MACHINE LEARNING

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What is Machine Learning?

- **ML studies algorithms that $\underbrace{\text{improve with}}_{\text{learn from}}$ experience.**

  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.

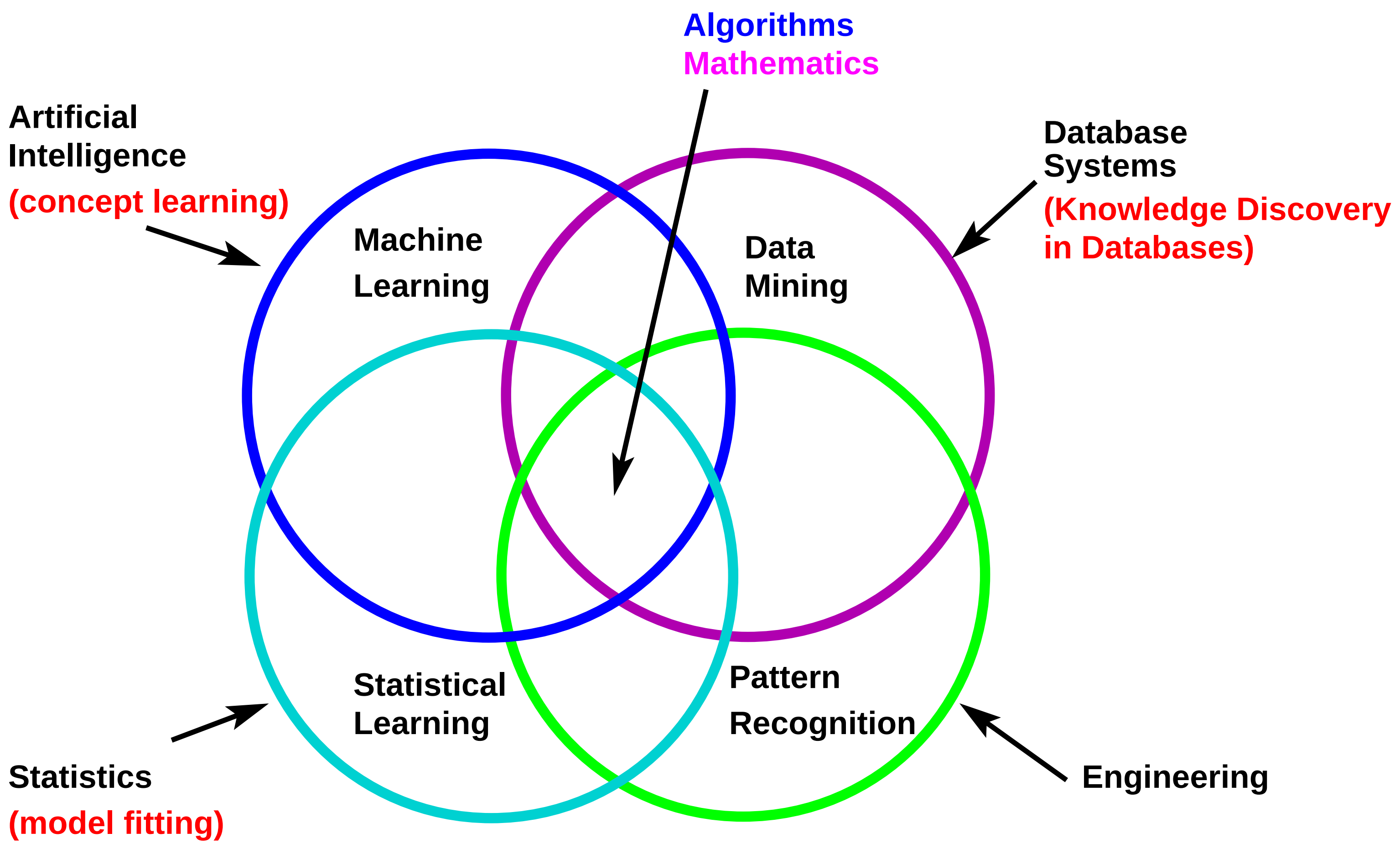
Related courses at FII

- 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)
   [and the relationship with Logistic Regression]
4. Instance-based Learning (T. Mitchell, ch. 8)
5. 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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2. “Machine Learning Foundations”
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3. “Deep Machine Learning Foundations”
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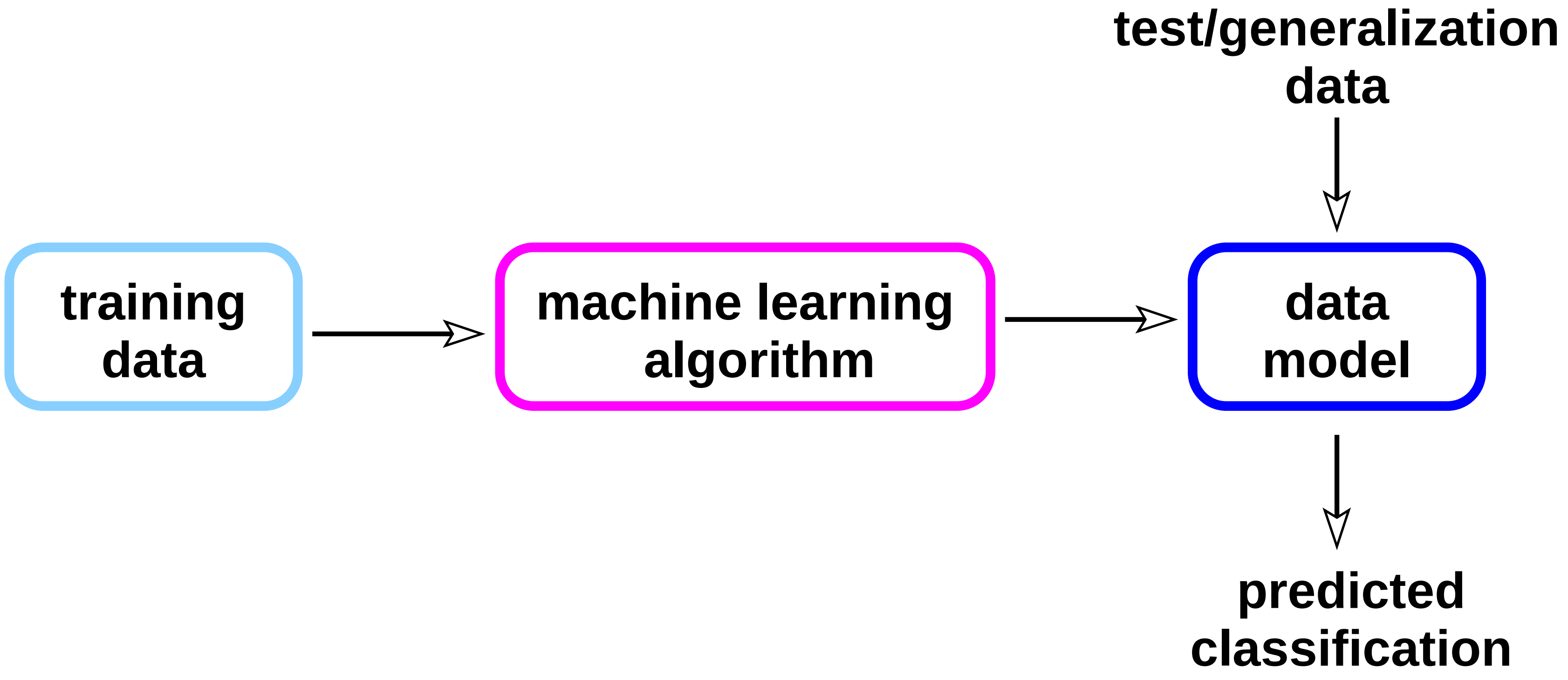
A general schema for machine learning methods



“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 $c : X \rightarrow \{0,1\}$
   example (labeled instance): $\langle x, c(x) \rangle$; positive examples, neg. examples
2. **hypotheses $h : X \rightarrow \{0,1\}$**
   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***$_h = \mid \{x \in X, h(x) \neq c(x)\} \mid$
   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.

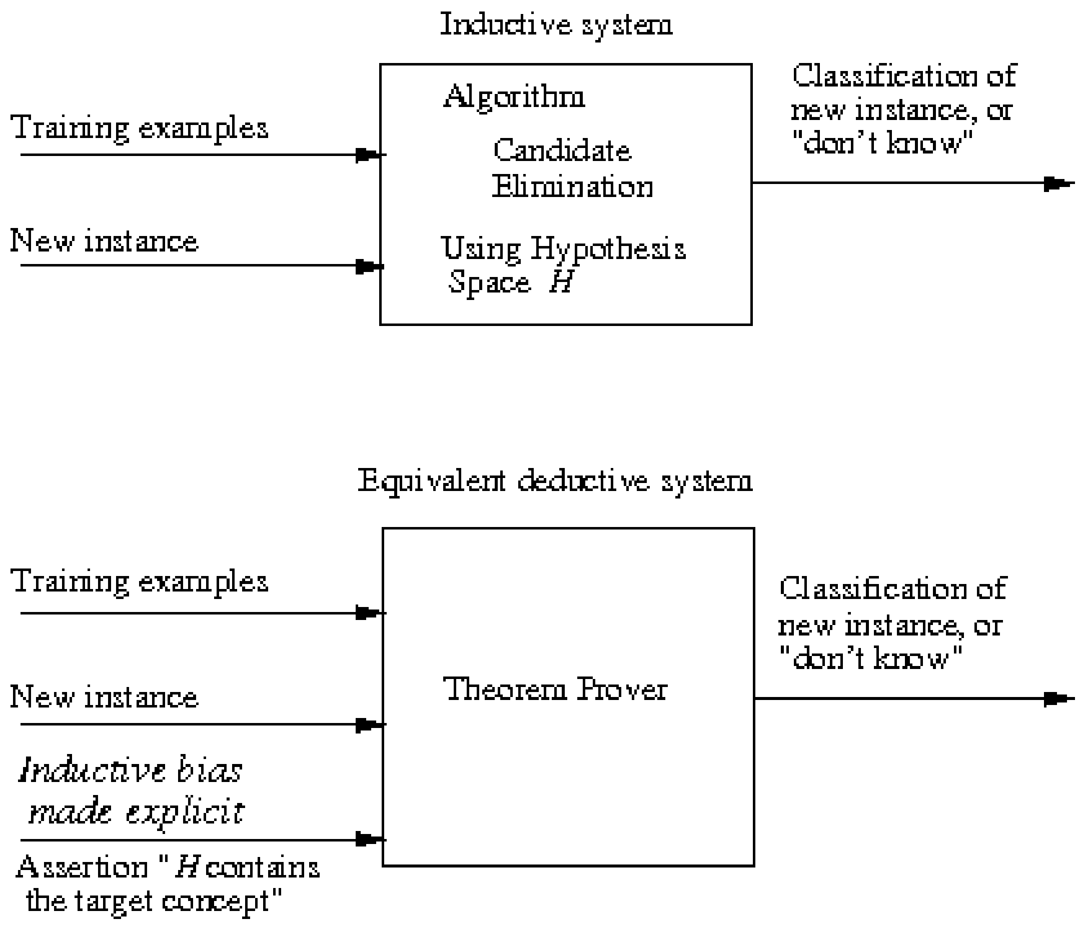
Definition:

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

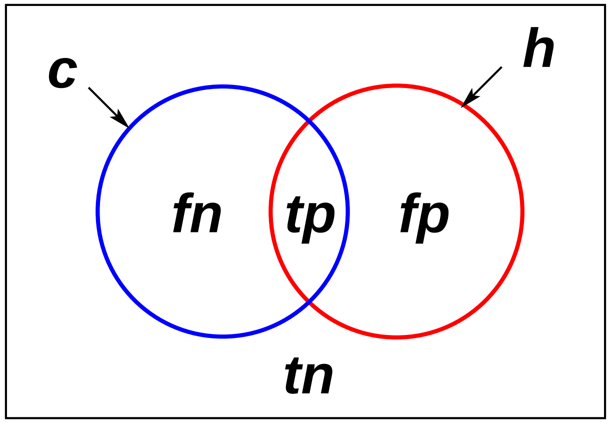
$$(\forall x_i \in X)[(B \vee D_c \vee x_i) \vdash L(x_i, D_c)]$$

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


Inductive system
Training examples
New instance
Algorithm
Candidate Elimination
Using Hypothesis Space *H*
Classification of new instance, or "don't know"
Equivalent deductive system
Training examples
New instance
Inductive bias made explicit
Assertion "*H* contains the target concept"
Theorem Prover
Classification of new instance, or "don't know"

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 $D_1(i) = \frac{1}{m}$, $i = 1, \ldots, m$.**
- **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**

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

  where $\alpha_t \overset{not.}{=} \frac{1}{2} \ln \frac{1 - \varepsilon_t}{\varepsilon_t}$, 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:**

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

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**

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

***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**

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

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:**

$$\begin{aligned} v_{MAP} &= \operatorname*{argmax}_{v_j \in V} P(v_j | a_1, a_2 \ldots a_n) = \operatorname*{argmax}_{v_j \in V} \frac{P(a_1, a_2 \ldots a_n | v_j) P(v_j)}{P(a_1, a_2 \ldots a_n)} \\ &= \operatorname*{argmax}_{v_j \in V} P(a_1, a_2 \ldots a_n | v_j) P(v_j) = \operatorname*{argmax}_{v_j \in V} \prod_i P(a_i | v_j) P(v_j) \overset{not.}{=} v_{NB} \end{aligned}$$

Logistic Regression

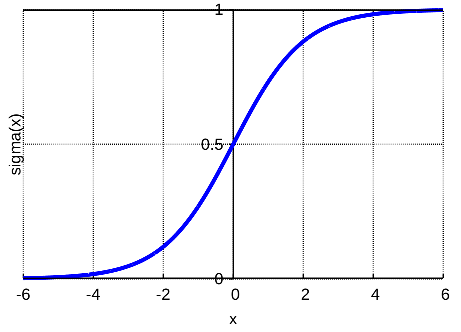
$$P(Y=1|X=x)=\sigma(z) \Leftrightarrow$$
$$P(Y=0|X=x)=1-\sigma(z),$$ **where**

$$\sigma(z) \overset{def.}{=} \frac{1}{1+e^{-z}} = \frac{e^z}{1+e^z},$$

$$z \overset{not.}{=} w_0 + \sum_{i=1}^{d} w_i x_i \overset{not.}{=} w \cdot x,$$ **with**

$$w \overset{not.}{=} (w_0, w_1, \ldots, w_d) \in \mathbb{R}^{d+1},$$

assuming $x_0 = 1$.



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**.**

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

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

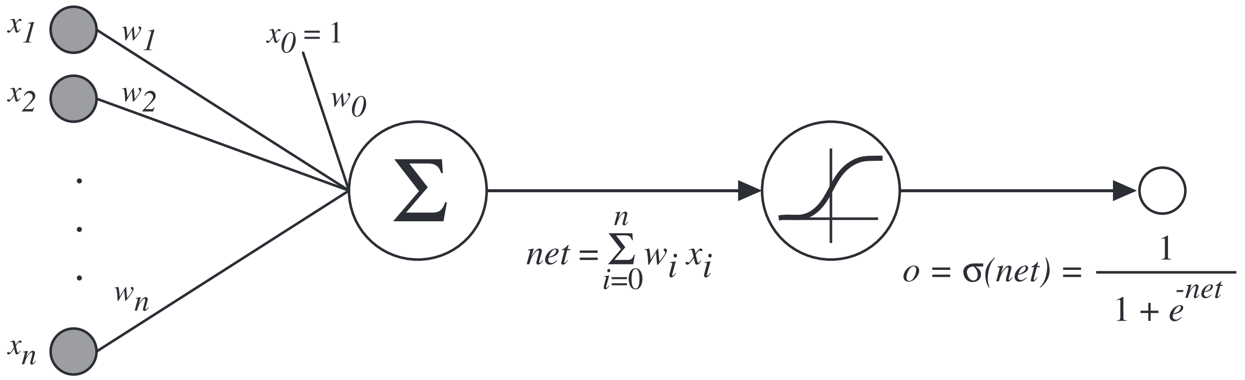
$$w_{LogR} \overset{def.}{=} \underset{w}{\text{argmax}}\, \ell(w) = \arg\min_{w}(-\ell(w)). \qquad (2)$$

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

For a more general result than (2)**, see Stanford, 2015 fall, Andrew Ng, HW 3, pr. 5.c.**

See the analogy with the sigmoidal perceptron

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


x_1
x_2
x_n
w_1
w_2
w_n
$x_0 = 1$
w_0
Σ
$net = \sum_{i=0}^{n} w_i x_i$
$o = \sigma(net) = \frac{1}{1 + e^{-net}}$

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**

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

where $1_{\{\,\cdot\,\}}$ 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: $\mathcal{P}(X) \times \mathcal{P}(X) \rightarrow R$
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 $\mu : \mathcal{P}(\mathcal{R}^m) \rightarrow \mathcal{R}^m$,

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)

$$\begin{tikzcd}
\text{t=0} \arrow[d] & & \\
\mu^{(t)} = (\mu_1^{(t)}, \ldots, \mu_K^{(t)}) \arrow[rr] & & \gamma_{ij}^{(t+1)} = \ldots \arrow[ddl] \\
& \boldsymbol{\mathit{min}}\ \mathbf{J(C, \mu)} & \\
& \mu_j^{(t+1)} = \dfrac{\sum \gamma_{ij}^{(t+1)} x_i}{\sum \gamma_{ij}^{(t+1)}} \arrow[uul, "\text{++t}"] &
\end{tikzcd}$$

$$\begin{tikzcd}
\text{t=0} \arrow[d] & & \\
\mu^{(t)} = (\mu_1^{(t)}, \ldots, \mu_K^{(t)}) \arrow[rr] & & C^{(t+1)} = \mathit{argmin}_{C}\ J(C, \mu^{(t)}) \arrow[ddl] \\
& \boldsymbol{\mathit{min}}\ \mathbf{J(C, \mu)} & \\
& \mu^{(t+1)} = \mathit{argmin}_{\mu}\ J(C^{(t+1)}, \mu) \arrow[uul, "\text{++t}"] &
\end{tikzcd}$$

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

$$\begin{tikzcd}
t=0 \arrow[d] & & \\
h^{(t)} \arrow[rr] & & E[Z \mid X, h^{(t)}] \arrow[dd] \\
& \ln P(X|h) & \\
h^{(t+1)} = \underset{h}{\mathit{argmax}}\; E_{P(Z|X;\, h^{(t)})} [\ln P(X,Z|h)] \arrow[uu, "++t"] & & \arrow[ll]
\end{tikzcd}$$

ADMINISTRATIVIA

Who is Liviu Ciortuz?

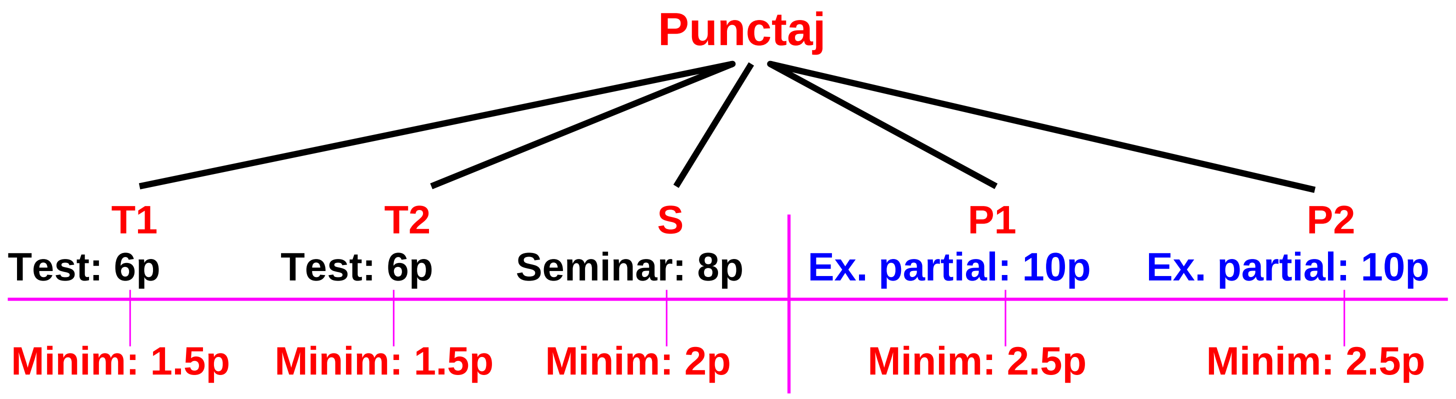
- Diploma (maths and CS) from UAIC, Iaşi, Romania, 1985
  PhD in CS from Université de Lille, France, 1996
- programmer:
  Bacău, Romania (1985-1987)
- full-time researcher:
  Germany (DFKI, Saarbrücken, 1997-2001),
  UK (Univ. of York and Univ. of Aberystwyth, 2001-2003),
  France (INRIA, Rennes, 2012-2013)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

Teaching assistants for the ML undergraduate course 2023 (fall semester)

- **Conf. dr. Anca Ignat (. . . Image processing)**
  https://profs.info.uaic.ro/∼ancai/ML/
- **Sebastian Ciobanu (PhD; Amazon)**
  https://sites.google.com/view/seminarml
- **Andi Munteanu**
  (PhD student at UAIC, and research assistent at Univ. of Cambridge)
- **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 2023

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*
http://profs.info.uaic.ro/∼ciortuz/fisa-disciplinei.pdf

• Bibliografie minimală: vezi slide #8

• Planificarea materiei, pentru fiecare săptămână (curs + seminar):
http://profs.info.uaic.ro/∼ciortuz/what-you-should-know.pdf

• 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 C308 — 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 http://profs.info.uaic.ro/∼ciortuz/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/fall2023/ml2023f/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 **din pagina de Resurse, de pe site-ul Piazza dedicat acestui curs.**

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/~ciortuz/SLIDES/foundations.pdf

https://profs.info.uaic.ro/~ciortuz/ML.ex-book/SLIDES/ML.ex-book.SLIDES.ProbStat.pdf
https://profs.info.uaic.ro/~ciortuz/ML.ex-book/SLIDES/ML.ex-book.SLIDES.DT.pdf
https://profs.info.uaic.ro/~ciortuz/ML.ex-book/SLIDES/ML.ex-book.SLIDES.Bayes.pdf
https://profs.info.uaic.ro/~ciortuz/ML.ex-book/SLIDES/ML.ex-book.SLIDES.IBL.pdf
https://profs.info.uaic.ro/~ciortuz/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/~ciortuz/SLIDES/ml0.pdf
http://profs.info.uaic.ro/~ciortuz/SLIDES/ml3.pdf
http://profs.info.uaic.ro/~ciortuz/SLIDES/ml6.pdf
http://profs.info.uaic.ro/~ciortuz/SLIDES/ml8.pdf
http://profs.info.uaic.ro/~ciortuz/SLIDES/cluster.pdf