AIMLab.

ML IN HEALTHCARE
BIOMEDICAL ENGINEERING

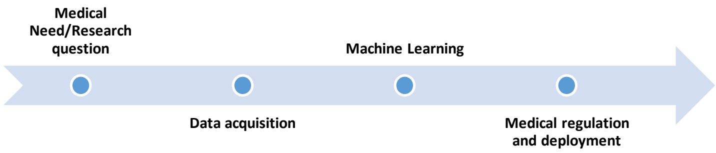
Contents

1. Introduction

With billions of mobile devices worldwide and the low cost of connected medical sensors, recording and transmitting medical data has become easier than ever. However, this ‘wealth’ of physiological data has not yet been harnessed to provide actionable clinical information. This is due to the lack of smart algorithms that can exploit the information encrypted within these ‘big databases’ of biomedical time series and images and take individual variability into account. Exploiting these data necessitates an in depth understanding of the physiology underlying these biomedical time series and images, the use of advanced digital signal processing and machine learning tools (e.g. deep learning) to recognize and extract characteristic patterns of health function, and the ability to translate these patterns into clinically actionable information. The creation of intelligent algorithms combined with existing and novel wearable and portable biosensors offer an unprecedented opportunity to monitor patients remotely (i.e. outside of the traditional clinical setting) and support the management of their condition.

In this course you will learn about aspects of information processing including data preprocessing, visualization, regression, dimensionality reduction (PCA, ICA), feature selection, classification (LR, SVM, NN) and their usage for decision support **in the context of healthcare**. The course aims to provide an overview of computer tools and machine learning techniques for dealing with **medical datasets** (time series and images). The course is practical with computer based tutorials and assignments. The necessary theory will be covered.

Each session is structured by two lectures and two hours of tutorial. All students will be expected to keep a digital log book of their code and results on their GitHub account for each tutorial session and share the results with the instructors by the end of the session – this will be used to track the class progress. Include your Python code, figure plots and explanations. Please label your figures clearly: parameters and units on both axes in a font large enough to be readable, with a legend describing each line and symbol you plot.



2. Course Summary

Course title:	Machine Learning in Healthcare
Short title:	ML in Healthcare
Course ref. no.	336546
Number of credits:	3
Number of weeks: - **Weekly lectures** - **Weekly tutorials**	13 2 hours (total 26 hours) 2 hours (total 26 hours) + 3 workshops of 2 hours (total 6 hours).
Course assessment:	Coursework + 3 assignments
Capacity:	12 Work station – Maximum 24 students.
Computer requirements:	Six GPU available from department cluster. Software: PyCharm, jupyter notebook, Git, Atom. Libraries: Numpy, Panda, Keras.
Lecturer(s):	Joachim Behar (JB), PhD
Teaching assistants:	Alon Begin (AB), MSc candidate Moran Davoodi (MD), MSc candidate
Guests Lecturers:	Anne Weill (AW), PhD, Technion, BME Doron Shaked (DS), PhD, GE Healthcare Danny Eytan (DE), MD-PhD, Rambam Hospital Uri Shalit (US), PhD, Technion, Industrial Engineering
Teaching objectives:	Students will acquire the following skills: • Python for data science. • Structuring machine learning projects. • Main classifiers, intuition and mathematical background. • Deep Learning. • ML in healthcare.

The lectures are divided in three sets: ML basis, Popular classifiers and Deep Learning.

3. Syllabus

Part I: ML basis

Week	Lecture	Subjects covered
1 **29/10/2019**	#C01 Introduction	- Course objectives and settings - Introduction to ML in healthcare - Supervised, unsupervised and deep learning - Polynomial curve fitting - Main concepts in ML - Notations features and variables
	#C02 Data Exploration and Preprocessing 1	- Exploratory data analysis - Data visualization - Abnormality detection and handling
2 **05/11/2019**	#C03 Data Exploration and Preprocessing 2	- Features scaling
	#C04 Linear Models for Regression	- Intuition - Calculus proof - Probabilistic proof - Sequential learning - Cost function - Gradient descent
3 **12/11/2019**	#C05 Linear Models for Classification	- Classification versus regression - LR hypothesis representation - LR Cost function - Gradient descent - Multiclass classification - Linear discriminant analysis
	#C06 Regularization	- Overfitting - Cost function - Regularized linear regression - Regularized logistic regression - Ridge, Lasso regression and geometrical interpretation
4 **19/11/2019**	#C07 Training a Classifier I	- Evaluating a model - Model selection and learning curves - Generalization performance
	#C08 Training a Classifier II	- Performance statistics - Cross validation techniques - Receiver operative curve

Part II: Popular classifiers

Week	Lecture	Subjects covered
5 **26/11/2019**	#C09 Case study: Obstructive sleep apnea detection using Lasso	- Practical machine learning.
	#C10 Getting nonlinear	- The XOR function - Quadratic discriminant analysis
6 **03/12/2019**	#C11 Support vector machines	- Maximum margin classifiers - Dual representation - Kernel trick - Grid search and random search
	#C12 Causal inference	- Causal inference (US)
7 **10/12/2019**	#C13 Feature selection	- Lasso - mRMR - Genetic algorithms
	#C14 K-means and GMM (Unsupervised Learning)	- K-nearest neighbor - Probabilistic data analysis: GMM
8 **17/12/2019**	#C15 Principal component analysis (Unsupervised Learning)	- Blind source separation - Principal component analysis - Change of basis - Mathematical proof - PCA in machine learning
	#C16 Independent component analysis (Unsupervised Learning)	- Independent component analysis - Statistical independence versus correlation - Whitening - Beyond ICA: t-SNE

Part III: Deep learning

Week	Lecture	Subjects covered
9 **22/12/2019** **(instead of ג)**	#C17 Artificial Neural Network	- Binary classification - Revisiting logistic regression - Cost function - Gradient descent - Intro to neural network
	#C18 Artificial Neural Network	- Data representation - Activation functions - Gradient descent for neural network - Backpropagation algorithm - Random initialization - Deep network
10 **31/12/2019**	#C19 Deep Learning CNN	- Foundation - Simple CNN - Striding, padding etc.
	#C20 Deep Learning CNN	-
11 **07/01/2019**	#C21 Deep Learning CNN	- Popular CNN and image segmentation (DS)
	#C22 Deep Learning CNN	- Popular CNN and image segmentation (DS)
12 **14/01/2019**	#C23 Deep Learning	- High Performance Computing (AW)
	#C24 Deep Learning	- High Performance Computing (AW)
13 **21/01/2019**	#S25 Recurrent Neural Network	- RNN, LSTM, GRU - Autoencoders
	#S26 Machine Learning in Healthcare	- Practical applications, opportunities and challenges (DE)

3. Assignments Description

Assignment	Week	Dataset type	Number of instances (n) and attributes (p)	Learning objectives
#A1 Cardiotography Data Set	W07	The dataset consists of measurements of fetal heart rate (FHR) and uterine contraction (UC) features on cardiotocograms labelled by expert obstetricians. The aim is to automate the analysis of the FHR and approach the obstetricians' labels. http://archive.ics.uci.edu/ml/datasets/Cardiotocography	n=2126 p=23	- Feature engineered from physiological time series - Classification
#A2 ICU Mortality prediction	W11	Features derived from physiological time series and demographics for the purpose of predicting what patients will die in the intensive care unit (ICU).	n=3000 p=35	- Classification-predicting what patients will die in the intensive care unit (ICU).
#A3 X-ray	“W16”	Medical images	n=400	- Deep Learning

4. Workshops

Workshop	Week	Learning objectives
#WS1 Crash course on Python	W01	Basics of Python and working environment.
#WS2 Supervised and unsupervised learning	W06	Hands on supervised and unsupervised classification tasks.
#WS3 Deep Learning	W10	Hands on deep learning classification tasks.

5. Mathematical notations and terminology

Some notations used in this course are adapted from the notations of the Stanford CS230 course. Reference: https://cs230.stanford.edu/files/Notation.pdf

(i)	Example number.
m	The number of examples in the dataset.
n_x	Number of features or input samples (input size).
n_y	Number of classes (output size).
$X \in \mathbb{R}^{n_x \times m}$	Input matrix i.e. matrix with input features n_x for all examples m.
$x^{(i)} \in \mathbb{R}^{n_x}$	Column vector of the i^{th} example.
$x_j^{(i)}$	Scalar value of the j^{th} feature for example i^{th}.
$Y \in \mathbb{R}^{n_y \times m}$	Target matrix i.e. matrix with targets n_y for all examples m.
$y^{(i)} \in \mathbb{R}^{n_y}$	Target label for the i^{th} example.
$\hat{y}^{(i)} \in \mathbb{R}^{n_y}$	The predicted output vector from the classifier.
$\underline{y} \in \mathbb{R}^{m}$	A vector of scalar targets for all examples m.
h	The hypothesis function.
f	Target function i.e. the function we aim to learn.
$\hat{h}$	The estimated target function using the hypothesis function h.
J	Cost function i.e. cost function for all m examples.[1]
E	Error i.e. for a single example.
$\mathcal{N}(\mu, \sigma)$	Normal distribution with mean μ and standard deviation σ.
$w \in \mathbb{R}^{n_x}$	Weights vector in linear and logistic regression.

[1] The function that we aim to minimize or maximize is called the objective function. As we are minimizing it is often called equivalently the cost function, loss function, or error function. The term “cost function” usually refers to an optimization problem and “loss function” usually refers to parameter estimation.

Notations specific for Neural Networks:

Hyperparameters in NN:

L	Number of layers in a neural network.
$n_h^{[l]}$	Number of hidden units of the l^{th} layer.
α	Learning rate.
$g^{[l]}$	Activation function for layer l.
	Number of iterations for gradient descent.

NN variables:

$W^{[l]} \in \mathbb{R}^{n_h^{[l]} \times n_h^{[l-1]}}$	Weight matrix for layer l.
$w_j^{[l]} \in \mathbb{R}^{n_h^{[l]}}$	Weight vector for j^{th} activation at layer l.
$w_{jk}^{[l]} \in \mathbb{R}$	k^{th} weight coefficient for j^{th} activation at layer l i.e. element of $W^{[l]}$ at (j, k)
$b^{[l]} \in \mathbb{R}^{n_h^{[l]}}$	Bias vector at layer l.
$b_j^{[l]} \in \mathbb{R}$	j^{th} bias activation at layer l.
$a^{[l]} \in \mathbb{R}^{n_h^{[l]}}$	Activation vector at layer l.
$a_j^{[l]} \in \mathbb{R}$	j^{th} activation at layer l.

Terminology

Example	Refers to a set of features describing an observation.
Target	The label we are aiming to learn to predict.

Other items to standardize in the slides set:
- Menu at the beginning of each lecture.
- Challenging questions/math demo. One per lecture.