MACHINE LEARNING

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What is Machine Learning?

- ML studies algorithms that improve with experience.

  learn from

  Tom Mitchell's Definition of the [*general*] *learning problem*:
  "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 on tasks in T, as measured by P, improves with experience E."

- Examples of [specific] learning problems (see next slide)
- [Liviu Ciortuz:] ML is data-driven programming
- [Liviu Ciortuz:] ML gathers a number of well-defined sub-domains/disciplines, each one of them aiming to solve in its own way the above-formulated [*general*] *learning problem*.

What is Machine Learning good for?

- natural language (text & speech) processing
- genetic sequence analysis
- robotics
- customer (financial risc) evaluation
- terrorist threat detection
- compiler optimisation
- semantic web
- computer security
- software engineering
- computer vision (image processing)
- etc.

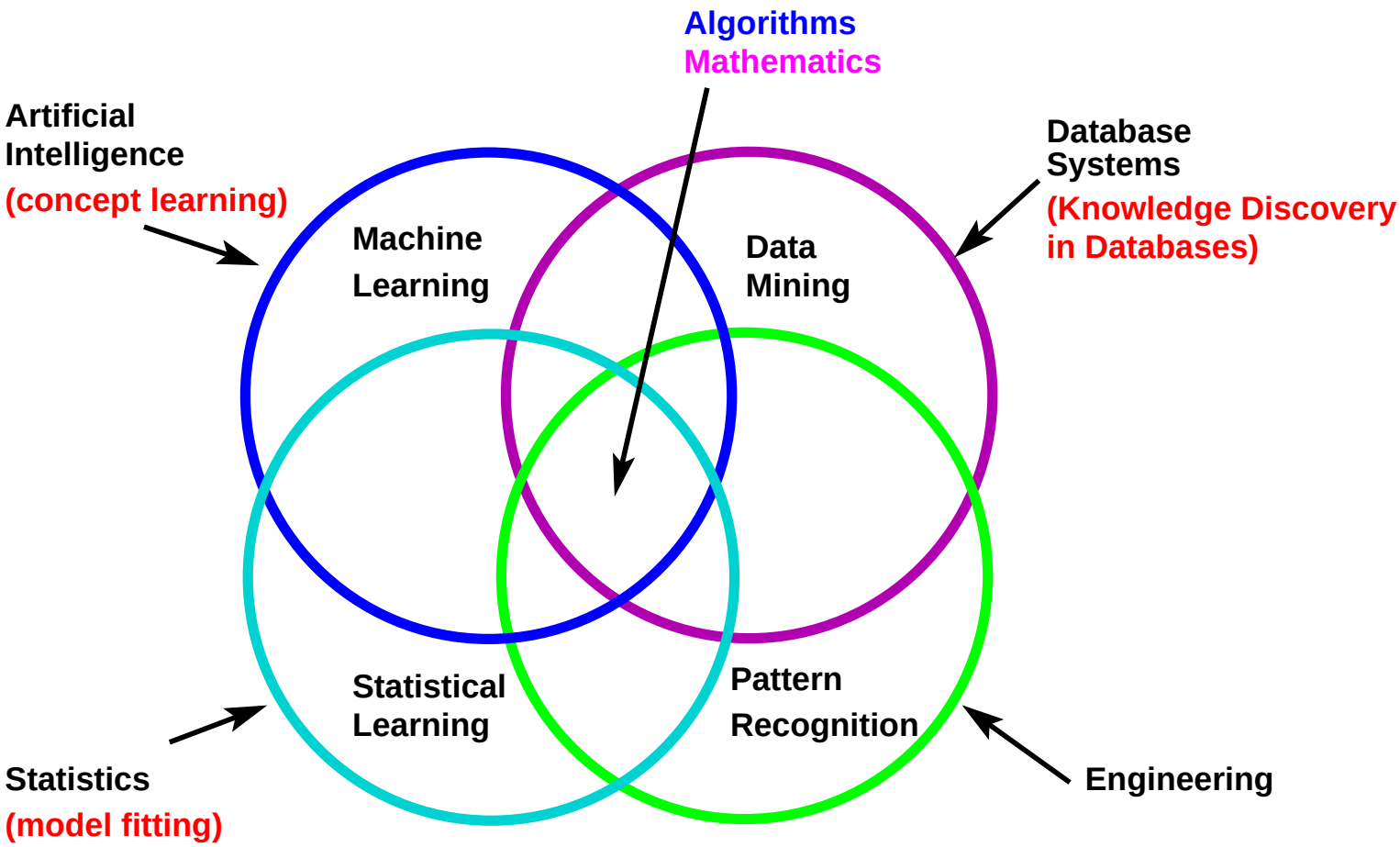
Related courses at FII

- Artificial Intelligence
- Genetic Algorithms
- Artificial Neural Networks
- Probabilistic programming

- Special Chapters of Machine Learning
- Special Chapters of Artificial Intelligence
- Special Chapters of Artificial Neural Networks
- Data Mining
- Nature-inspired computing methods
- Big Data Analytics
- Image Processing
- Computer Vision

- Bioinformatics

A multi-domain view



The Machine Learning Undergraduate Course: Plan

0. Introduction to Machine Learning (T. Mitchell, ch. 1)

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1. Probabilities Revision (Ch. Manning & H. Schütze, ch. 2)

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2. Decision Trees (T. Mitchell, ch. 3)
3. Bayesian Learning (T. Mitchell, ch. 6)
4. Maximum Likelihood Estimation (MLE)
5. Logistic Regression
   [and the relationship with Bayesian classification]
6. Instance-based Learning (T. Mitchell, ch. 8)
7. Clustering Algorithms (Ch. Manning & H. Schütze, ch. 14)

The Machine Learning Master Course:

Tentative Plan

1. Decision Trees: Boosting
2. Support Vector Machines (N. Cristianini & J. Shawe-Taylor, 2000)
3. Computational Learning Theory (T. Mitchell, ch. 7)

Probabilities Revision (Ch. Manning & H. Schütze, ch. 2)

4. Gaussian Bayesian Learning
5. The EM algorithmic schemata (T. Mitchell, ch. 6.12)
6. Hidden Markov Models (Ch. Manning & H. Schütze, ch. 9)

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3. **"Deep Machine Learning Foundations"**
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4. **"Foundations of Statistical Natural Language Processing"**
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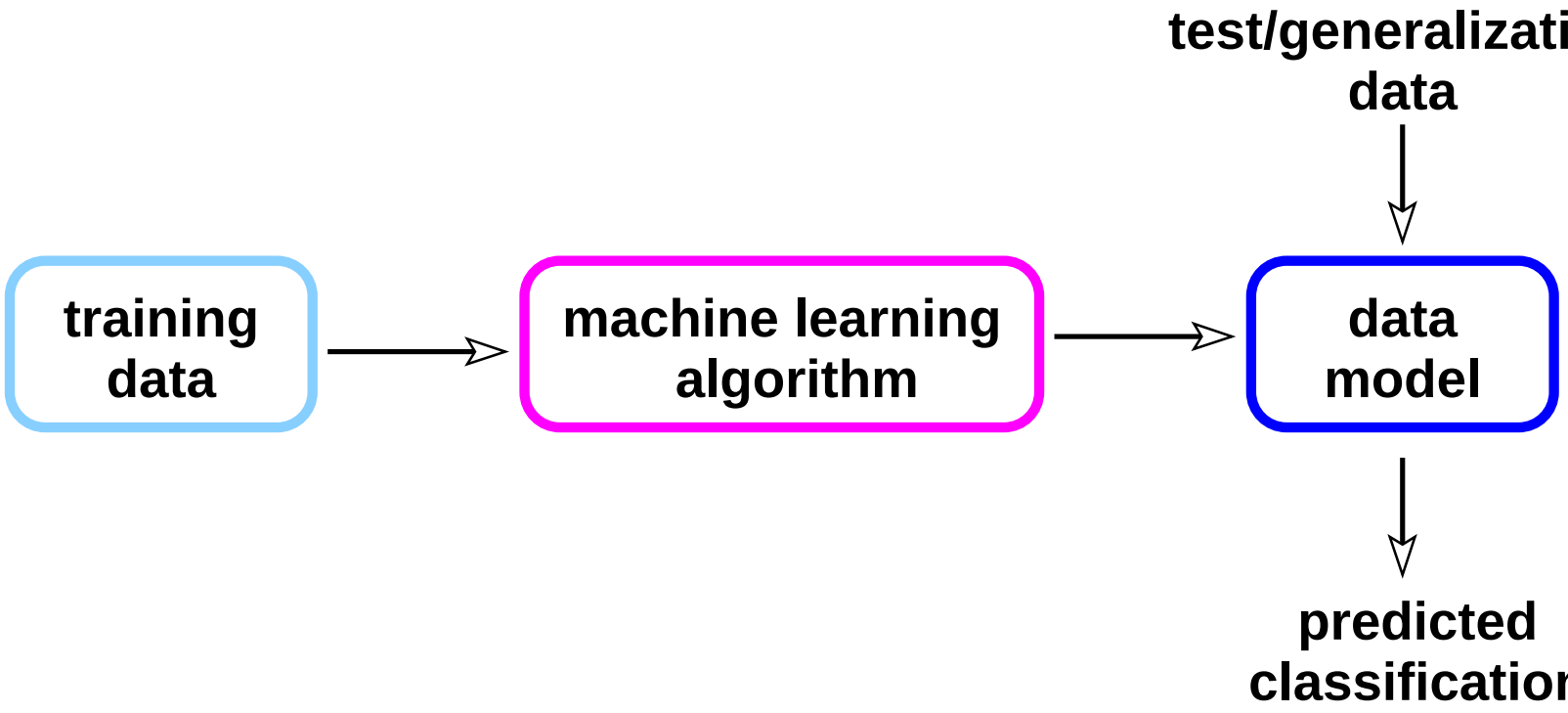
5. **"Support Vector Machines and other kernel-based learning methods"**
   Nello Cristianini, John Shawe-Taylor. Cambridge University Press, 2000.

A general schema for machine learning methods



"We are drawning in information but starved for knowledge."

John Naisbitt, "Megatrends" book, 1982

Basic ML Terminology

1. **instance x, instance set X**
   concept $c \subseteq X$, or $c : X \to \{0, 1\}$
   example (labeled instance): $\langle x, c(x) \rangle$; positive examples, neg. examples
2. **hypotheses $h : X \to \{0, 1\}$**
   hypotheses representation language
   hypotheses set H
   hypotheses consistent with the concept c: $h(x) = c(x), \forall$ example $\langle x, c(x) \rangle$
   version space
3. **learning = train + test**
   supervised learning (classification), unsupervised learning (clustering)
4. ***error***$_h = |\{x \in X, h(x) \neq c(x)\}|$
   training error, test error
   accuracy, precision, recall
5. **validation set, development set**
   n-fold cross-validation, leave-one-out cross-validation
   overfitting

The Inductive Learning Assumption

Any hypothesis found to conveniently approximate the target function over a sufficiently large set of training examples

will also conveniently approximate the target function over other unobserved examples.

Inductive Bias

Consider

- a concept learning algorithm L
- the instances X, and the target concept c
- the training examples $D_c = \{\langle x, c(x)\rangle\}$.
- Let $L(x_i, D_c)$ denote the classification assigned to the instance x_i by L after training on data D_c.

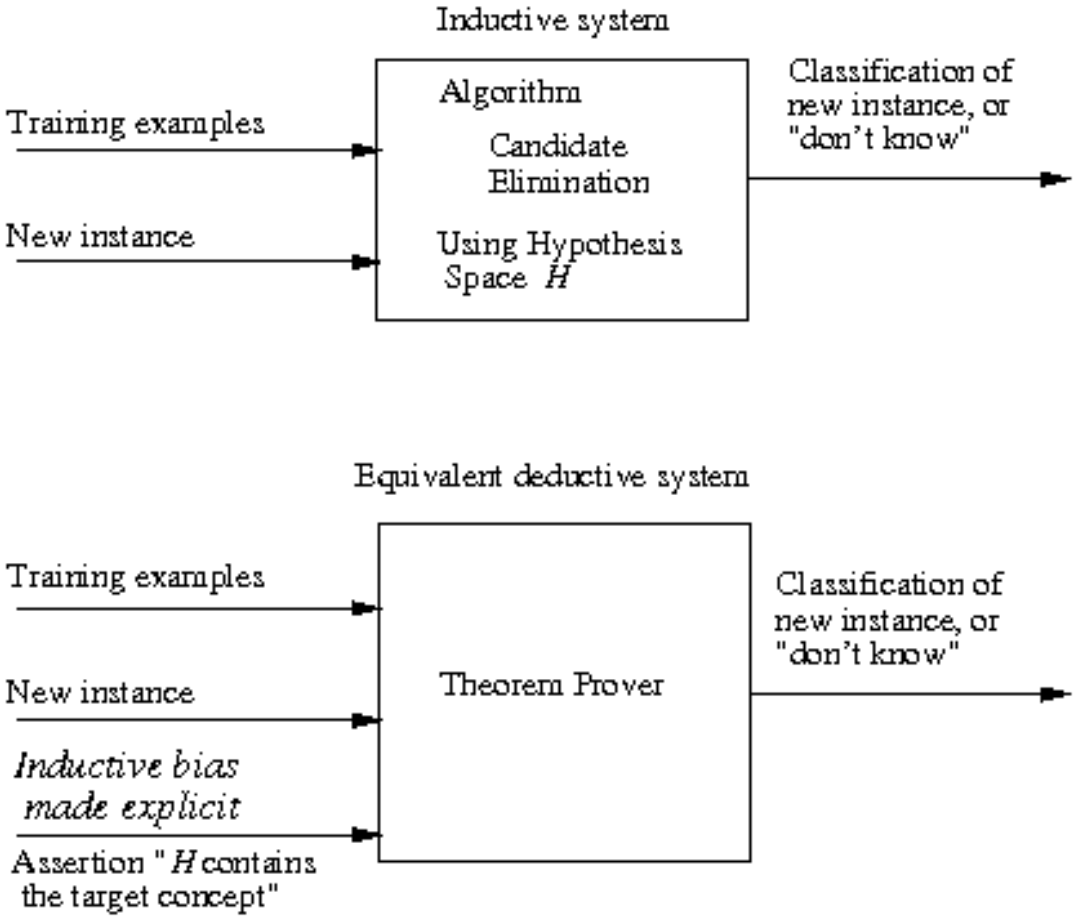
Definition:

The inductive bias of L is any minimal set of assertions B such that

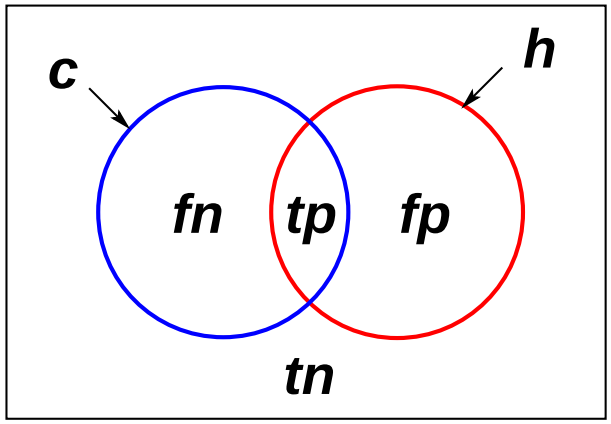
$$(\forall x_i \in X)[(B \vee D_c \vee x_i) \vdash L(x_i, D_c)]$$

for any target concept c and corresponding training examples D_c. ($A \vdash B$ means A logically entails B)

Inductive systems can be modelled by equivalent deductive systems



Evaluation measures in Machine Learning



tp – true positives
fp – false positives
tn – true negatives
fn – false negatives

accuracy: $Acc = \frac{tp + tn}{tp + tn + fp + fn}$

precision: $P = \frac{tp}{tp + fp}$

recall (or: sensitivity): $R = \frac{tp}{tp + fn}$

F-measure: $F = \frac{2\ P \times R}{P+R}$

specificity: $Sp = \frac{tn}{tn + fp}$

follout: $= \frac{fp}{tn + fp}$

Mathew's Correlation Coefficient:

$$MCC = \frac{tp \times tn - fp \times fn}{\sqrt{(tp + fp) \times (tn + fn) \times (tp + fn) \times (tn + fp)}}$$

Lazy learning vs. eager learning algorithms

Eager: generalize before seeing query

- ID3, Backpropagation, Naive Bayes, Radial basis function networks, ...
- Must create global approximation

Lazy: wait for query before generalizing

- k-Nearest Neighbor, Locally weighted regression, Case based reasoning
- Can create many local approximations

Does it matter?

If they use the same hypothesis space H, lazy learners can represent more complex functions.

E.g., a lazy Backpropagation algorithm can learn a NN which is different for each query point, compared to the eager version of Backpropagation.

Basic Machine Learning Algorithms

ID3 algorithm: a simplified version

Ross Quinlan, 1979, 1986

START

create the root *node*;
assign all examples to the root node;

Main loop:

1. $A \leftarrow$ **the "best" decision attribute for the next** *node*;
2. **for each value of** A**, create a new descendant of** *node*;
3. **sort training examples to leaf nodes;**
4. **if training examples are perfectly classified, then STOP;**
   else iterate over the new leaf nodes

AdaBoost algorithm [Yoav Freund, Robert Schapire, 1996, 1997, 1999]

Consider m training examples $S = \{(x_1, y_1), \ldots, (x_m, y_m)\}$, where $x_i \in \mathcal{X}$ and $y_i \in \{-1, +1\}$. Suppose we have a *weak learning algorithm* A which produces a hypothesis $h : \mathcal{X} \to \{-1, +1\}$ given any distribution D of examples.

- **Begin with a uniform distribution $D_1(i) = \dfrac{1}{m}$, $i = 1, \ldots, m$.**
- **At each iteration $t = 1, \ldots, T$,**
  - **run the weak learning algo A on the distribution D_t and produce the hypothsis h_t;**

  ***Note* (1): Since A is a weak learning algorithm, the produced hypothesis h_t at round t is only slightly better than random guessing, say, by a margin γ_t:**

$$\varepsilon_t = err_{D_t}(h_t) = \Pr_{x \sim D_t}[y \neq h_t(x)] = \frac{1}{2} - \gamma_t.$$

  ***Note* (2): If at a certain iteration $t \leq T$ the weak classifier A cannot produce a hypothesis better than random guessing (i.e., $\gamma_t = 0$) or it produces a hypothesis for which $\varepsilon_t = 0$, then the AdaBoost algorithm should be stopped.**

  - **update the distribution**

$$D_{t+1}(i) = \frac{1}{Z_t} \cdot D_t(i) \cdot e^{-\alpha_t y_i h_t(x_i)} \text{ for } i = 1, \ldots, m, \tag{1}$$

  where $\alpha_t \overset{not.}{=} \dfrac{1}{2} \ln \dfrac{1 - \varepsilon_t}{\varepsilon_t}$, and Z_t is the normalizer.
- **In the end, deliver $H_T = sign\left(\sum_{t=1}^{T} \alpha_t h_t\right)$ as the learned hypothesis, which will act as a *weighted majority vote*.**

AdaBoost as an instance of a more general *stepwise algorithm*

Input: S, T, $\mathcal{H}$, ϕ, **where**

$S = \{(x_1, y_1), \ldots, (x_m, y_m)$ **is the training dataset, with** $y_i \in \{-1, +1\}$

T **is the number of iterations to be executed,**

$\mathcal{H}$ **is a set of "hypotheses",**

$\phi(y, y')$ **is a "loss" / "cost" / "risk" function;**

Procedure:

Initialize the classifier by taking $f_0(x) = 0$ (the constant function 0),
and $D_1(i) = 1/m$ for $i = 1, \ldots, m$

for $t = 1$ to T do:

1. Compute
   $(h_t, \alpha_t) = \arg\min_{\alpha \in \mathbb{R}, h \in \mathcal{H}} \sum_{i=1}^{m} \phi(y_i, f_{t-1}(x_i) + \alpha h(x_i))$
2. Update the classifier
   $f_t(x) = f_{t-1}(x) + \alpha_t h_t(x)$
   compyte D_{t+1}

end for

return the classifier *sign* $(f_T(x))$

***Note*: At each step, the algorithm greedily adds a hypothesis $h \in \mathcal{H}$ to the current *combined hypothesis* to minimize the ϕ-loss.**

A Generalized AdaBoost Algorithm

[MIT, 2003 fall, Tommi Jaakkola, HW4, pr. 2.1-3]

Initialization: $\tilde{W}_i^{(1)} = 1/m$ **and** $f_0(x_i) = 0$ **for** $i = 1, \ldots, m$.

Loop: **for** $t = 1$ **to** T **do:**

***Step 1*:** **Find a classifier** $h(x; \hat{\theta}_t)$ **performing better than chance wrt the weighted training error:**

$$\varepsilon_t \stackrel{not.}{=} \sum_{i\,:\,y_i \neq h(x_i;\hat{\theta}_t)} \tilde{W}_i^{(t)} y_i h(x_i;\theta) = \frac{1}{2}\Big(1 - \sum_{i=1}^{m} \tilde{W}_i^{(t)} y_i h(x_i;\hat{\theta}_t)\Big).$$

Note: **Minimizing** ε_t **is equivalent to finding** $\hat{\theta}_t$ **that minimizes** $\frac{\partial}{\partial \alpha} J_t(\alpha, \theta_t)_{|\alpha=0}$ **wrt** θ_t**, where**

$$J_t(\alpha, \theta_t) = \frac{1}{m} \sum_{i=1}^{m} \mathrm{Loss}(y_i\, f_{t-1}(x_i) + y_i\, \alpha\, h(x_i;\theta_t)).$$

***Step 2*:** **Set the votes** α_t **for the new component by minimizing the overall empirical loss:**

$$\alpha_t \quad = \quad \arg\min_{\alpha \geq 0} J_t(\alpha, \hat{\theta}_t).$$

***Step 3*:** **Recompute the normalized weights for the next iteration according to**

$$\tilde{W}_i^{(t+1)} = -c_t \cdot dL(\underbrace{y_i\, f_{t-1}(x_i) + y_i\, \alpha_t\, h(x_i;\hat{\theta}_t)}_{y_i\, f_t(x_i)}) \quad \text{for } i = 1, \ldots, m,$$

where c_t **is chosen so that** $\sum_{i=1}^{m} \tilde{W}_i^{(t+1)} = 1$.

Output: f_T

The Naive Bayes Classifier

- **Assume that the attributes $< a_1, \ldots, a_n >$ that describe instances are conditionally independent w.r.t. to the given classification:**

$$P(a_1, a_2 \ldots a_n | v_j) = \prod_i P(a_i | v_j)$$

- **Training procedure:**

  NAIVE_BAYES_LEARN(*examples*)

  for each value v_j **of the output attribute**

  $\hat{P}(v_j) \leftarrow$ **estimate** $P(v_j)$

  for each value a_i **of each input attribute** a

  $\hat{P}(a_i | v_j) \leftarrow$ **estimate** $P(a_i | v_j)$

- **The *decision rule* of the Naive Bayes classifier is:**

$$v_{MAP} = \underset{v_j \in V}{\operatorname{argmax}} P(v_j | a_1, a_2 \ldots a_n) = \underset{v_j \in V}{\operatorname{argmax}} \frac{P(a_1, a_2 \ldots a_n | v_j) P(v_j)}{P(a_1, a_2 \ldots a_n)}$$

$$= \underset{v_j \in V}{\operatorname{argmax}} P(a_1, a_2 \ldots a_n | v_j) P(v_j) = \underset{v_j \in V}{\operatorname{argmax}} \prod_i P(a_i | v_j) P(v_j) \overset{not.}{=} v_{NB}$$

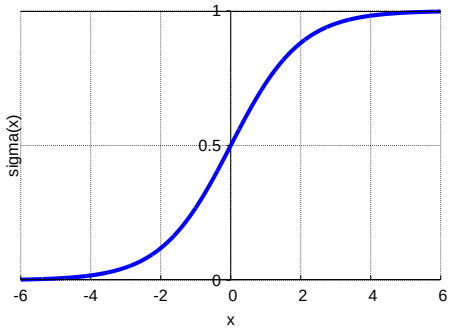
Logistic Regression

Given the dataset $\{(x^{(1)}, y^{(1)}),\ (x^{(2)}, y^{(2)}), \ldots,\ (x^{(n)}, y^{(n)})\}$, **where each vector** $x^{(i)}$ **has** d **features / attributes, and** $y^{(i)} \in \{0, 1\}$ **for** $i = 1, \ldots, n$**, its complete *log-likelihood* is:**

$$\begin{aligned} \textit{log-likelihood} &= \ln \prod_{i=1}^{n} P(x^{(i)}, y^{(i)}) = \ln \prod_{i=1}^{n} (P_{Y|X}(y^{(i)}|x^{(i)})\, P_X(x^{(i)})) \\ &= \ln \left(\left(\prod_{i=1}^{n} P_{Y|X}(y^{(i)}|x^{(i)}) \right) \cdot \left(\prod_{i=1}^{n} P_X(x^{(i)}) \right) \right) \\ &= \ln \prod_{i=1}^{n} P_{Y|X}(y^{(i)}|x^{(i)}) + \ln \prod_{i=1}^{n} P_X(x^{(i)}) \overset{not.}{=} \ell(w) + \ell_x. \end{aligned}$$

Note that ℓ_x **does not depend on the parameter** w**.**

$$P(Y = 1|X = x) = \sigma(z) \Leftrightarrow$$
$$P(Y = 0|X = x) = 1 - \sigma(z), \text{ where}$$
$$\sigma(z) \overset{def.}{=} \frac{1}{1 + e^{-z}} = \frac{e^z}{1 + e^z},$$
$$z \overset{not.}{=} w_0 + \sum_{i=1}^{d} w_i x_i \overset{not.}{=} w \cdot x, \text{ with}$$
$$w \overset{not.}{=} (w_0, w_1, \ldots, w_d) \in \mathbb{R}^{d+1},$$
$$\text{assuming } x_0 = 1.$$



It can be shown that the conditional *log-likelihood* function $\ell(w)$ **can be written as:**

$$\ell(w) = \sum_{i=1}^{n} \left(y^{(i)} \ln \sigma(w \cdot x^{(i)}) + (1 - y^{(i)}) \ln(1 - \sigma(w \cdot x^{(i)})) \right)$$

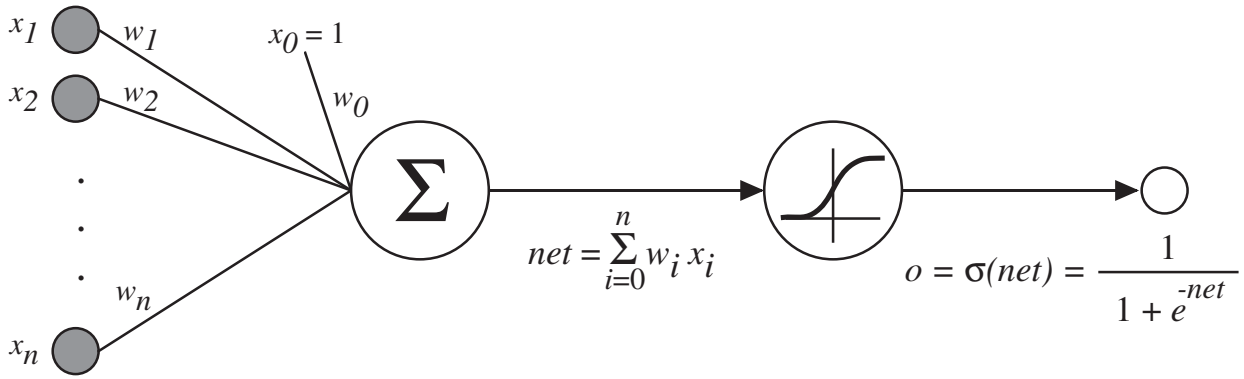
$$w_{LogR} \overset{def.}{=} \underset{w}{\operatorname{argmax}}\, \ell(w) = \arg\min_{w}(-\ell(w)). \qquad (2)$$

Note that $-\ell(w)$ **is a cross-entropy.**

For a more general result than (2)**, see Stanford, 2015 fall, Andrew Ng, HW3, pr. 5.c.**

See the analogy with the sigmoidal perceptron

CMU, 2011 fall, Eric Xing, HW1, pr. 3.3



The k-Nearest Neighbor Argorithm

Evelyn Fix, Joseph Hodges, 1951; Thomas Cover, Peter Hart, 1967

Training:

Store all training examples.

Classification:

Given a query/test instance x_q,
first locate the k nearest training examples $x_1, \ldots, x_k$,
then estimate $\hat{f}(x_q)$:

- **take a vote among its k nearest neighbors**

$$\hat{f}(x_q) \leftarrow \underset{v \in V}{\operatorname{argmax}} \sum_{i=1}^{k} 1_{\{f(x_i)=v\}}$$

where $1_{\{\,.\,\}}$ is the well-known *indicator function*.

The Bottom-up Hierarchical Clustering Algorithm

Given: **a set** $X = \{x_1, \ldots, x_n\}$ **of objects**
a function sim: $\mathcal{P}(X) \times \mathcal{P}(X) \to R$
for $i = 1, n$ **do**
$c_i = \{x_i\}$ **end**
$C = \{c_1, \ldots, c_n\}$
$j = n + 1$
while $\mid C \mid > 1$
$(c_{n_1}, c_{n_2}) = \text{argmax}_{(c_u, c_v) \in C \times C}$ **sim**(c_u, c_v)
$c_j = c_{n_1} \cup c_{n_2}$
$C = C \backslash \{c_{n_1}, c_{n_2}\} \cup \{c_j\}$
$j = j + 1$

The k-Means Algorithm

S. P. Lloyd, 1957

Given: a set $X = \{x_1, \ldots, x_n\} \subseteq \mathcal{R}^m$,
a distance measure d on $\mathcal{R}^m$,
a function for computing the mean $\mu : \mathcal{P}(\mathcal{R}^m) \to \mathcal{R}^m$,

built k clusters so as to satisfy a certain ("stopping") criterion (e.g., maximization of group-average similarity).

Procedure:

Select (arbitrarily) k initial centers $f_1, \ldots, f_k$ in $\mathcal{R}^m$;
while the stopping criterion is not satisfied
for all clusters c_j do $c_j = \{x_i \mid \forall f_l \; d(x_i, f_j) \leq d(x_i, f_l)\}$ end
for all means f_j do $f_j \leftarrow \mu(c_j)$ end

K-Means algorithm revisited (I)

- **Se iniţializează în mod arbitrar centroizii $\boldsymbol{\mu}_1, \boldsymbol{\mu}_2, \ldots, \boldsymbol{\mu}_K$ şi se ia $C = \{1, \ldots, K\}$.**

- **Atâta timp cât valoarea criteriului J descreşte în mod strict, repetă:**

  Pasul 1:
  Calculează γ astfel:

  $$\gamma_{ij} \leftarrow \begin{cases} 1, & \text{dacă } \|\mathbf{x}_i - \boldsymbol{\mu}_j\|^2 \leq \|\mathbf{x}_i - \boldsymbol{\mu}_{j'}\|^2, \ \forall j' \in C, \\ 0, & \text{în caz contrar.} \end{cases}$$

  În caz de egalitate, alege în mod arbitrar cărui cluster (dintre cele eligibile) să-i aparţină $\mathbf{x}_i$.

  Pasul 2:

  Recalculează $\boldsymbol{\mu}_j$ folosind matricea γ actualizată:
  Pentru fiecare $j \in C$, dacă $\sum_{i=1}^{n} \gamma_{ij} > 0$, asignează

  $$\boldsymbol{\mu}_j \leftarrow \frac{\sum_{i=1}^{n} \gamma_{ij} \mathbf{x}_i}{\sum_{i=1}^{n} \gamma_{ij}}.$$

  Altfel, menţine neschimbat centroidul μ_j.

Algoritmul de clusterizare K-means poate fi văzut [şi reformulat] ca un *algoritm de optimizare*, folosind metoda *descreşterii pe coordonate*.

***Obiectivul* este acela de a minimiza o funcţie obiectiv care măsoară (indirect) coeziunea intra-clustere:**

$$J(L, \mu) = \sum_{i=1}^{n} ||x_i - \mu_{l_i}||^2,$$

Algoritmul K-means face *iniţializarea* centroizilor clusterelor μ cu anumite valori, după care procedează astfel:

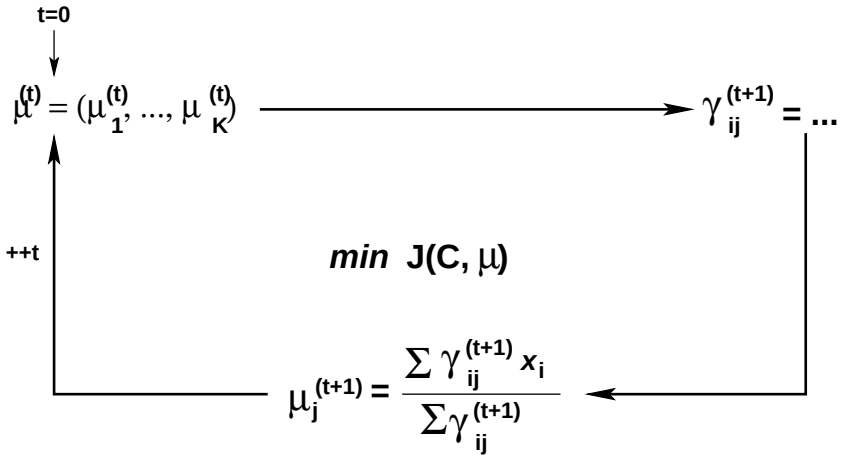
***Pasul 1*:**
Păstrând μ fixat, găseşte acea asignare L a instanţelor la clustere care minimizează funcţia $J(L, \mu)$;

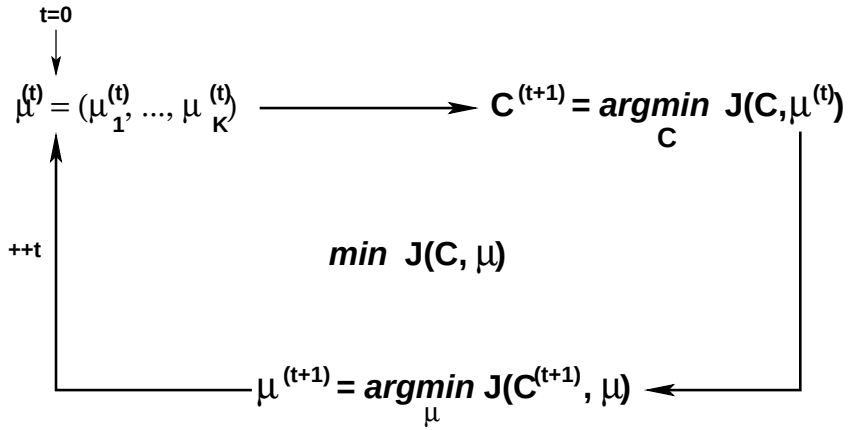
***Pasul 2*:**
Păstrând asignarea L fixată, găseşte acea valoare pentru μ pentru care se minimizează $J(L, \mu)$.

***Criteriul de oprire*: Dacă [aceasta nu este prima iteraţie şi] niciuna dintre asignările din lista L nu s-a modificat în raport cu precedenta iteraţie, se trece la pasul următor (Terminare); altfel se repetă de la Pasul 1.**

***Terminare*: Returnează L şi μ.**

K-Means algorithm revisited (II)





The General EM Problem

Given

- **observed data** $X = \{x_1, \ldots, x_m\}$ **independently generated using the parameterized distributions/hypotheses** $h_1, \ldots, h_m$
- **unobserved data** $Z = \{z_1, \ldots, z_m\}$

determine

$\hat{h}$ **that (locally) maximizes** $P(X|h)$**.**

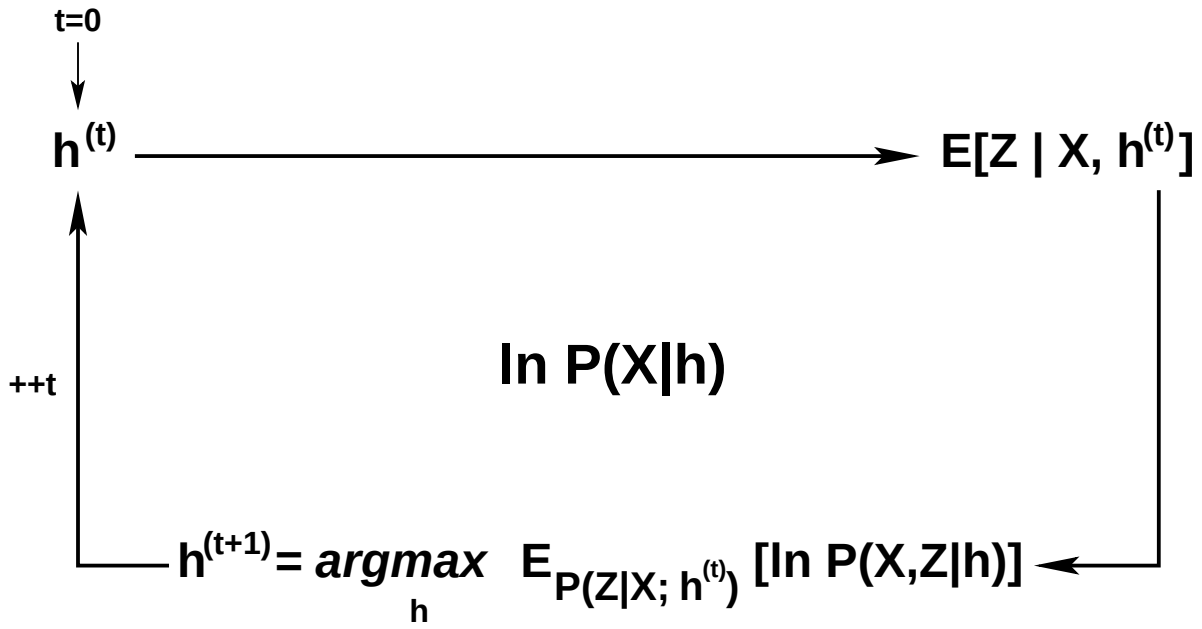
Approach

Start with $h^{(0)}$**, an arbitrarily/conveniently chosen value of** h**.**

Repeatedly

1. **Use the observed data** X **and the current hypothesis** $h^{(t)}$ **to estimate [the probabilities associated to the values of] the unobserved variables** Z**, and further on compute their expectations,** $E[Z]$**.**
2. **The expected values of the unobserved variables** Z **are used to calculate an improved hypothesis** $h^{(t+1)}$**, based on maximizing the mean of a log-likelihood function:** $E[\ln P(Y|h)|X, h^{(t)}]$**, where** $Y = \{y_1, \ldots, y_m\}$ **is the complete (observed and unobserved) data, i.e.** $y_i = (x_i, z_i)$**, for** $i = 1, \ldots, m$**.**

The EM algorithmic Schema



ADMINISTRATIVIA

Who is Liviu Ciortuz?

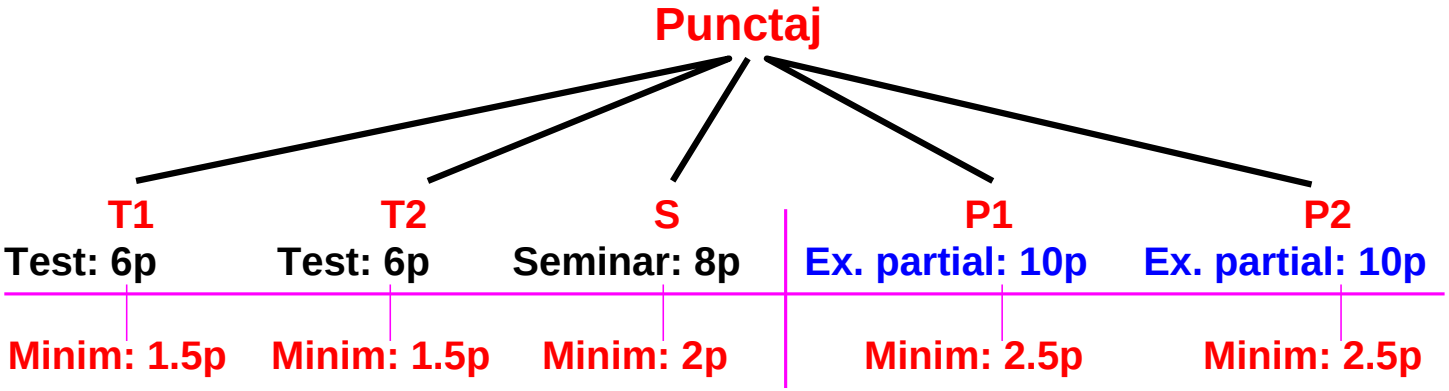
- Diploma (maths and CS) from UAIC, Iaşi, Romania, 1985
  PhD in CS from Université de Lille, France, 1996
- programmer:
  Bacău, Romania (1985-1987)
- full-time researcher:
  Germany (DFKI, Saarbrücken, 1997-2001),
  UK (Univ. of York and Univ. of Aberystwyth, 2001-2003),
  France (INRIA, Rennes, 2012-2013)
- assistant, lecturer, and then associate professor:
  Univ. of Iaşi, Romania (1990-1997, 2003-2012, 2013-today)

Teaching assistants for the ML undergraduate course 2024 (fall semester)

- **Conf. dr. Anca Ignat (... Image processing)**
  https://profs.info.uaic.ro/anca.ignat/ML/
- **Sebastian Ciobanu (PhD; Amazon)**
  https://sites.google.com/view/seminarml
- **Cristian Simionescu (PhD student; Nexus)**
- **Ramona Albert (PhD student; Amazon)**
- **Ştefan Panţiru (MSc; Mambu)**
- **Corina Dimitriu (MSc student)**

Grading standards for the ML undergraduate course 2024

Obiectiv: Învăţare pe tot parcursul semestrului!



Prezenta la curs: recomandata!
Prezenta la seminar: obligatorie!
Penalizare: 0.2p pentru fiecare absenta de la a doua incolo!

Nota = (10 + T1 + T2 + S + P1 + P2) / 5
Pentru promovare: Nota >= 4.5 <=> T1 + T2 + S + P1 + P2 >= 12.5

REGULI generale pentru cursul de Învăţare automată de la licenţă

Regulile de organizare a cursului de Învăţare Automată (engl., Machine Learning, ML), sem. I, sunt specificate în *fişa disciplinei* fisa-disciplinei.pdf de pe site-ul Piazza:
https://piazza.com/info.uaic.ro/spring2024/ml2024f

- **Bibliografie minimală: vezi slide #8**
- **Planificarea materiei, pentru fiecare săptămână (curs + seminar): what-you-should-know.pdf din pagina de Resurse, de pe site-ul Piazza dedicat acestui curs**
- **Prezenţa la curs: recomandată!**
- **Regula 0: Prezenţa la seminar: obligatorie!**

Pentru fiecare absenţă la seminar, începând de la a doua absenţă încolo, se aplică o penalizare/depunctare de 0.2 puncte. (Vezi formula de notare.)
Regulile se aplică inclusiv studenţilor reînmatriculaţi.

- **Săptămânal — marţea, între orele 18–20, în sala C412 — se va ţine un seminar suplimentar, destinat pentru acei studenţi care sunt foarte interesaţi de acest domeniu şi cărora le plac demonstraţiile matematice. (Vedeţi secţiunile "Advanced issues" din documentul what-you-should-know.pdf.)**

REGULI generale pentru cursul de Învăţare automată de la licenţă (cont.)

Regula 1: **Pentru seminarii, nu se admit mutări ale studenţilor de la o grupă la alta, decât în cadrul grupelor care au acelaşi asistent / profesor responsabil de seminar.**

Regula 2: **Nu se fac echivalări de punctaje pentru studenţii care nu au promovat cursul în anii precedenţi.**

Regula 3: **Profesorul responsabil pentru acest curs, Liviu Ciortuz,**
NU va răspunde la email-uri care pun întrebări pentru care raspunsul a fost deja dat
– fie în aceste slide-uri,
– fie pe site-ul Piazza dedicat acestui curs:
https://piazza.com/info.uaic.ro/spring2024/ml2024f/home,
– fie la curs.

Recomandare importantă (1) **La fiecare curs şi seminar, studenţii vor avea culegerea de *Exerciţii de învăţare automată* (de L. Ciortuz et al) — vă recomandăm să imprimaţi capitolele *Clasificare bayesiană*, *Învăţare bazată pe memorare*, *Arbori de decizie* şi *Clusterizare* — şi eventual slide-urile indicate în slide-ul următor.**

Recomandare importantă (2) **Consultaţi săptămânal documentul** what-you-should-know.pdf **de pe site-ul Piazza.**

REGULI generale pentru cursul de Învăţare automată de la licenţă (cont.)

- **Slide-uri de imprimat** (în această ordine şi, de preferat, COLOR):

http://profs.info.uaic.ro/liviu.ciortuz/SLIDES/foundations.pdf

https://edu.info.uaic.ro/invatare-automata/ML.ex-book/SLIDES/ML.ex-book.SLIDES.ProbStat.pdf
https://edu.info.uaic.ro/invatare-automata/ML.ex-book/SLIDES/ML.ex-book.SLIDES.Regression.pdf
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https://edu.info.uaic.ro/invatare-automata/ML.ex-book/SLIDES/ML.ex-book.SLIDES.Cluster.pdf

(Atenţie: acest set de slide-uri poate fi actualizat pe parcursul semestrului!)

- De imprimat (ALB-NEGRU):

http://profs.info.uaic.ro/liviu.ciortuz/SLIDES/ml0.pdf
http://profs.info.uaic.ro/liviu.ciortuz/SLIDES/ml3.pdf
http://profs.info.uaic.ro/liviu.ciortuz/SLIDES/ml6.pdf
http://profs.info.uaic.ro/liviu.ciortuz/SLIDES/ml8.pdf
http://profs.info.uaic.ro/liviu.ciortuz/SLIDES/cluster.pdf