

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**:

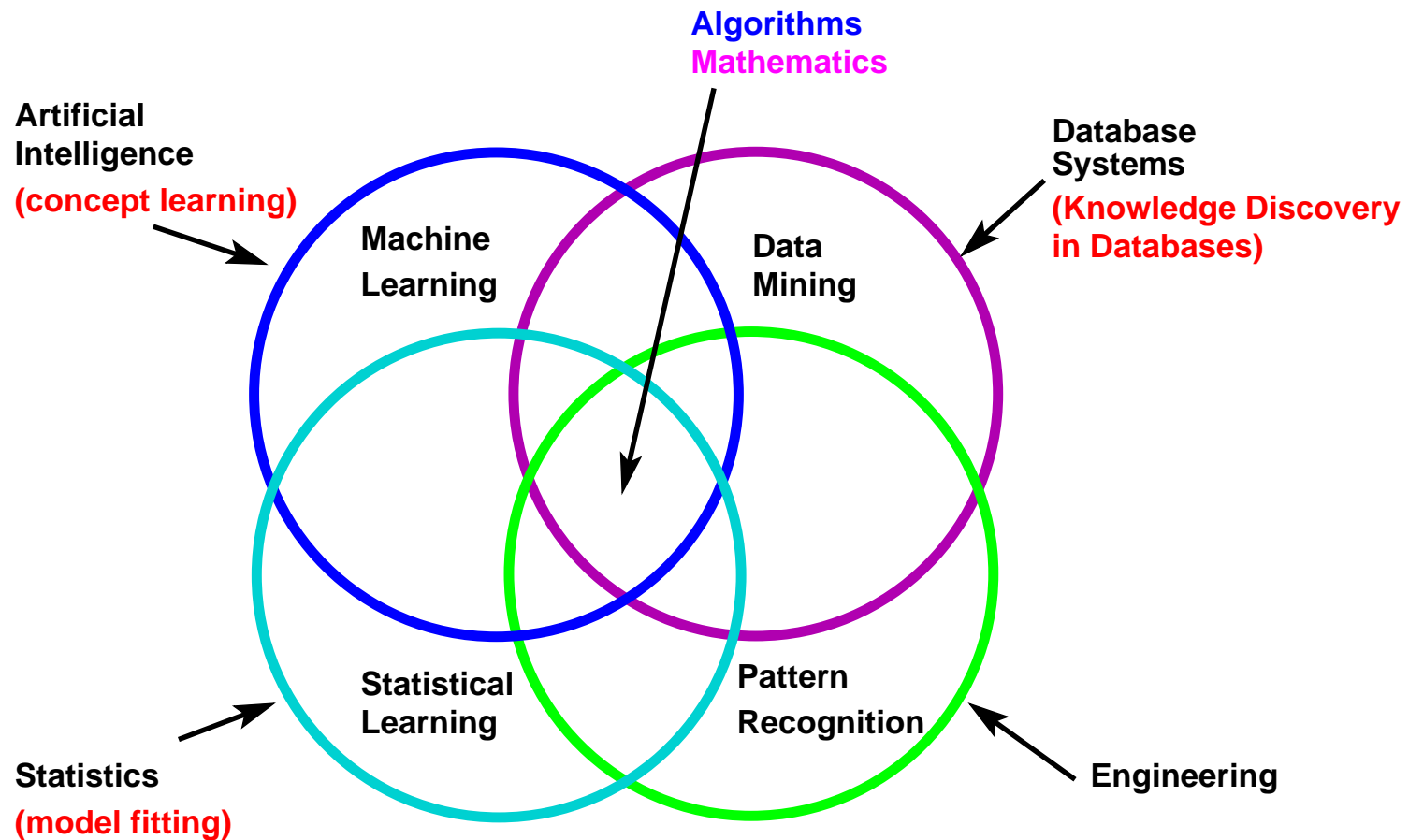
“A computer program is said to *learn* from experience E with respect to some class of *tasks* T and *performance measure* P , if its performance on tasks in T , as measured by P , improves with experience E .”

- 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 risk) evaluation
- terrorist threat detection
- compiler optimisation
- semantic web
- computer security
- software engineering
- computer vision (image processing)
- etc.

A multi-domain view



The Machine Learning Undergraduate Course: Plan

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

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

2. Decision Trees (T. Mitchell, ch. 3)

3. Parameter estimation for probabilistic distributions

(see *Estimating Probabilities*, additional chapter to T. Mitchell's book, 2016)

4. Bayesian Learning (T. Mitchell, ch. 6)
and the relationship with Logistic Regression

5. Instance-based Learning (T. Mitchell, ch. 8)

6. Clustering Algorithms (Ch. Manning & H. Schütze, ch. 14)

The Machine Learning Master Course:

Tentative Plan

1. **Probabilities Revision** (Ch. Manning & H. Schütze, ch. 2)
 2. Decision Trees: Boosting
 3. Gaussian Bayesian Learning
 4. The EM algorithmic schemata (T. Mitchell, ch. 6.12)
 5. Support Vector Machines (N. Cristianini & J. Shawe-Taylor, 2000)
-
6. **Hidden Markov Models** (Ch. Manning & H. Schütze, ch. 9)
 7. **Computational Learning Theory** (T. Mitchell, ch. 7)

Bibliography

0. **“Exerciții de învățare automată”**

L. Ciortuz, A. Munteanu E. Bădăraș.

Iași, Romania, 2019

www.info.uaic.ro/~ciortuz/ML.ex-book/book.pdf

1. **“Machine Learning”**

Tom Mitchell. McGraw-Hill, 1997

2. **“The Elements of Statistical Learning”**

Trevor Hastie, Robert Tibshirani, Jerome Friedman. Springer, 2nd ed. 2009

3. **“Machine Learning – A Probabilistic Perspective”**

Kevin Murphy, MIT Press, 2012

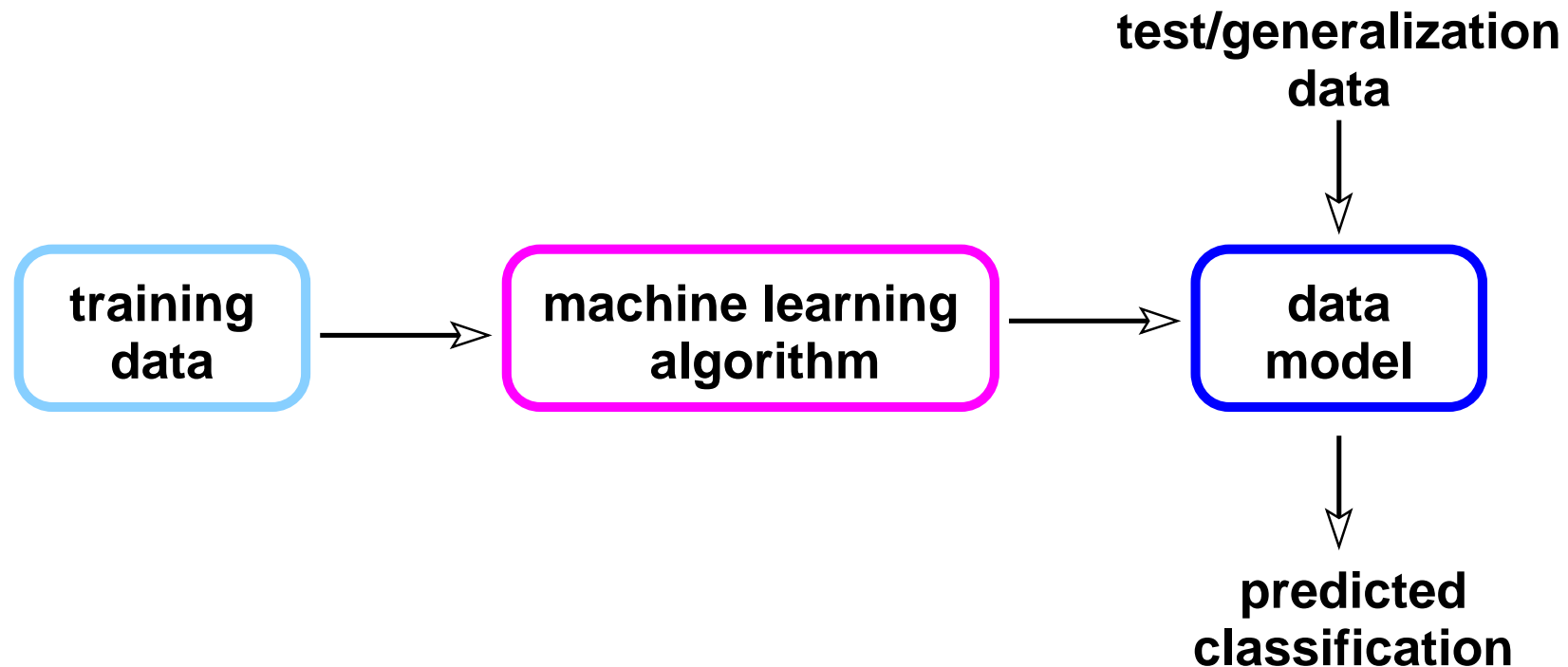
4. **“Pattern Recognition and Machine Learning”**

Christopher Bishop. Springer, 2006

5. **“Foundations of Statistical Natural Language Processing”**

Christopher Manning, Hinrich Schütze. MIT Press, 2002

A general schema for machine learning methods



*“We are drowning 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. $error_h = | \{x \in X, h(x) \neq c(x)\} |$
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 .

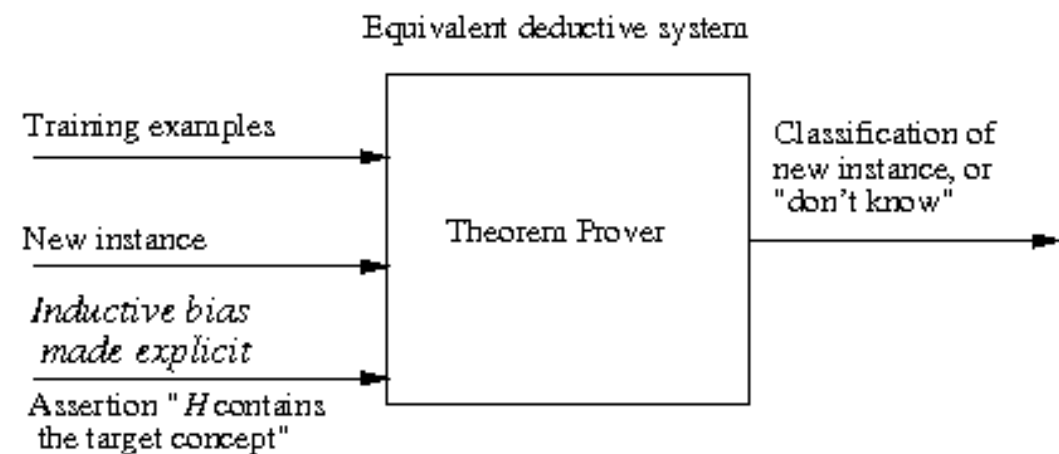
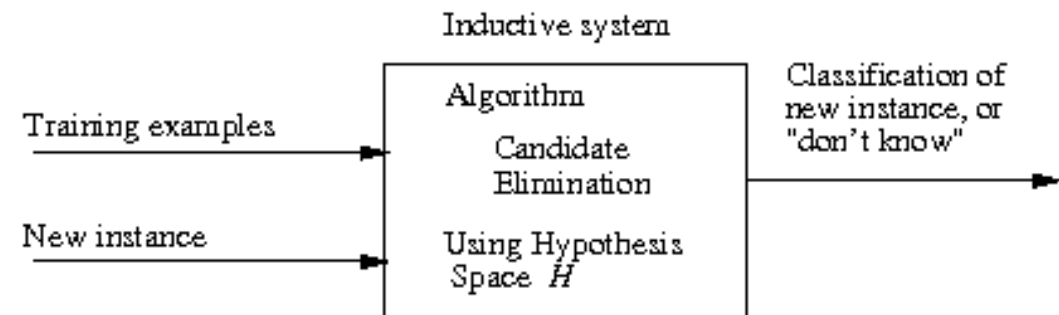
Definition:

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

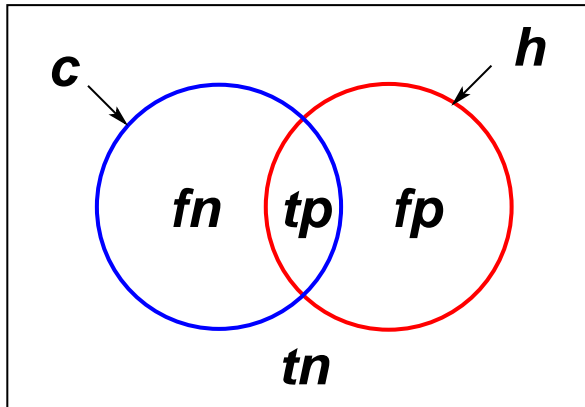
$$(\forall x_i \in X)[(B \vee D_c \vee x_i) \vdash L(x_i, D_c)]$$

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.

Who is Liviu Ciortuz?

- Diploma (maths and CS) from UAIC, Iași, 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 Iasi, Romania (1990-1997, 2003-2012, 2013-today)

ADDENDA

“...colleagues at the Computer Science department at Saarland University have a strong conviction, that **nothing is as practical as a good theory.**”

Reinhard Wilhelm,
quoted by Cristian Calude,
in *The Human Face of Computing*,
Imperial College Press, 2016



“**Mathematics** translates **concepts** into **formalisms** and applies those formalisms to derive **insights** that are usually NOT amenable to a LESS formal analysis.”

Jürgen Jost,
Mathematical Concepts,
Springer, 2015



“**Mathematics** is a journey that must be shared, **and** by sharing our own journey with others, **we, together, can change the world.**”

“Through the power of mathematics, we can explore the uncertain, the counterintuitive, the invisible; **we can reveal order and beauty**, and at times **transform theories into practical objects, things or solutions that you can feel, touch or use.**”



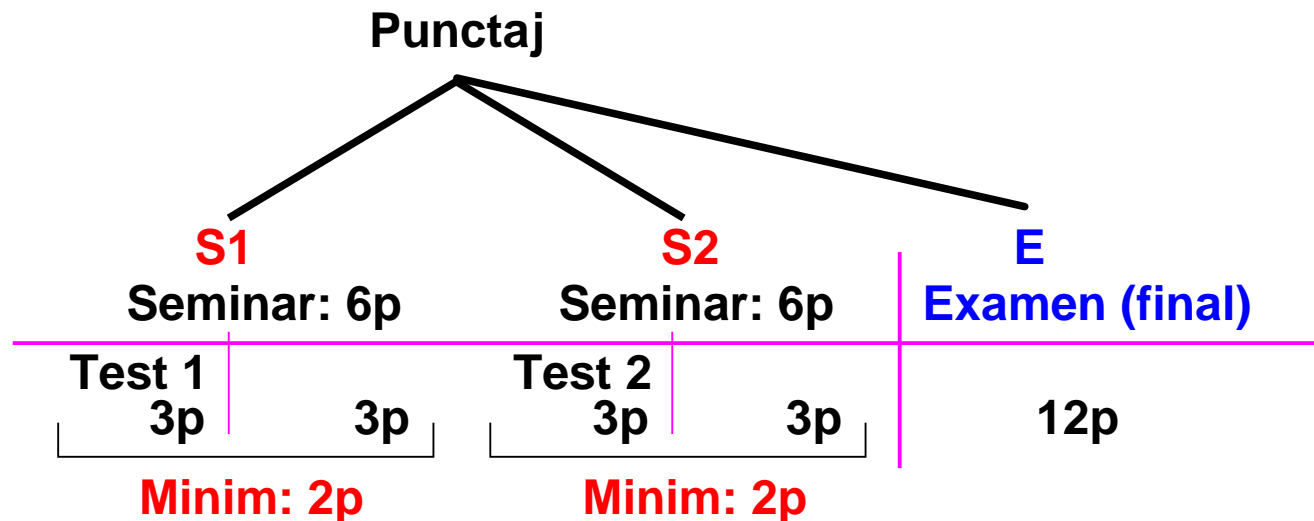
Cedric Villani,
winner of the Fields prize, 2010

cf. <http://www.bbc.com/future/sponsored/story/20170216-inside-the-mind-of-a-mathematician>, 15.03.2017

ADMINISTRATIVA

Grading standards for the ML undergraduate course 2019

Obiectiv: invatare pe tot parcursul semestrului!



Prezenta la seminar: obligatorie!

Penalizare: 0.1p pentru fiecare absenta de la a doua incolo

Nota = $(6 + S1 + S2 + E) / 3$

Pentru promovare: $S1 + S2 + E \geq 7.5$

REGULI generale pentru cursul de Învățare automată (cont.)

Sistemul de notare la licență

$\text{Nota} = (6 + S1 + S2 + E) / 3,$
unde

S1 = punctajul la seminar pe prima jumătate de semestru (0-6 puncte)

S2 = punctajul la seminar pe a doua jumătate de semestru (0-6 puncte)

E = punctajul la examenul din sesiune (0-12 puncte)

Punctajele S1 si S2 se obțin (fiecare) ca suma a două punctaje, pentru

- test scris (anunțat în prealabil)
- răspunsuri “la tablă”

Condiții de promovare:

$S1 \geq 2; S2 \geq 2; \text{nota} \geq 4.5$

În consecință, punctajul minimal de îndeplinit din suma $S1+S2+E$ este 7.5.

Atenție:

$S1 < 2$ (sau $S2 < 2$) implică imediat nepromovarea acestui curs în anul universitar 2019-2020!

REGULI generale pentru cursul de Învățare automată (cont.) pentru cursul de la licență

- **Slide-uri de imprimat** (în această ordine și, 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.EstimP.pdf>]

[<https://profs.info.uaic.ro/~ciortuz/ML.ex-book/SLIDES/ML.ex-book.SLIDES.Regression.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>

(Atenție: 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>

REGULI generale pentru cursul de Învățare automată (cont.) pentru cursul de la master

- **Slide-uri de imprimat** (în această ordine și, 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.EstimP.pdf>

<https://profs.info.uaic.ro/~ciortuz/ML.ex-book/SLIDES/ML.ex-book.SLIDES.Regression.pdf>

[<https://profs.info.uaic.ro/~ciortuz/ML.ex-book/SLIDES/ML.ex-book.SLIDES.Cluster.pdf>]

<https://profs.info.uaic.ro/~ciortuz/ML.ex-book/SLIDES/ML.ex-book.SLIDES.EM.pdf>

<https://profs.info.uaic.ro/~ciortuz/ML.ex-book/SLIDES/ML.ex-book.SLIDES.SVM.pdf>

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

- De imprimat (ALB-NEGRU):

<http://profs.info.uaic.ro/~ciortuz/SLIDES/svm.pdf>

- De imprimat opțional (ALB-NEGRU):

Companion-ul practic pentru culegerea „Exerciții de învățare automată“:

<https://profs.info.uaic.ro/~ciortuz/ML.ex-book/implementation-exercises/ML.ex-book.Companion.pdf>

REGULI generale pentru cursul de Învățare automată (cont.)

Observație (1)

Este **recomandabil** ca la fiecare curs și seminar, studenții să vină cu cartea de exerciții și probleme (de L. Ciortuz et al) și cu o fasciculă conținând slide-urile imprimate.

Observație (2)

Profesorul responsabil pentru acest curs, Liviu Ciortuz NU va răspunde la email-uri care pun întrebări pentru care răspunsul a fost deja dat

- fie în aceste slide-uri,
- fie la curs