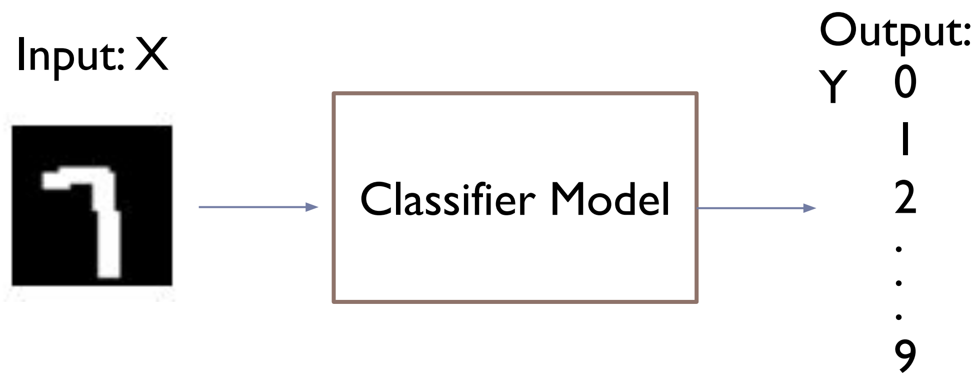
0.9	2.3	0
3.5	2.6	0
2.6	3.3	0
2.7	4.1	0
1.8	3.9	0
3.5	3	1
4.2	3.7	1
4.9	4.5	1
3.9	4.5	1
5.8	4.1	1
6.1	2.6	1

Handwritten Digit Recognition Example

- Data: labeled samples



Handwritten Digit Recognition Example



Components of (Supervised) Learning

- Unknown target function: $f: \mathcal{X} \to \mathcal{Y}$
  - Input space: $\mathcal{X}$
  - Output space: $\mathcal{Y}$

- Training data: $(\boldsymbol{x}_1, y_1), (\boldsymbol{x}_2, y_2), \ldots, (\boldsymbol{x}_N, y_N)$

- Pick a formula $g: \mathcal{X} \to \mathcal{Y}$ that approximates the target function f
  - selected from a set of hypotheses $\mathcal{H}$

Components of (Supervised) Learning

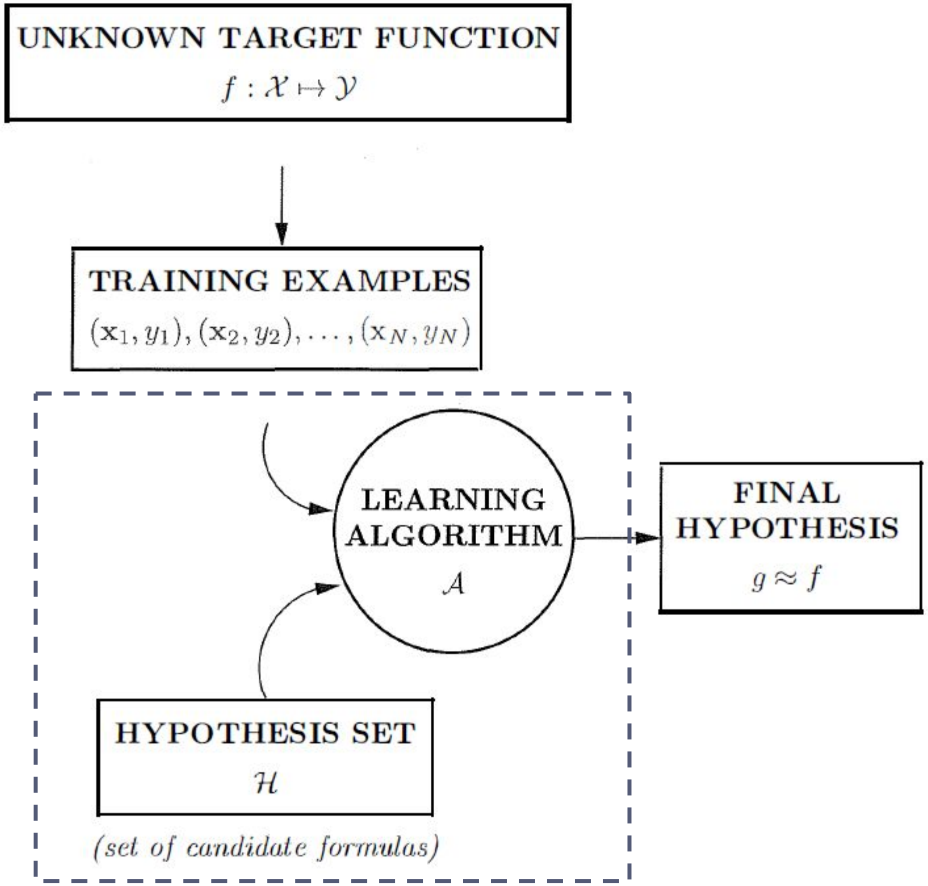
- We have some example pairs of (input, output) called training samples
  - $(\boldsymbol{x}^{(1)}, y^{(1)}), \dots, (\boldsymbol{x}^{(N)}, y^{(N)})$

- We want to select a function from the input space to the output space
  - $f: \mathcal{X} \to \mathcal{Y}$

- We choose a set of hypotheses (candidate formulas)
  - e.g., linear functions

- We use a learning algorithm to select a function from hypothesis set that approximates the target function

Components of (Supervised) Learning



Learning moc

Source: Yaser Abou Mostafa, Learning from Data

(Supervised) Learning problem

- Selecting a **hypothesis space**
  - Hypothesis space: a set of mappings from feature vector to target

- **Learning**: find mapping $\hat{f}$ (from hypothesis set) based on the training data
  - Which notion of error should we use? (loss functions)
  - Optimization of loss function to find mapping $\hat{f}$

- **Evaluation**: we measure how well $\hat{f}$ generalizes to unseen examples (generalization)

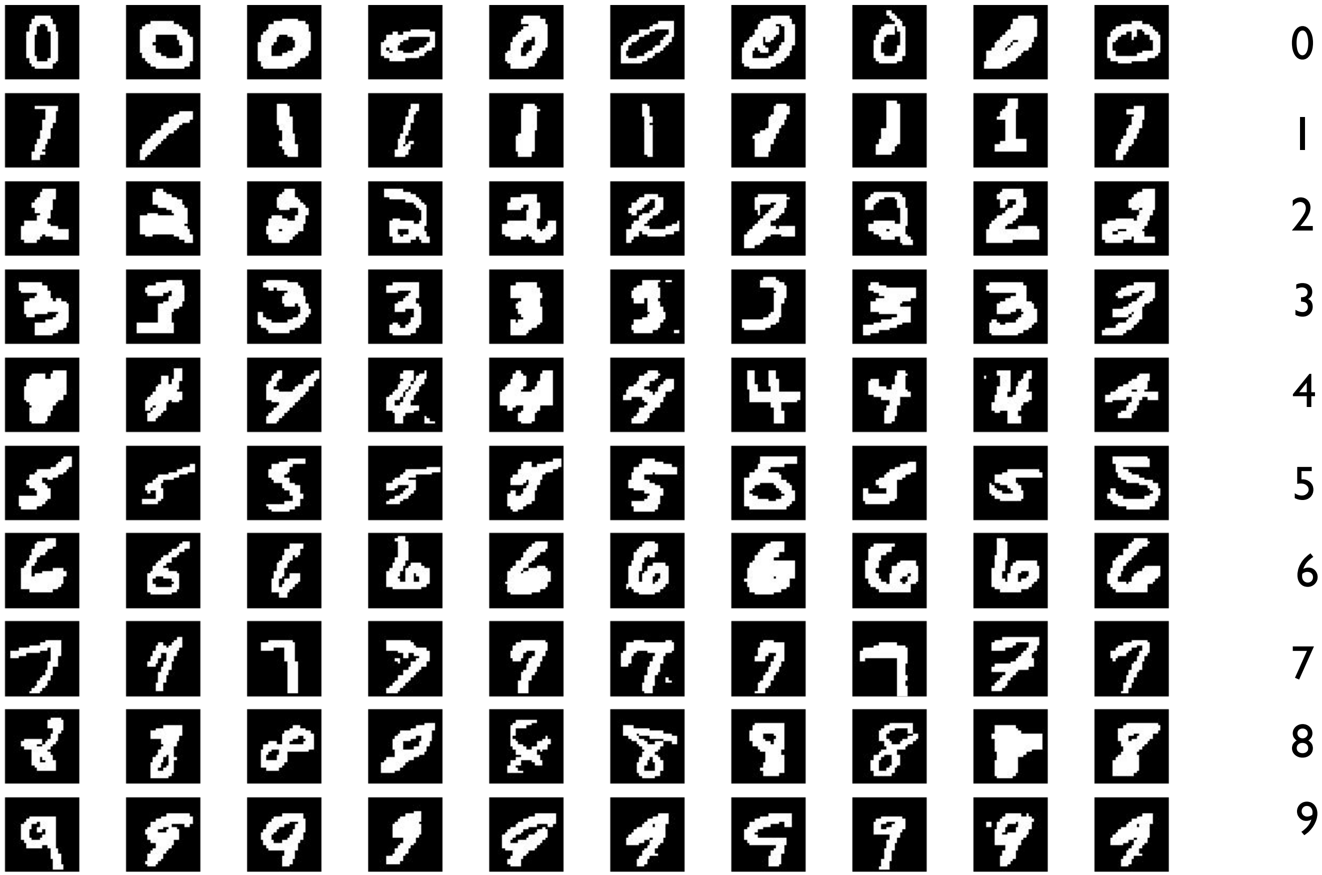
Solution Components

- Learning model composed of:
  - Hypothesis set
  - Learning algorithm

- Perceptron example

Handwritten Digit Recognition Example

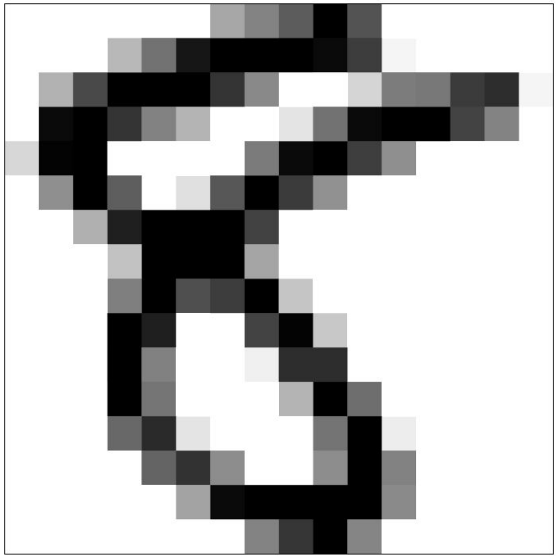
- Data: labeled samples



Example: Input representation

'raw' input $\mathbf{x} = (x_0, x_1, x_2, \cdots, x_{256})$

linear model: $(w_0, w_1, w_2, \cdots, w_{256})$



Features: Extract useful information, e.g.,

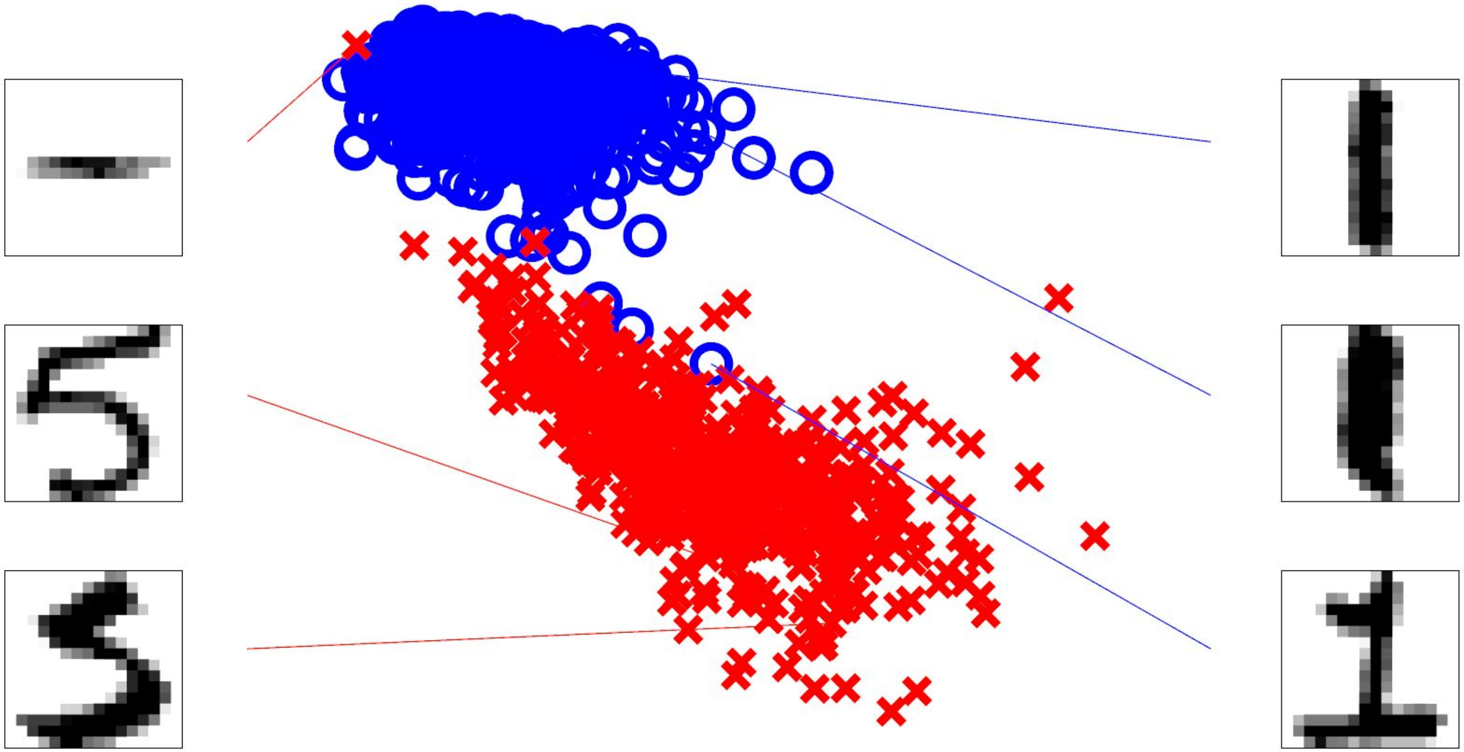
intensity and symmetry $\mathbf{x} = (x_0, x_1, x_2)$

linear model: (w_0, w_1, w_2)

Data Source: Yaser Abou Mostafa, Learning from

Example: Illustration of features

$\mathbf{x} = (x_0, x_1, x_2)$ x_1: intensity x_2: symmetry

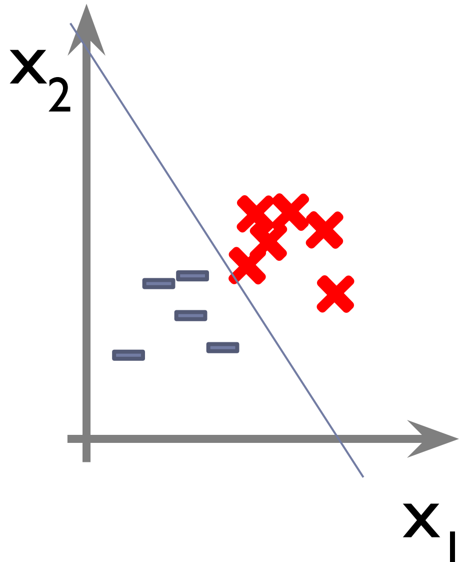


Data Source: Yaser Abou Mostafa, Learning from

Perceptron classifier

- Input $\boldsymbol{x} = [x_1, \dots, x_d]$
- Classifier:
  - If $\sum_{i=1}^{d} w_i x_i >$ threshold then output 1
  - else output -1
- The linear formula $g \in \mathcal{H}$ can be written:

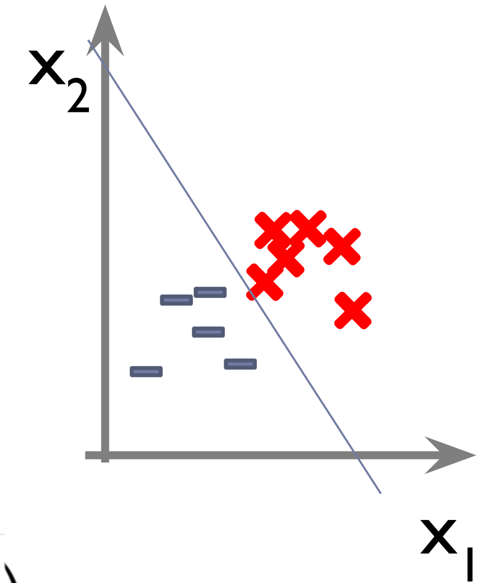
$$g(\boldsymbol{x}) = \mathrm{sign}\left(\sum_{i=1}^{d} w_i x_i - \text{threshold}\right)$$



Perceptron classifier

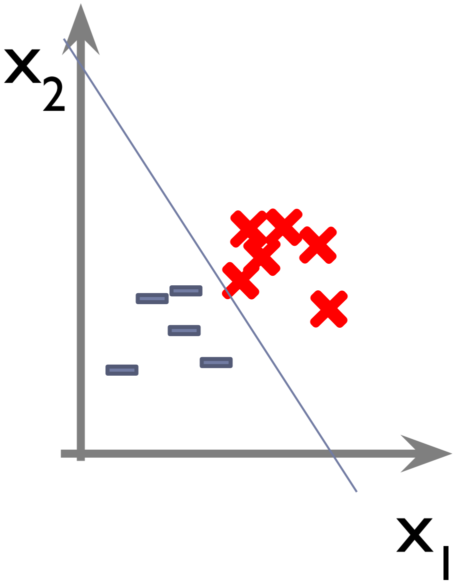
- Input $\boldsymbol{x} = [x_1, \dots, x_d]$
- Classifier:
  - If $\sum_{i=1}^{d} w_i x_i >$ threshold then output 1
  - else output -1
- The linear formula $g \in \mathcal{H}$ can be written:

$$g(\boldsymbol{x}) = \text{sign}\left(\sum_{i=1}^{d} w_i x_i + w_0\right)$$



Perceptron classifier

- Input $\boldsymbol{x} = [x_1, \dots, x_d]$
- Classifier:
  - If $\sum_{i=1}^{d} w_i x_i > \text{threshold}$ then output 1
  - else output -1



- The linear formula $g \in \mathcal{H}$ can be written:

$$g(\boldsymbol{x}) = \text{sign}\left(\sum_{i=1}^{d} w_i x_i \quad + \quad w_0\right)$$

If we add a coordinate $x_0 = 1$ to the input:

$$g(\boldsymbol{x}) = \text{sign}\left(\sum_{i=0}^{d} w_i x_i\right)$$

Vector form

$$g(\boldsymbol{x}) = \text{sign}(\boldsymbol{w}^T \boldsymbol{x})$$

Perceptron learning algorithm: linearly separable data

- Give the training data $(\boldsymbol{x}^{(1)}, y^{(1)}), \dots, (\boldsymbol{x}^{(N)}, y^{(N)})$

- Misclassified data $(\boldsymbol{x}^{(n)}, y^{(n)})$:

$$\mathrm{sign}(\boldsymbol{w}^T \boldsymbol{x}^{(n)}) \neq y^{(n)}$$

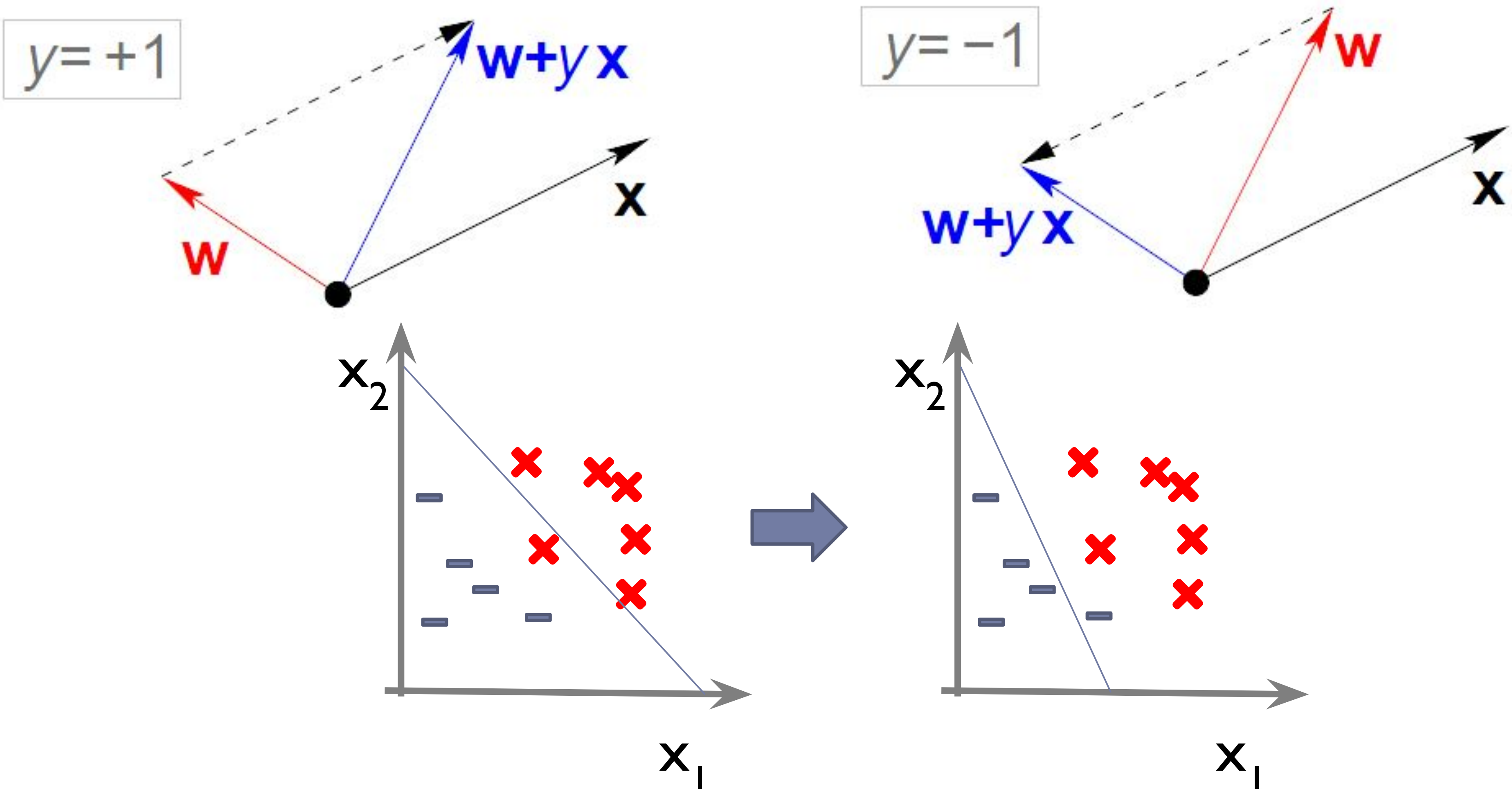
Repeat

Pick a misclassified data $(\boldsymbol{x}^{(n)}, y^{(n)})$ from training data and update $\boldsymbol{w}$:

$$\boldsymbol{w} = \boldsymbol{w} + y^{(n)} \boldsymbol{x}^{(n)}$$

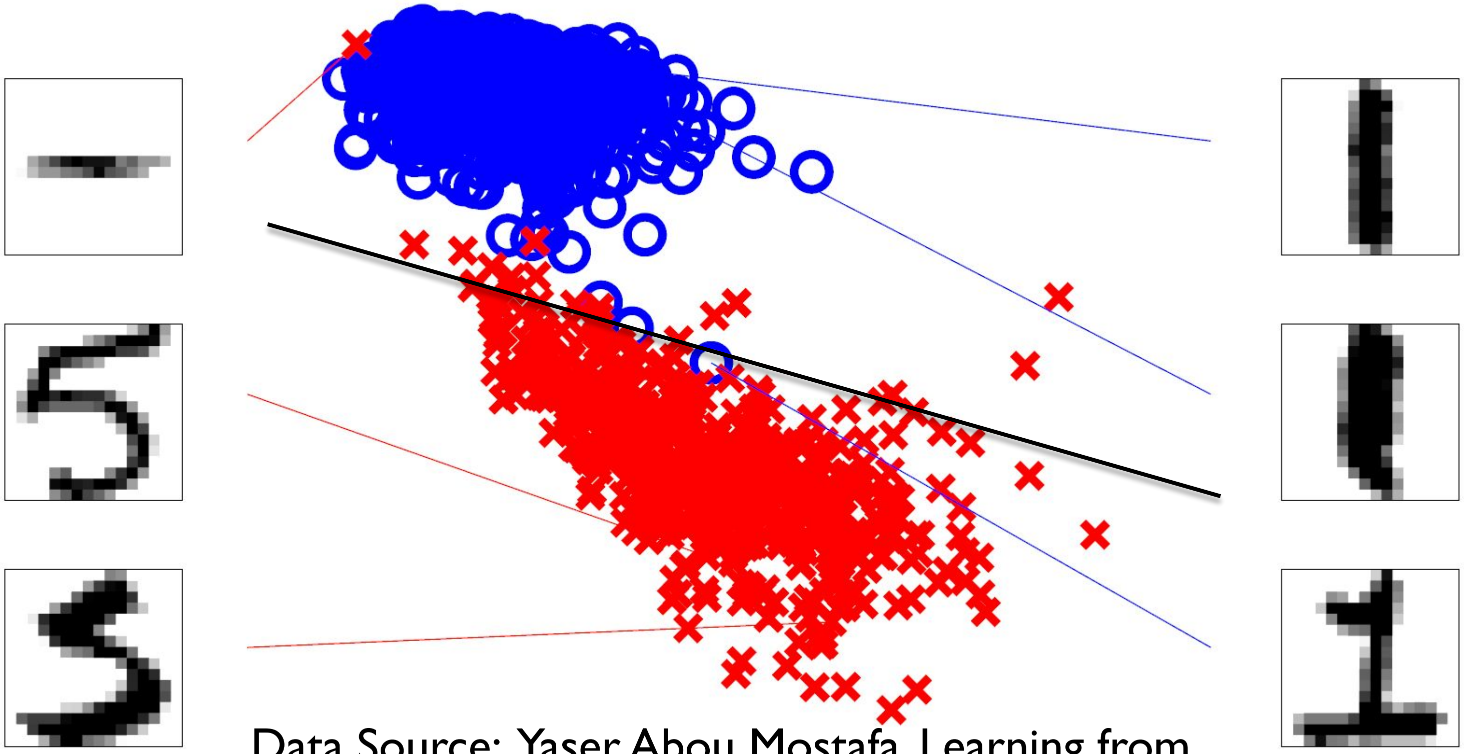
Until all training data points are correctly classified by g

Perceptron learning algorithm: Example of weight update



Example: linear classifier

$\mathbf{x} = (x_0, x_1, x_2)$ $\qquad x_1$: intensity $\qquad x_2$: symmetry



Data Source: Yaser Abou Mostafa, Learning from

(Supervised) Learning problem

- Selecting a **hypothesis space**
  - Hypothesis space: a set of mappings from feature vector to target

- **Learning (estimation)**: optimization of a cost function
  - Based on the training set $D = \left\{\left(\boldsymbol{x}^{(i)}, y^{(i)}\right)\right\}_{i=1}^{n}$ and a cost function we find (an estimate) $f \in F$ of the target function

- **Evaluation**: we measure how well $\hat{f}$ generalizes to unseen examples

Generalization

- We don't intend to memorize data but want to distinguish the pattern.

- A core objective of learning is to generalize from the experience.
  - Generalization: ability of a learning algorithm to perform accurately on new, unseen examples after having experienced.

Paradigms of ML

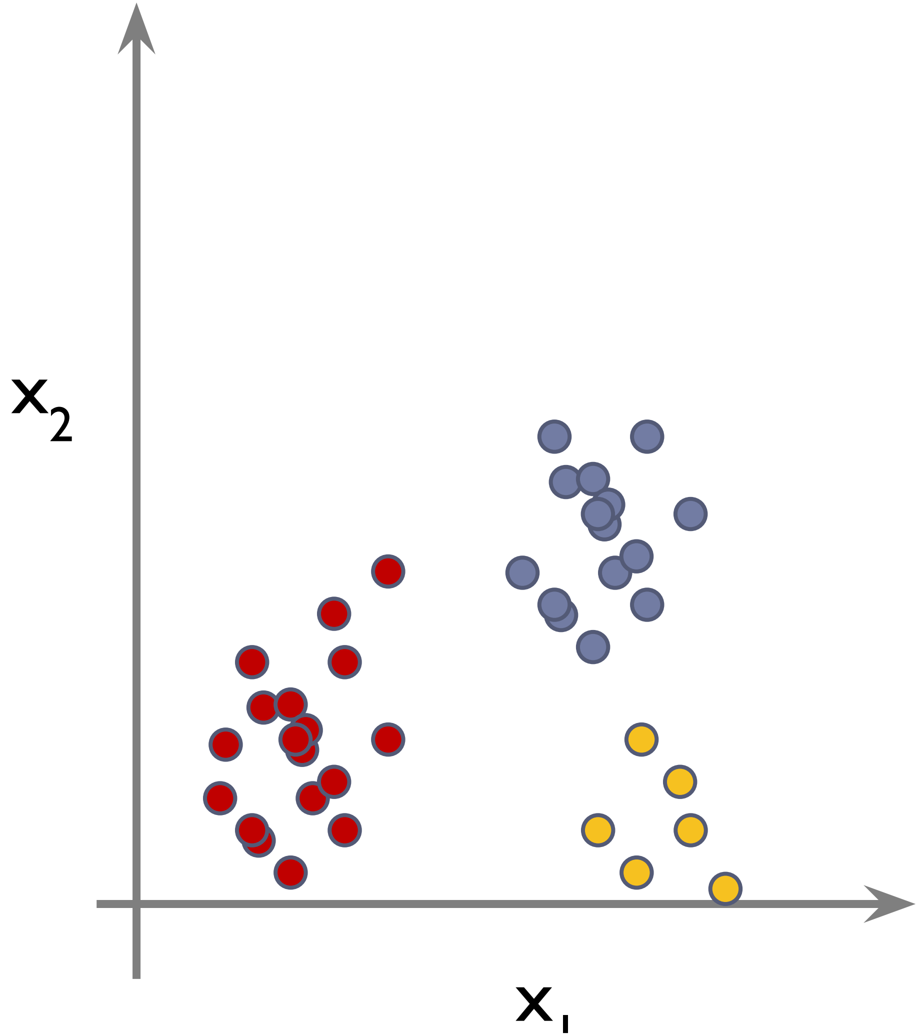
- Supervised learning (regression, classification)
  - predicting a target variable for which we get to see examples.
- Unsupervised learning
  - revealing structure in the observed data

Supervised Learning vs. Unsupervised Learning

- Supervised learning
  - Given: Training set
    - labeled set of N input-output pairs $D = \{(\boldsymbol{x}^{(i)}, y^{(i)})\}_{i=1}^{N}$
  - Goal: learning a mapping from $\boldsymbol{x}$ to y

- Unsupervised learning
  - Given: Training set
    - $\{\boldsymbol{x}^{(i)}\}_{i=1}^{N}$
  - Goal: find groups or structures in the data
    - Discover the intrinsic structure in the data

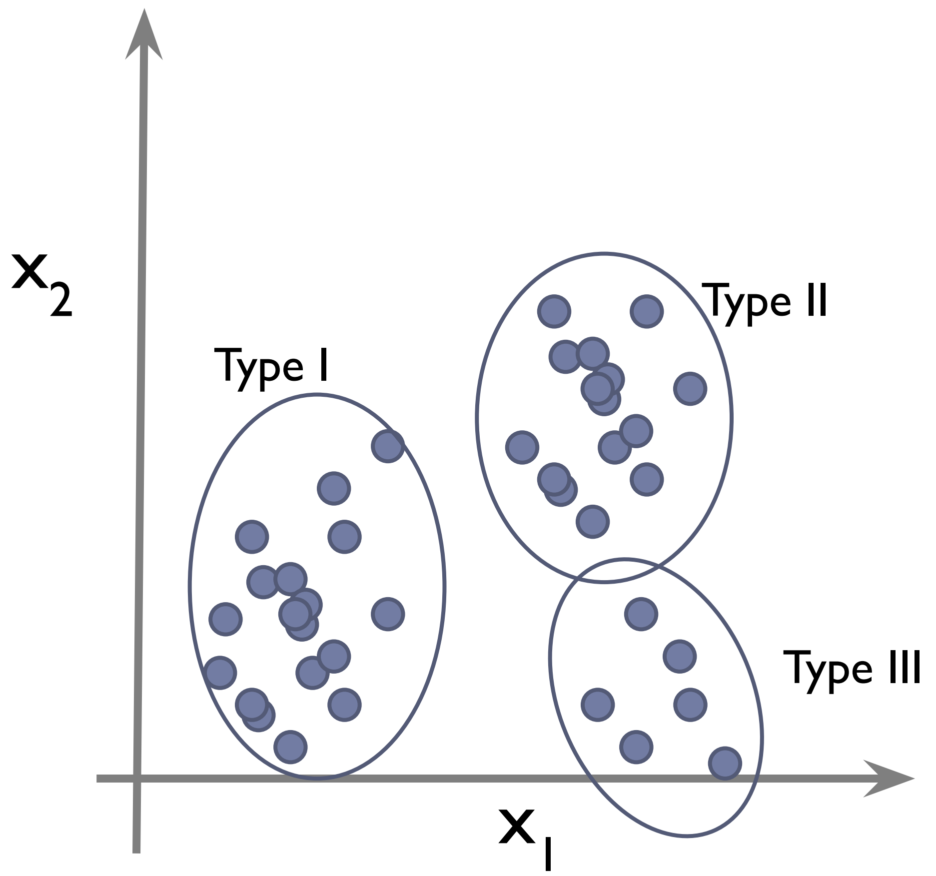
Supervised Learning: Samples



Classification

Unsupervised Learning: Samples

- Wants to use data to improve their knowledge on a task



Clustering

Sample Data in Unsupervised Learning

- Unsupervised Learning:

Columns:
Features/attributes/dimensions

Rows:
Data/points/instances/examples /samples

	…			
				Sample 1
				Sample 2
				…
				Sample n-1
				Sample n

Unsupervised learning

- **Clustering**: partitioning of data into groups of similar data points.

- **Dimensionality reduction**: data representation using a smaller number of dimensions while preserving (perhaps approximately) some properties of the data.

- **Density estimation & generative models**

Some clustering purposes

- **Preprocessing stage** to index, compress, or summarize the data
- As a tool to **understand the hidden structure** in data or to **group** them
  - To gain knowledge (insight into the structure of the data) or
  - To group the data when no label is available

Clustering: Example Applications

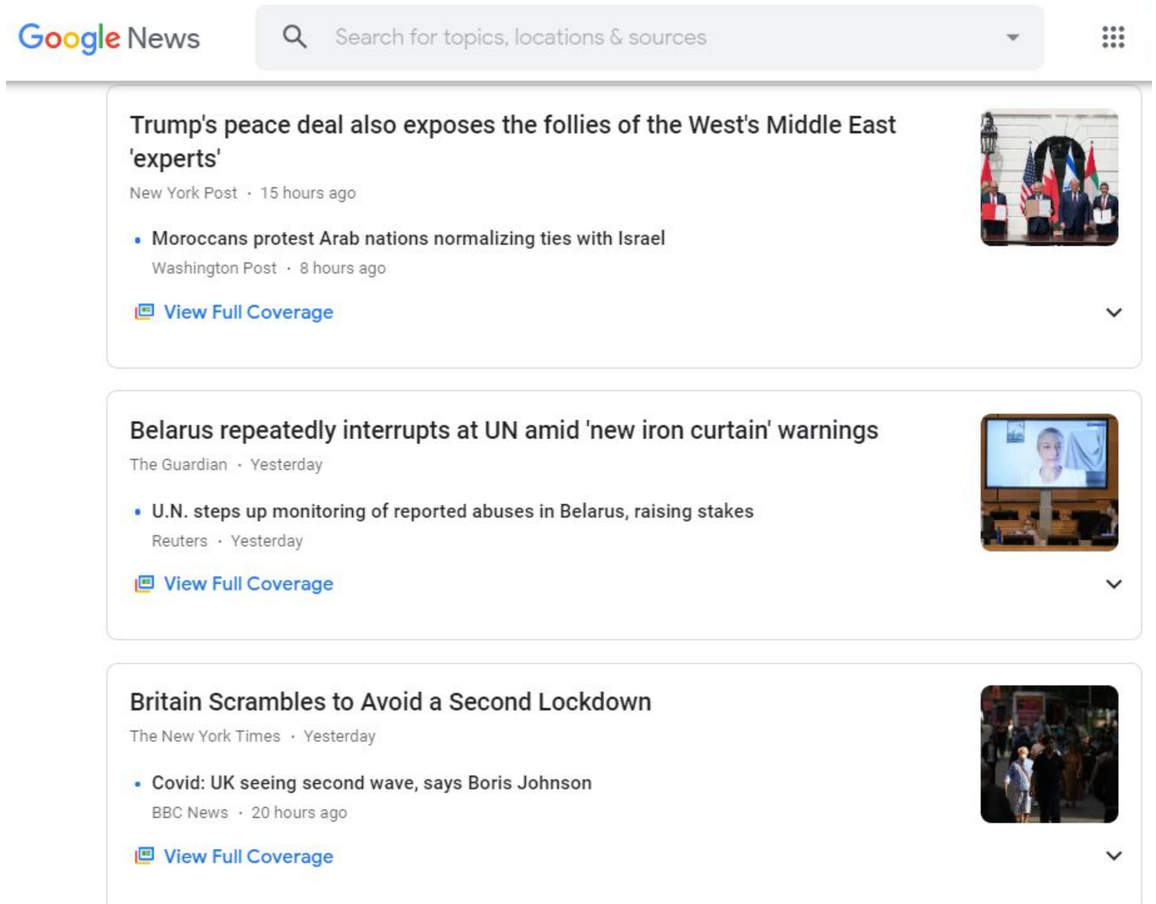
- Clustering docs based on their similarities
  - Grouping new stories in the Google news site

- Market segmentation: group customers into different market segments given a database of customer data.

- Community detection in social networks

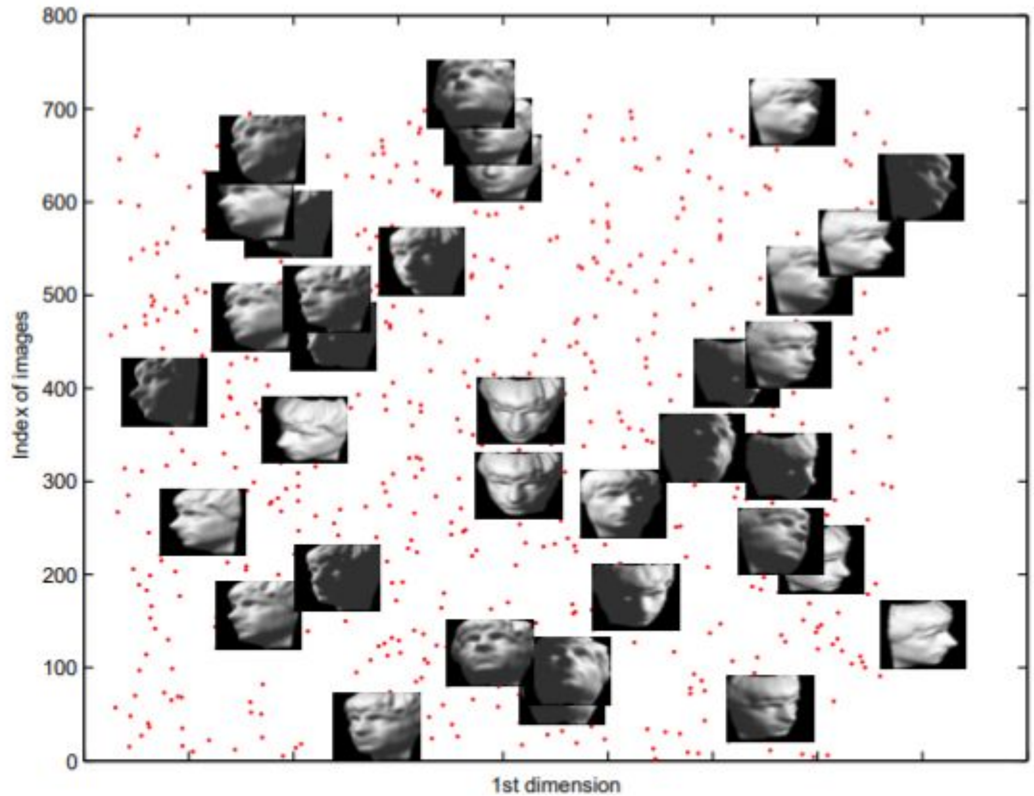
Clustering of docs

- Google news



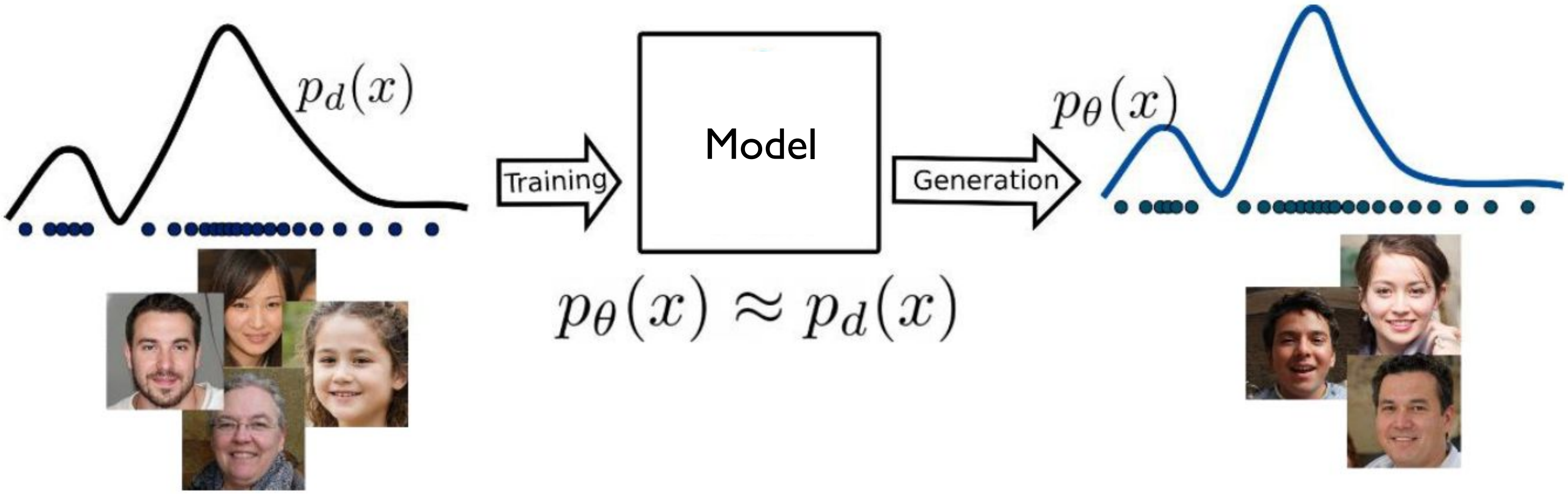
Dimensionality reduction: Example

How to map the high dimensional data into a lower dimensional space in which the distance is more meaningful.



[Ali Ghodsi, 2006]

Generative models: Example



Paradigms of ML

- Supervised learning (regression, classification)
  - predicting a target variable for which we get to see examples.
- Unsupervised learning
  - revealing structure in the observed data
- Other paradigms: semi-supervised learning, weakly supervised, self-supervised learning, active learning, etc.

Three axes of ML

- Task (i.e. what is the type of knowledge that we seek from data)
- Data
- Algorithm

Three axes of ML

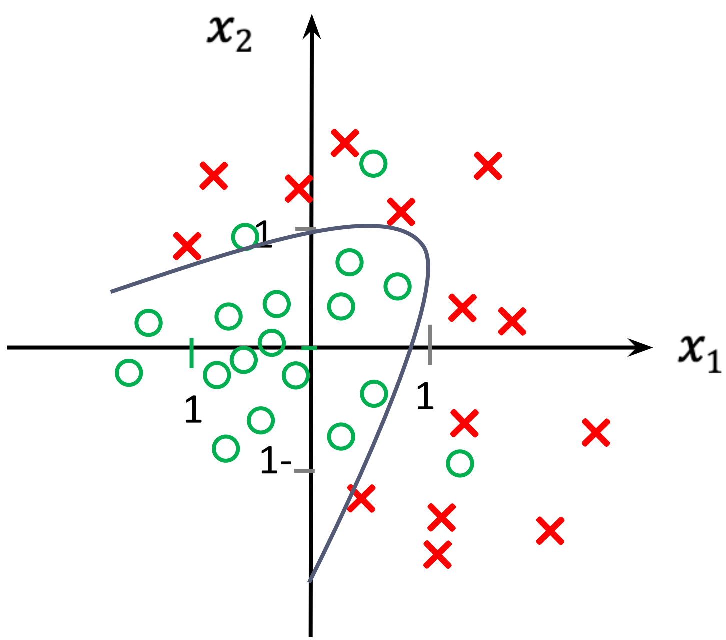
- Task (i.e. what is the type of knowledge that we seek from data)
  - Prediction (i.e. classification or regression)
  - Control
  - Description

- Data
  - Fully observed / Partially observed
  - Passively / Actively collecting data
  - Online / Offline

- Algorithm
  - Parametric / Nonparametric models
  - …

Parametric models

- We consider a parametric boundary (e.g., hyper-plane, hyperbola, …) and learn its parameters form data
  - The set of parameters does not grow with increasing the data

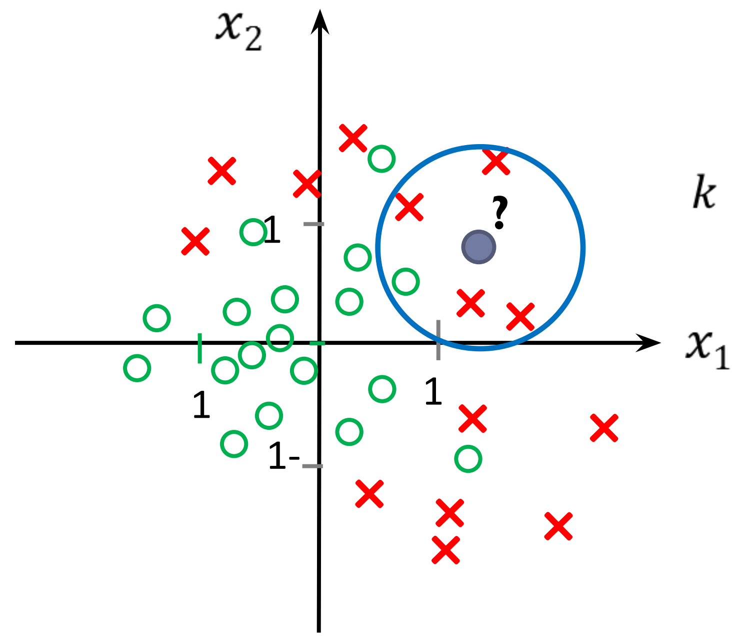


Nonparametric models

- We must store data and for each prediction, we need to process training data
- More data means a more complex model
  - Models that grow with the data

Nonparametric models

- k-NN classifier
  - Label for $\boldsymbol{x}$ predicted by majority voting among its k-NN.



Find k nearest training data to the new input and predict its label from the labels of its k nearest neighbors

The number of points to search scales with the training data

ML in Computer Science

- Why ML applications are growing?
  - Improved machine learning algorithms
  - Availability of data (Increased data capture, networking, etc)
  - Software too complex to write by hand
    - Demand for complex systems (on high-dimensional, multi-modal, or heterogeneous data)
    - Demand for self-customization to user or environment

Relation to other fields

- **Statistics:** the goal is the understanding of the data at hand
- **Artificial Intelligence:** the goal is to build an intelligent agent
- **Data Mining:** the goal is to extract patterns from large-scale data
- **Data Science:** the science encompassing collection, analysis, and interpretation of data

- The goal of machine learning is the underlying mechanisms and algorithms that allow improving our knowledge with more data

Some Learning Application Areas

- Computer Vision (Photo tagging, face recognition, …)
- Natural language processing (e.g., machine translation)
- Robotics
- Speech recognition
- Autonomous vehicles
- Social network analysis
- Web search engines
- Medical outcomes analysis
- Market prediction (e.g., stock/house prices)
- Computational biology (e.g., annotation of biological sequences)
- Self-customizing programs (recommender systems)

Topics of this course

- Regression & generalization
- Evaluation & Model Selection
- Classification
  - Linear classifier
  - Probabilistic classifiers
  - SVM & kernel
  - Decision tree
- Neural Networks
- Learning Theory
- Non-parametric methods
- Ensemble learning
- Dimensionality reduction
- Clustering