Lecture 1: Machine Learning

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Main Literature

- Christopher M. Bishop, Pattern Recognition and Machine Learning (Information Science and Statistics), Springer 2006
 - https://www.microsoft.com/en-us/research/people/cmbishop/#!prml-book



• Simon O. Haykin, Neural Networks and Learning Machine, (3rd Edition), Pearson 2008



Deep Learning, I. Goodfellow, Y. Bengio, A. Courville MIT Press 2016

https://www.deeplearningbook.org

Main Literature



 Machine Learning - A Journey to Deep Learning, A. Wichert, Luis Sa-Couto, World Scientific, 2021



- Intelligent Big Multimedia Databases, A. Wichert, World Scientific, 2015
 - Preprocessing, Feature Extraction like DFT, Wavelets, will be not covered in the lecture....

Additional Literature



 Machine Learning: A Probabilistic Perspective, K. Murphy, MIT Press 2012



- Introduction To The Theory Of Neural Computation (Santa Fe Institute Series Book 1), John A. Hertz, Anders S. Krogh, Richard G. Palmer, Addison-Wesley Pub. Co, Redwood City, CA; 1 edition (January 1, 1991)
 - I find this book to be one of the best written mathematical guides for Neural Networks. See Perceptron, Backpropagation...

Literature Software



- Hands-On Machine Learning with Scikit-Learn and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems 1st Edition, Aurélien Géron, O'Reilly Media; 1 edition (April 9, 2017)
 - <u>https://github.com/amitanalyste/aurelienGeron</u>



<u>https://scikit-learn.org/stable/index.html</u>



http://www.numpy.org

I) Outline:

Introduction: What is Machine Learning?

- 1. Introduction
- 2. <u>Decision Trees</u>

Mathematical Tools:

- 3. Probability theory & Information (Naive Bayes)
- 4. Linear Algebra & Optimization (Simple NN)

Road to deep learning: Error Minimization (Loss), Regularization, Optimization by Gradient descent

- 5. Linear Regression & Bayesian Linear Regression
- 6. Perceptron & Logistic Regression
- 7. Multilayer Perceptrons

II) Outline

Why do the neural works work :

- 8. Learning theory, Bias-Variance
- 9. K-Means, EM-Clustering
- 10. Kernel Methods & RBF
- 11. <u>Support Vector Machines</u>

How to use the models:

12. Model Selection

III) Outline

Deep Learning **solves** the problem of **high dimensionality** which is related to the **training database size**!

13. Deep Learning

- 14. Convolutional Neural Networks
- 15. <u>Recurrent Neural Networks</u>

Dimension Reduction:

- 16. <u>PCA, ICA</u>
- 17. <u>Autoencoders</u>

IV) Outline

Alternative Road to Machine Learning (Classical Approach):

- 18. Feature Extraction (FFT, SFT, Edge Detection)
- 19. k Nearest Neighbour & Locally Weighted Regression
- 20. Ensemble Methods

Probabilistic and Stochastic Approach:

- 21. Bayesian Networks
- 22. Stochastic Methods

What is machine Learning?

- Parallels between "animals" and machine learning
- Many techniques derived from efforts of psychologist / biologists to make more sense "animal" learning through computational models

Machine Learning

- Statistical Machine Learning
 - Linear Regression
 - Clustering, Self Organizing Maps (SOM)
 - Artificial Neural Networks, Kernel Machines
 - Bayesian Network
- We will not cover....
 - Inductive Learning (ID3)
 - Knowledge Learning
 - Analogical Learning
 - SOAR: Model of Cognition and Learning

An Example of Symbolical Learning (Patrick Winston-1975)



An Example (Patrick Winston-1975)



An Example (Patrick Winston-1975)

c. Given background knowledge that bricks and pyramids are both types of polygons



d. Generalization that includes both examples



An Example (Patrick Winston-1975)

a. Candidate description of an arch



b. A near miss and its description



c. Arch description specialized to exclude the near miss



Statistical Machine Learning

- Changes in the system that perform tasks associated with AI
 - Recognition
 - Prediction
 - Planning
 - Diagnosis

Learning Input output functions

- Supervised
 - With a teacher
- Unsupervised
 - Without a teacher
- Reinforcemet Learning
 - Actions within & responses from the environment
 - Absence of a designated teacher to give positive and negative examples







- We might add other features that are not correlated with the ones we already have. A precaution should be taken not to reduce the performance by adding such "noisy features"
- Ideally, the best decision boundary should be the one which provides an optimal performance such as in the following figure:



 However, our satisfaction is premature because the central aim of designing a classifier is to correctly classify novel input







- *10*⁴⁰ Neurons
- 10⁴⁻⁵ connections

per neuron









Perceptron (1957)

• Linear threshold unit (LTU)



McCulloch-Pitts model of a neuron (1943)

Linearly separable patterns





- (a) The two classes 1 (indicated by a big point) and -1 (indicated by a small point) are separated by the line -1 + x1 + x2 = 0.
- (b) The hyperplane -1+x1+x2 = y defines the line for y=0.

- The goal of a perceptron is to correctly classify the set of pattern
 D={x₁, x₂,...x_m} into one of the classes C₁ and C₂
- The output for class C₁ is o=1 and for C₂ is o=-1



Perceptron learning rule

- Consider linearly separable problems
- How to find appropriate weights
 - Initialize each vector **w** to some small random values
- Look if the output pattern *o* belongs to the desired class, has the desired value *d*

$$w^{new} = w^{old} + \Delta w \qquad \Delta w = \eta \cdot (d - o) \cdot x$$

- η is called the **learning rate**
- $0 < \eta \leq 1$



- In supervised learning the network has its output compared with known correct answers
 - Supervised learning
 - Learning with a teacher
- (d-o) plays the role of the error signal

Algorithm

- 1. iterations=0;
- 2. $\eta \in (0,1];$
- 3. Initialise all the weights w_0, w_1, \dots, w_D to some random values;
- Choose a pattern x_k out of the training set;
- 5. Compute $net_k = \sum_{i=1}^{D} w_j \cdot x_{k,j} + w_0 = \langle \mathbf{x}_k | \mathbf{w} \rangle + w_0 \cdot x_0;$
- 6. Compute the output by the activation function $o_k = sgn(net_k)$;
- 7. Compute $\Delta w_j = \eta \cdot (t_k o_k) \cdot x_{k,j};$
- 8. Update the weights $w_j = w_j + \Delta w_j$;
- 9. iterations++;
- If no change in weights for all training set or maximum number of iteration THEN STOP ELSE GOTO 4;

Constructions


Frank Rosenblatt

• 1928-1971









Rosenblatt's bitter rival and professional nemesis was Marvin Minsky of Carnegie Mellon University

- Minsky despised Rosenblatt, hated the concept of the perceptron, and wrote several polemics against him
- For years Minsky crusaded against Rosenblatt on a very nasty and personal level, including contacting every group who funded Rosenblatt's research to denounce him as a charlatan, hoping to ruin Rosenblatt professionally and to cut off all funding for his research in neural nets

XOR problem and Perceptron

• By Minsky and Papert in mid 1960



k Means Clustering (Unsupervised Learning)

• The standard algorithm was first proposed by Stuart Lloyd in 1957



Back-propagation (1980)

- Back-propagation is a learning algorithm for multi-layer neural networks
- It was invented independently several times
 - Bryson an Ho [1969]
 - Werbos [1974]
 - Parker [1985]
 - Rumelhart et al. [1986]

Parallel Distributed Processing - Vol. 1

Foundations David E. Rumelhart, James L. McClelland and the PDP Research Group

What makes people smarter than computers? These volumes by a pioneering neurocomputing.....



The good old days...



6



Everyone was doing Back-propagation....





NETtalk Sejnowski et al 1987







Typical input images

90% accurate learning head pose, and recognizing 1-of-20 faces





Typical input images

 $\rm http://www.cs.cmu.edu/{\sim}tom/faces.html$



Kunihiko Fukushima





Kunihiko Fukushima received a B.Eng. degree in electronics in 1958 and a PhD degree in electrical engineering in 1966 from Kyoto University, Japan. He was a professor at Osaka University from 1989 to 1999, at the University of Electro-Communications from 1999 to 2001, at Tokyo University of Technology from 2001 to 2006; and a visiting professor at Kansai University from 2006 to 2010. Prior to his Professorship, he was a Senior Research Scientist at the NHK Science and Technology Research Laboratories. He is now a Senior Research Scientist at Fuzzy Logic Systems Institute (part-time position), and usually works at his home in Tokyo.









Polynomial Curve Fitting



Sum-of-Squares Error Function



Oth Order Polynomial



1st Order Polynomial



3rd Order Polynomial



9th Order Polynomial



Over-fitting



Root-Mean-Square (RMS) Error: $E_{\rm RMS} = \sqrt{2E(\mathbf{w}^{\star})/N}$

Polynomial Coefficients

		λ /Γ 1	1/ 9	
	M = 0	M = 1	M = 3	M = 9
w_0^\star	0.19	0.82	0.31	0.35
w_1^\star		-1.27	7.99	232.37
w_2^\star			-25.43	-5321.83
w_3^\star			17.37	48568.31
w_4^\star				-231639.30
w_5^\star				640042.26
w_6^\star				-1061800.52
w_7^\star				1042400.18
w_8^\star				-557682.99
w_9^\star				125201.43

Data Set Size:
$$N = 15$$

9th Order Polynomial



Data Set Size:
$$N = 100$$

9th Order Polynomial



Regularization

Penalize large coefficient values

$$\widetilde{E}(\mathbf{w}) = \frac{1}{2} \sum_{n=1}^{N} \{y(x_n, \mathbf{w}) - t_n\}^2 + \frac{\lambda}{2} \|\mathbf{w}\|^2$$

Regularization:
$$\ln \lambda = -18$$



Problem of Local Minima

- The immediate solution to this is to build networks with more hidden layers with regularization
- "Deep Learning"...
 Déjà vu?

Artificial intelligence pioneer (Geoffrey Hinton) says we need to start over



- Back-propagation still has a core role in Al's future.
- Entirely new methods will probably have to be invented
- "I don't think it's how the brain works," he said. "We clearly don't need all the labeled data.

- What makes something similar to something else (specifically what makes, for example, an uppercase letter 'A' recognisable as such)
- Metamagical Themas, Douglas Hoffstader, Basic Books, 1985





- What is the essence of dogness or house-ness?
- What is the essence of 'A'-ness?
- What is the essence of a given person's face, that it will not be confused with other people's faces?
 - How to convey these things to computers, which seem to be best at dealing with hard-edged categories--categories having crystal-clear, perfectly sharp boundaries?
- What Next?
- Example of what is machine learning: Decision Trees

Literature



- Simon O. Haykin, Neural Networks and Learning Machine, (3rd Edition), Pearson 2008
 - Chapter 1



- Christopher M. Bishop, Pattern Recognition and Machine Learning (Information Science and Statistics), Springer 2006
 - Section 1.1

Literature



- Machine Learning A Journey to Deep Learning, A. Wichert, Luis Sa-Couto, World Scientific, 2021
 - Chapter 1