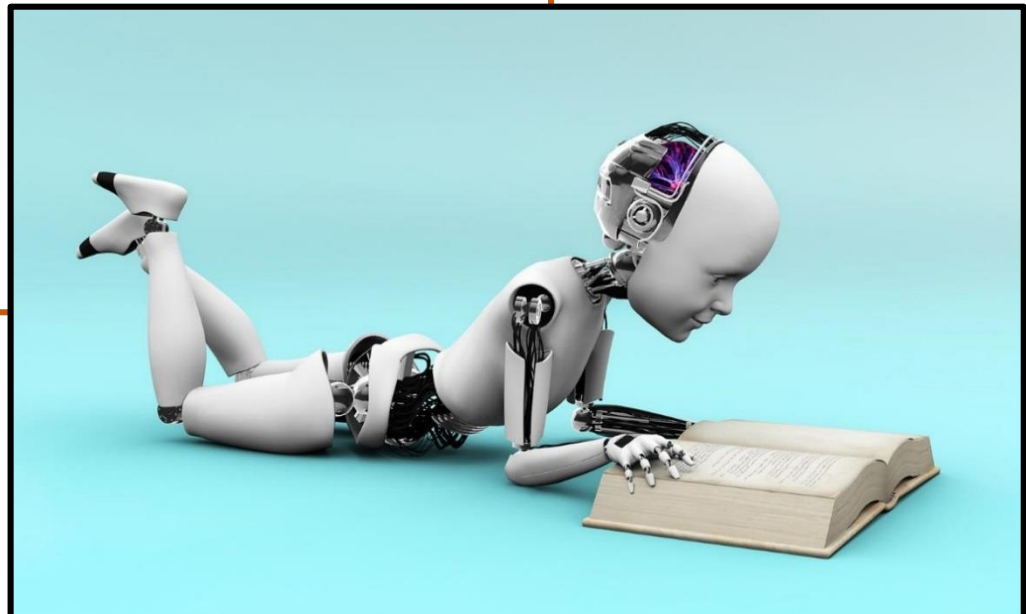


# Machine Learning from Data

Zohar Yakhini

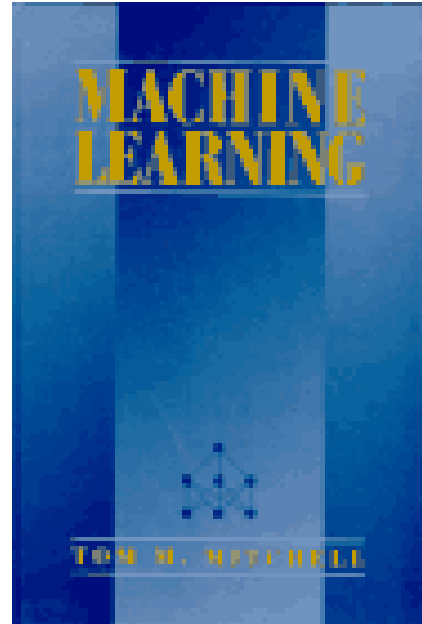
IDC Herzliya

2022/TASHPAB

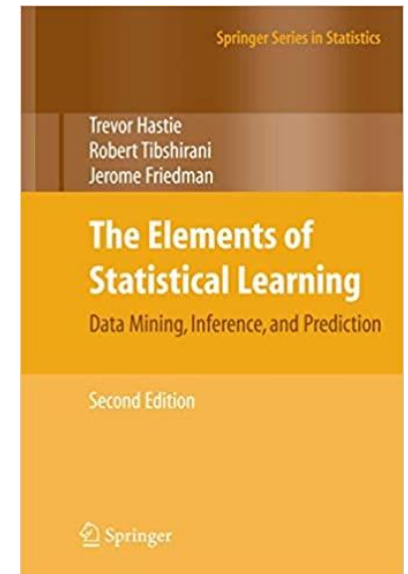
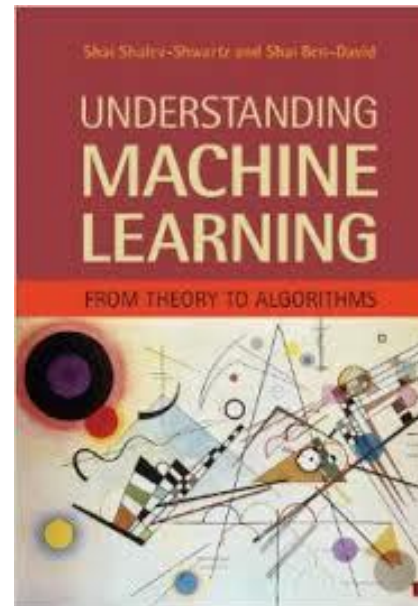


# General

- Instructors: Zohar Yakhini, Ariel (Arik) Shamir
- Slides (all in English) all prepared by Zohar Yakhini, Arik Shamir, Leon Anavy and Ben Galili + others as noted
- Principal TA: Ben Galili
- TAs and recitation instructors:  
Saar Buchnik (MSc student IDC),  
Shuli Finley (MSc student IDC),  
Yarden Rachamim (MSc student IDC),  
Yinnon Meshi (PAN, MSc EE Technion)
- Grade:
  - +  $0.5 * \text{HW} + 0.5 * \text{exam}$
  - + Must pass BOTH exam AND HW
  - + Returning students w high HW grades ( $>80$ ) can be exempt from some HW.



1. Tom Mitchel: Machine Learning
2. Duda, Hart, Stork:  
Pattern Classification
3. C Bishop:  
Pattern recognition and machine learning
4. T Hastie, R Tibshirani, J Friedman:  
Elements of Statistical Learning
5. Ben-David and Shalev-Schwarz:  
Understanding ML
6. Partial lecture notes (will be distributed as alpha version)
7. Internet ...



# HW Assignments

- 6 homework assignments, only 5 will count (n-1)
- But
  - + **HWA5 (theory assignment) is mandatory**  
**(at least 4 more out of the other 5 are required)**
  - + **There will be NO changes to the due dates of the HWAs**
- First one assigned this week, after the Thu English class
- Programming assignments will be done in Python using Jupyter notebooks.  
Help on Python will be available in the first two weeks of the semester  
(by appointment; please write if you are interested)
- Assignments in PAIRS  
(Singles only in exceptional cases and with specific explicit email approval from Ben)



# Office hours

- TAs: will publish on Moodle and Piazza and in the recitation slides
- Zohar Yakhini Thu 10-11, by email appointment
- Special Python office hours will be held by volunteer students. By email appointment.

# Background and pre-requisites

- Linear algebra and calculus
- Probability and statistics
- Algorithms, data structures
- Programming skills  
(Python will be further developed, at the necessary level, during the course)

Today ...

- Why machine learning?
- What is machine learning?
- Types of Learning Problems/Tasks
- First example of a learning algorithm: how to learn a function?
  - Linear Regression

# Why Machine Learning?

- Complex tasks that require processing that can not be done manually
- Data Mining:  
Convert data into information and knowledge.  
Find patterns in the data that lead to insights.  
Sometimes actionable insights.
- ML:  
Construct mechanisms for supporting data driven predictions and decisions.  
Replace human generated or curated rules.
- Rapidly developing industry – almost everything today needs or uses learning and data science techniques



# ML Applications - examples

- Spam filtering
- Credit card fraud detection
- Face recognition/detection/identification in images
- Recommendation systems (books, movies, travel destinations)
- Bioinformatics and analysis of scientific data
- Healthcare and medical science applications
- Self driving cars
- Predictive maintenance
- NLP: translation, text completion
- ...

# Example: hospital ER

- Consider patients arriving in the ER with, say, chest pain.
- When considering their discharge, can we predict, based on features we may be able to measure, if they will need to be re-hospitalized within the coming week (day, month, etc ...)?
- When admitted in the ER can we predict, based on features we can measure, whether they will develop an acute event within the next 4 hours?



# ER acute events – Rules based approach



- In the rules based approach we will collect input from doctors and other sources and write an algorithm/protocol:
  - Rule1:  
**If**  $\langle BP \rangle 150$  OR HR at rest  $> 150$  **then** RE-Hospitalized within one week
  - Rule 2: ....
  - Etc ...

Acute event



- Collect data with features including, for example:
  - Glucose level
  - Type of surgery performed, if any
  - Age
  - Type of insurance
  - Gender
  - Medications taken and adherence
  - Blood neutrophils, other serological parameters
  - Weight, BMI
  - ECG characteristics
  - Address, last name
- Also collect labels – acute event YES or NO
- Some measured features are more important than others in affecting the prediction values.
- Some may turn out to be not useful at all ...
- How do we know?

# LEARNING

Use the collected data and  
apply a (learning) algorithm  
to output a set of rules  
(protocol) as above

# Example: Spam Filtering

In 2016 spam accounted for 14.5 billion messages globally per day, which constitutes ~50% of all emails.

We would like to build effective and efficient filters.



# How To Filter Spam?

- Every email containing some suspicious words.  
“Viagra”, “cheap”, “free tickets”?
- Flashy text in the message
- Other attributes/features:
  - + Where did the message come from?
  - + Software that had sent the message
  - + Date? Time? Length?
- Rule based approach:  
develop a protocol based on the above.
- Learning approach:
  - + Collect (a lot of) data
  - + Determine feature values and a label (spam or not)
  - + LEARN a protocol – which words, features, attributes are associated with spam and what function to apply

# Learning Essentials

1. Collect data, examples: both good and bad (positive and negative).  
These are called “**samples**” or “**instances**”.
2. Gather information regarding the instances.  
Values for selected measurable “**features**”  
(note: some features are relevant and some are irrelevant; we don’t necessarily know apriori which is which). Assign “**labels**” to the instances.
3. Then what? - the inference stage.  
This stage uses a  
LEARNING “**technique**” or “**algorithm**”

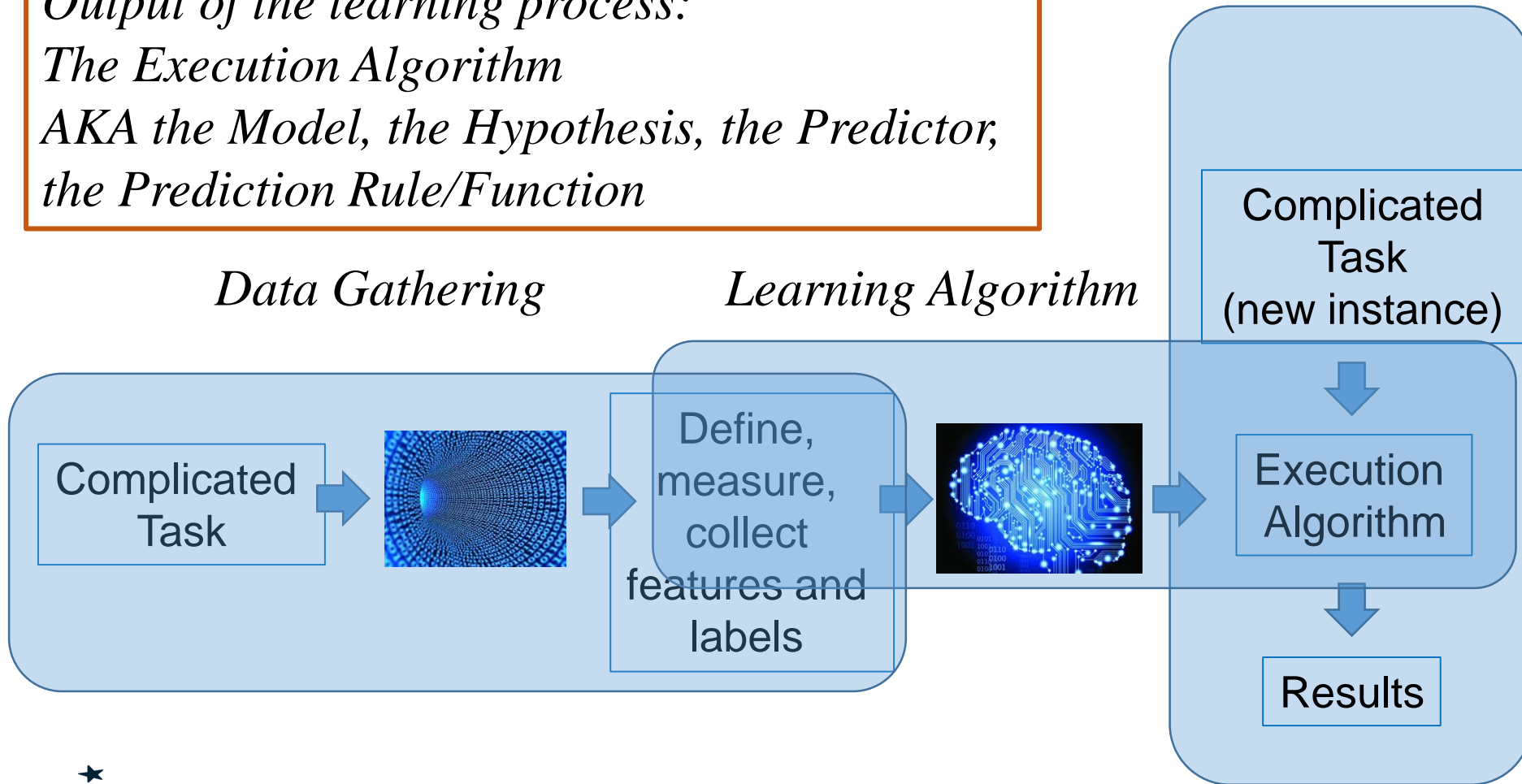


# Supervised Learning

*Output of the learning process:  
The Execution Algorithm  
AKA the Model, the Hypothesis, the Predictor,  
the Prediction Rule/Function*

*Data Gathering*

*Learning Algorithm*



# Learning

- We do not provide the rules of the execution algorithm ourselves
- We expect the “computer” to learn them by itself, from the data provided
- How?
- We apply a “learning algorithm” or a “learning technique”
- This is the primary subject of this course!

# Performance Evaluation

- How do we measure if we learned a good execution algorithm?
- Can we prove that we have learned something?
- What is the error of a proposed model?
- How much error do we allow? Do we need 100% performance? Can we expect that?
- How can we assess if a body of data and a technique is expected to allow for sufficiently accurate learning?  
(cast in a probabilistic framework)

# Types of learning tasks that will be addressed in the course

- Regression
  - + Given  $\{x_i, y_i\}$  find  $f$  such that  $y = f(x)$
- Classification
  - + Given  $\{x_i, y_i\}$  where  $y_i \in \{0,1\}$  for training, determine, for any new  $x$ , if  $x \in C_0$  or  $x \in C_1$
- Density Estimation
  - + Given  $\{x_i\}$  find a probability distribution that best explains the data  
(possibly from within a family of distributions)
- Clustering
  - + Given  $\{x_i\}$  find a “good” partition into  $k$  subsets

# First Example: Regression

- We want to represent a quantity as a function of other observed/measurable quantities.
- For example: determine the price of a used Subaru based on Kms driven, age of the car, age of driver(s), color integrity ....
- Assume that our explaining features are numerical – each instance is represented by a vector of features  $\mathbf{x} \in \mathbb{R}^n$
- We want to learn a function that predicts a real valued output from these features –

$$f: \mathbb{R}^n \rightarrow \mathbb{R}$$

# Regression Slide-set ...