*** Applied Machine Learning Fundamentals ***
Machine Learning Introduction

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SAP SE

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Section:

General Overview

Why Machine Learning?

- *'We are drowning in information and starving for knowledge.'*

  – John Naisbitt

- **Era of big data:**
  - In 2017 there are about **1.8 trillion** web-pages on the internet
  - **20 hours** of video are uploaded to YouTube every minute
  - Walmart handles more than **1 million** transactions per hour and has data bases containing more than **2.5 peta-bytes** (2.5×10^15) of information
- **No human being can deal with this data avalanche!**

Why Machine Learning? (Ctd.)

*'I keep saying the sexy job in the next ten years will be **statisticians** and **machine learners**. People think I'm joking, but who would've guessed that computer engineers would've been the sexy job of the 1990s? The ability to take data - to be able to understand it, to process it, to extract value from it, to visualize it, to communicate it - that's going to be a hugely important skill in the next decades.'*

*– **Hal Varian**, Chief Economist at Google, 2009*

Definition of Machine Learning

- *'[Machine Learning is the] field of study that gives computers the ability to learn without being explicitly programmed.'*

  – ***Arthur Samuel**, 1959*

- *'A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E.'*

  – ***Tom Mitchell**, 1997*

A more abstract Definition

- Our task is to learn a mapping from input to output:

$$h : \mathcal{I} \mapsto \mathcal{O}$$

- Put differently, we want to predict the output from the input:

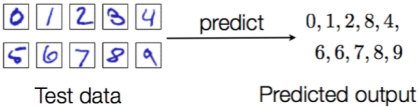
$$y = h(\boldsymbol{x}; \boldsymbol{\theta}) \qquad \text{also:} \quad y = h_{\boldsymbol{\theta}}(\boldsymbol{x})$$

- $\boldsymbol{x} \in \mathcal{I}$ (Input)
- $y \in \mathcal{O}$ (Output)
- $\boldsymbol{\theta} \in \boldsymbol{\Theta}$ (Parameters: What needs to be 'learned')

General Paradigm

Training

Testing



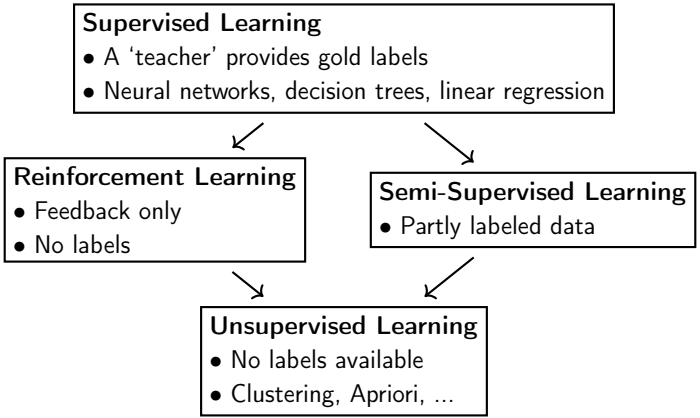
Section:

Problem Types in Machine Learning

Type of Training Information

- **Supervised learning**
  - 'Teacher' provides **gold labels**
  - E. g. neural networks, decision trees, linear regression
- **Unsupervised learning**
  - Labels are **not** known during training
  - E. g. clustering, density estimation, association rule mining
- **Reinforcement learning**
  - Environment provides rewards for actions but correct action is unknown
  - E. g. policy-iteration, Q-learning, SARSA
- **Semi-supervised learning** (partly labeled data)

Type of Training Information (Ctd.)

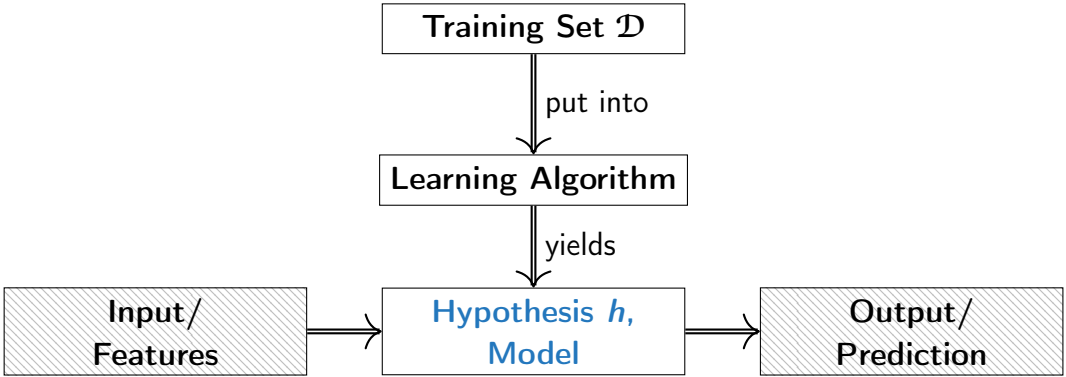


Supervised Learning

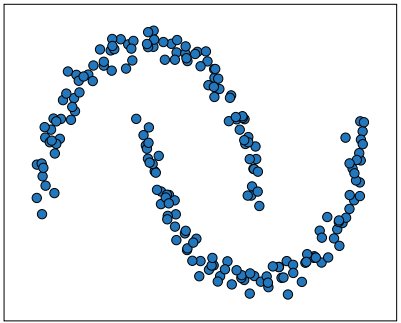
- A single row is called **example**
- An example without class label is called **instance**
- **Predictors:**
  - Outlook $\in \{sunny, overcast, rainy\}$
  - Temperature $\in \{hot, mild, cool\}$
  - Humidity $\in \{high, normal\}$
  - Wind $\in \{weak, strong\}$
- **Label:**
  - PlayGolf $\in \{yes, no\}$
  - Given a new instance we want to predict the label
- **Label for the new instance???**

Outlook	Temperature	Humidity	Wind	PlayGolf
sunny	hot	high	weak	**no**
sunny	hot	high	strong	**no**
overcast	hot	high	weak	**yes**
rainy	mild	high	weak	**yes**
rainy	cool	normal	weak	**yes**
rainy	cool	normal	strong	**no**
overcast	cool	normal	strong	**yes**
sunny	mild	high	weak	**no**
sunny	cool	normal	weak	**yes**
rainy	mild	normal	weak	**yes**
sunny	mild	normal	strong	**yes**
overcast	mild	high	strong	**yes**
overcast	hot	normal	weak	**yes**
rainy	mild	high	strong	**no**
rainy	mild	normal	strong	???

Supervised Learning: General Approach



Unsupervised Learning



- There are **no** labels
- Try to find regularities in the data
- Examples for unsupervised learning:
  - **Clustering**
  - **Density estimation**
  - **Dimensionality reduction**

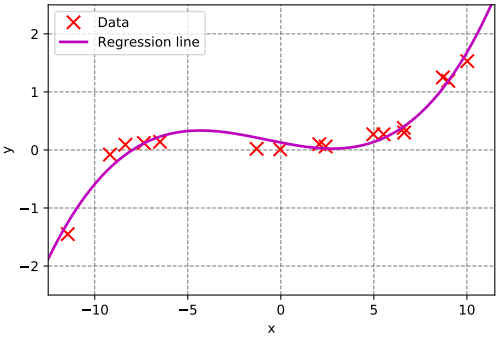
Availability of Training Examples

- **Batch Learning**
  - The learner is provided with a fixed set of training examples
  - See weather data set
  - E. g. neural networks, decision trees
- **Incremental/Online Learning**
  - Constant stream of training examples
  - The model is updated as new training examples arrive
  - E. g. k-nearest-neighbors
- Active Learning (*not covered*)

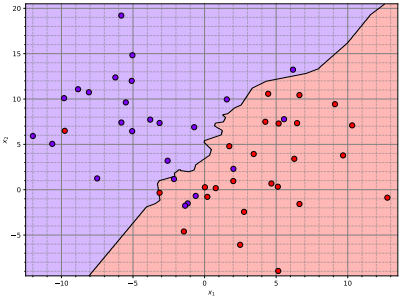
Type of Target Variable: Regression

Regression

- Learn a mapping into a continuous space
  - $\mathcal{O} = \mathbb{R}$
  - $\mathcal{O} = \mathbb{R}^3$
- E. g. curve fitting, financial analysis, housing prices, ...



Type of Target Variable: Classification



Classification

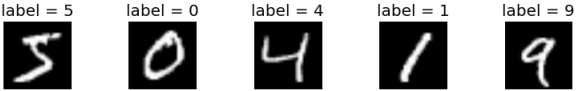
- Learn a mapping into a discrete space, e. g.
  - $\mathcal{Y} = \{0, 1\}$ (binary classification)
  - $\mathcal{Y} = \{0, 1, 2, 3, ...\}$
  - $\mathcal{Y} = \{\textit{verb}, \textit{noun}, \textit{adverb}, ...\}$
- Examples:
  - Spam / no spam
  - Digit recognition
  - Part of speech tagging

Section:

Key Challenges in Machine Learning

Generalization from Training Data

- Learning doest not mean memorizing the training data
- What if we see input that we **haven't seen before**?
- Example OCR (**O**ptical **C**haracter **R**ecognition):



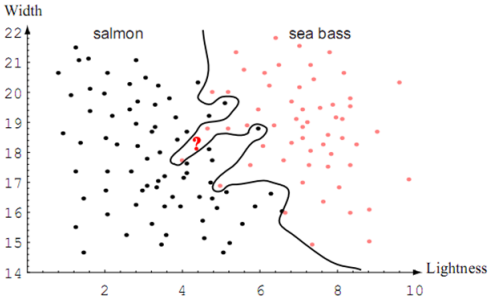
Hand-written digits from the MNIST data set

- Predict the character given the input image
- **People have different hand-writings**

Generalization from Training Data (Ctd.)

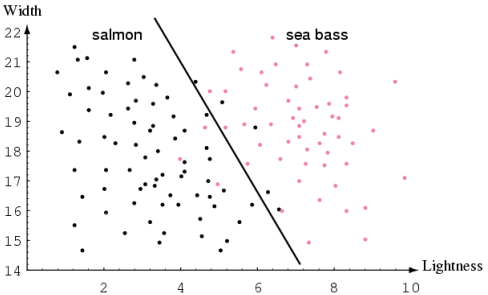
What is the problem here?

- Complex decision boundary
- This leads to Overfitting
  - The model is too expressive...
  - ...and adapts to **idiosyncrasies** of the training data



Solution: Choose a simpler model (c. f. **Occam's razor**)

Generalization from Training Data (Ctd.)



- Linear (less complex) model
- Allow for **misclassifications** of some training examples
- **Better generalization** to unseen instances

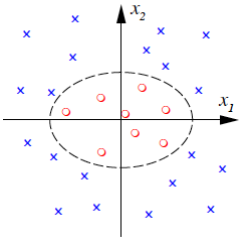
A Prominent Example of Overfitting

Choosing the right Features

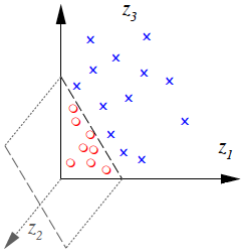
When stuck, move to a different perspective!

$\mathcal{X}$

Input space



$\phi : \mathcal{X} \mapsto \mathcal{F}$



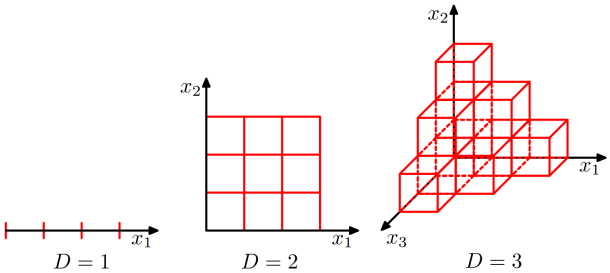
$\mathcal{F}$

Feature space

$$\phi(x_1, x_2) \mapsto \left(x_1^2, \sqrt{2}x_1x_2, x_2^2\right) = (z_1, z_2, z_3)$$

Choosing the right Features

But: Beware of the curse of dimensionality!



- Too many features significantly **slow down** the ML algorithm
- Need **exponential** amount of training data
- Dimensionality reduction

Image taken from [] p. 35

Performance Measurement

- How do we measure performance?
  - 99 % correct classification in speech recognition: What does it really mean?
  - *We understand the meaning of the sentence?*, *We understand every word?*, *For all speakers?*
- We need more **concrete numbers**:
  - % of correctly classified letters
  - Average distance driven (until accident, ...)
  - % of games won
  - % of correctly recognized words, sentences, etc.
- **Training vs. testing performance**

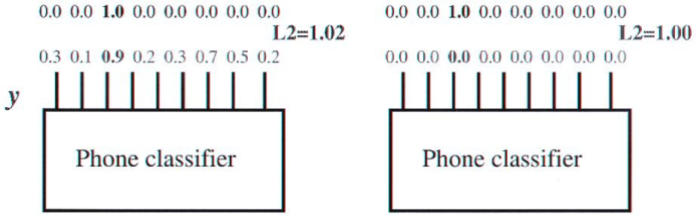
Training vs. Testing Performance

- Evaluate on data which was **not used** for training (**out-of-sample testing**)
- Two-way split: *Train* - *Test*
- Even better: *Train* - *Dev* - *Test*

Train: Train model
Dev: Tune hyper-parameters
Test: Test final model

Performance Measurement (Ctd.)

- We also need to define the right **error metric**:

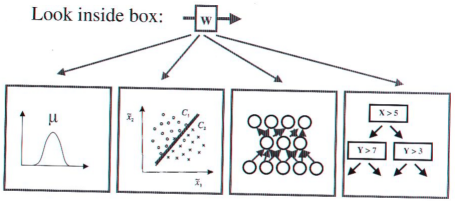


- Which is better?
- Euclidean distance (L2-norm) might be useless

Model Selection

- What is the **right model**?
- The learned parameters (here: $\boldsymbol{w}$) can mean a lot of different things:

- May characterize a family of functions
- May be parameters of a probability distribution
- $\boldsymbol{w}$ may be a vector, adjacency matrix, graph, ...



Computation

Even if the other problems are solved, **computation is usually quite hard**:

- Learning involves optimization of parameters
- Find / Search for best model parameters
  - GoogleNet has $\approx$ 6.5 million parameters
  - Often GPUs (**G**raphics **P**rocessing **U**nit) are needed
  - Google invented TPUs (**T**ensor **P**rocessing **U**nit)
- Often we have to deal with thousands, millions, ... of training examples
- Given a model, the prediction has to be computed efficiently

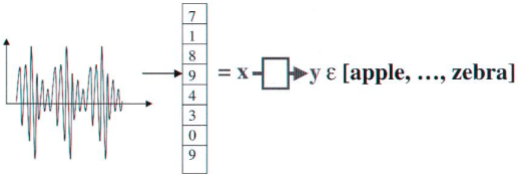
Section:

Machine Learning Applications

Applications in Natural Language Processing

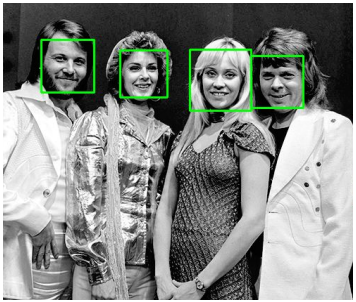
- **E-mail filtering:**

- **Speech Recognition:**



Applications in Computer Vision

Face detection:



Traffic sign detection:

Applications in Computer Vision (Ctd.)

Optical character recognition:

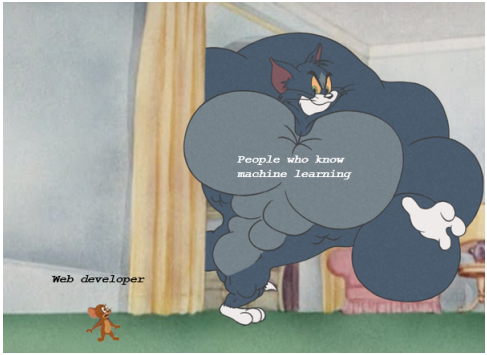
See Demonstration LeNet

Applications in Robotics

Robot control:

Autonomous driving:

Why Machine Learning?



Summary

Lecture Overview

Unit I: Machine Learning Introduction

Self-Test Questions

Recommended Literature and further Reading

[1] Machine Learning

Tom Mitchell. McGraw-Hill Science. 1997.

→ See chapter 1 (Introduction)

Thank you very much for the attention!

Topic: *** Applied Machine Learning Fundamentals *** Machine Learning Introduction
Date: August 8, 2019

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Do you have any questions?