BABEŞ-BOLYAI UNIVERSITY
Faculty of Computer Science and Mathematics

ARTIFICIAL INTELLIGENCE

Intelligent systems

Machine learning

Decision trees

Useful information

- Chapter VI (18) of *S. Russell, P. Norvig, Artificial Intelligence: A Modern Approach, Prentice Hall, 1995*
- Chapters 10 and 11 of *C. Groşan, A. Abraham, Intelligent Systems: A Modern Approach, Springer, 2011*
- Chapter V of *D. J. C. MacKey, Information Theory, Inference and Learning Algorithms, Cambridge University Press, 2003*
- Chapters 3 of *T. M. Mitchell, Machine Learning, McGraw-Hill Science, 1997*

Content

- Intelligent systems
  - Automatic learning systems (ALS)
    - Machine Learning - ML
      - Problem
      - Design
      - Typology
        - Supervised learning
        - Unsupervised learning
        - Reinforcement learning
        - Learning theory
    - Systems
      - Decision trees

Intelligent systems – Machine Learning (ML)

- Problem
  - “How can we build computer systems that automatically improve with experience, and what are the fundamental laws that govern all learning processes?”

- Applications
  - Image and voice recognition
    - Handwritten recognition
    - Face detection
  - Computer vision
    - Obstacle detection
    - Footprint recognition
  - Bio-surveillance
  - Robot control
  - Predictions
  - Medical diagnostic
  - Fraud detection

Intelligent systems – Machine Learning (ML)

- Definition
  - Arthur Samuel (1959)
    - “field of study that gives computers the ability to learn without being explicity programmed”
  - Herbert Simon (1970)
    - “Learning is any process by which a system improves performance from experience.”
  - Tom Mitchell (1998)
    - “a well-posed learning problem is defined as follows: He says that a computer program is set to learn from an experience E with respect to some task T and some performance measure P if its performance on T as measured by P improves with experience E”
  - Ethem Alpaydin (2010)
    - Programming computers to optimize a performance criterion using example data or past experience.

- Necessity
  - Better computational systems
    - To difficult or to expensive to be constructed manually
      - Systems that automatically adapt
        - Spam filters
      - Systems that discovers information in large database → data minin
        - Financial analysis
        - Text/image analyses
  - Understanding the biological systems

Intelligent systems – Machine Learning (ML)

- Design
  - Improve of task T
    - Establish the goal (what has to be learn) – objective function – and its representation
    - Select a learning algorithms to perform the inference of the goal based on experience
  - Respect a performance metric P
    - Evaluation of the algorithm’s performances
  - Based on experience E
    - Select an experience database
  - Example
    - T: playing checkers
    - P: percent of winning games
    - E: playing the game

    - T: handwritten recognition
    - P: percent of correct recognized words
    - E: database of images with different words

    - T: separate the spams
    - P: percent of correct classified emails
    - E: databases with annotated emails

Intelligent systems – Machine Learning (ML)

- Design → choose the objective function
  - Which is the function that must be learn?
    - Ex.: checkers game → a function that:
      - Selects the next move
      - Evaluates a move
    - In order to identify the best move
  - Representation of objective function
    - Different representations
      - Tabel
      - Symbolic rules
      - Numeric functions
      - Probabilistic functions
    - Ex. Checkers game
      - A linear combinations of # white pieces, # black pieces, # of white compromised pieces, # black compromised pieces
    - There is a trade-off between
      - Expressiveness of representation
      - Easy of learning
    - Objective function computation
      - Polynomial time
      - Non-polynomial time

Intelligent systems – Machine Learning (ML)

- Design → select a learning algorithm
  - Algorithm
    - By using the training data
    - Induce the hypothesis definition that
      - Match the data
      - Generalize the un - seen data
  - Main principle
    - Error minimisation (cost function – loss function)

- Design → evaluation of a learning system
  - Experimental
    - By comparing different methods on different data (cross-validation)
    - Collect data based on performances
      - Accuracy, training time, testing time
    - Statistical analyse of the differences
  - Theoretic
    - Mathematical analyse of algorithms and theorem proving
      - Computational complexity
      - Ability to match the training data
      - Complexity of the most relevant sample for learning

Intelligent systems – Machine Learning (ML)

- Design → evaluation of a learning system
  - Comparing the performances of 2 algorithms for solving a given problem
    - Performance measures
      - Parameters of a statistic series
      - Proportion (percent) computed for a statistical series (ex. Accuracy)
    - Comparing based on confidence intervals
      - For a problem and 2 solving algorithms with performances p_1 and p_2
      - Confidence intervals $I_1=[p_1-\Delta_1,p_1+\Delta_1]$ și $I_2=[p_2-\Delta_2,p_2+\Delta_2]$
      - If $I_1 \cap I_2=\emptyset$ ➔ algorithm 1 works better than algorithm 2 (for the given problem)
      - if $I_1 \cap I_2 \neq \emptyset$ ➔ impossible to decide
    - Confidence interval for the mean (average)
      - For a statistical series of n data, with computed mean m and dispersion σ, determine the confidence interval of the mean μ
      - $P(-z \le (m-\mu)/(\sigma/\sqrt{n}) \le z) = 1 - \alpha$ ➔ $\mu \in [m-z\sigma/\sqrt{n}, m+z\sigma/\sqrt{n}]$
      - $P = 95\%$ ➔ $z = 1.96$
    - Confidence interval for accuracy
      - For an accuracy p computed for n data, determine the confidence interval of accuracy
      - $p \in [p-z(p(1-p)/n)^{1/2}, p+z(p(1-p)/n)^{1/2}]$
      - $P = 95\%$ ➔ $z = 1.96$

$P=1-\alpha$	z
99.9%	3.3
99.0%	2.577
98.5%	2.43
97.5%	2.243
95.0%	1.96
90.0%	1.645
85.0%	1.439
75.0%	1.151

Intelligent systems – Machine Learning (ML)

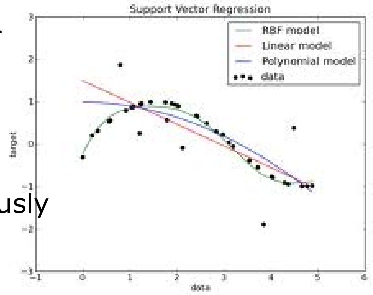
- Design → choose the training database
  - Based on
    - Direct experience
      - Pairs (in, out) that are useful for the objective function
      - Eg. Checkers game→ board game annotated by correct or incorrect move
    - Indirect experience
      - Useful feedback (unlike i/o pairs) for the objective function
      - Eg. Checkers game→ sequences of moves and the final score of the game
  - Data sources
    - Random generated examples
      - Positive and negative examples
    - Positive examples collected by a learner
    - Real examples
  - Content
    - Training data
    - Test data
  - Characteristics
    - Independent data
      - Otherwise → collective learning
    - Training and testing data must respect the same distribution law
      - Otherwise → *transfer learning/inductive transfer*
        - Vehicle recognition → truck recognition
        - Text analyses
        - Spam filters

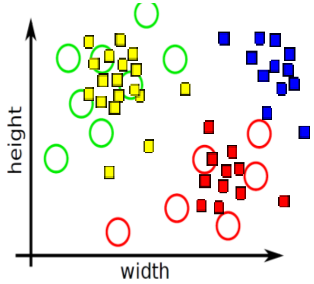
Intelligent systems – Machine Learning (ML)

- Design → choose the training database
  - Characteristics extracted (attributes) from raw data
    - Quantitative characteristics → nominal or rational scale
      - Continuous values → weight
      - Discrete values → # of computers
      - Range values → event times
    - Qualitative characteristics
      - Nominal → colour
      - Ordinal → sound intensity (low, medium, high)
    - Structured
      - Trees – root is a generalisation of children (vehicle → car, bus, tractor, truck)
  - Data transformation
    - Standardisation → numerical attributes
      - Remove the scale effect (different scale and units)
      - Raw values are transformed in z scores
        - $Z_{ij} = (x_{ij} - \mu_j)/\sigma_j$, where x_{ij} – value of j^{th} attribute of i^{th} instance, μ_j (σ_j) is the mean (standard deviation) of j^{th} attribute for all instances
    - Selection of some attributes

Intelligent systems – Machine Learning (ML)

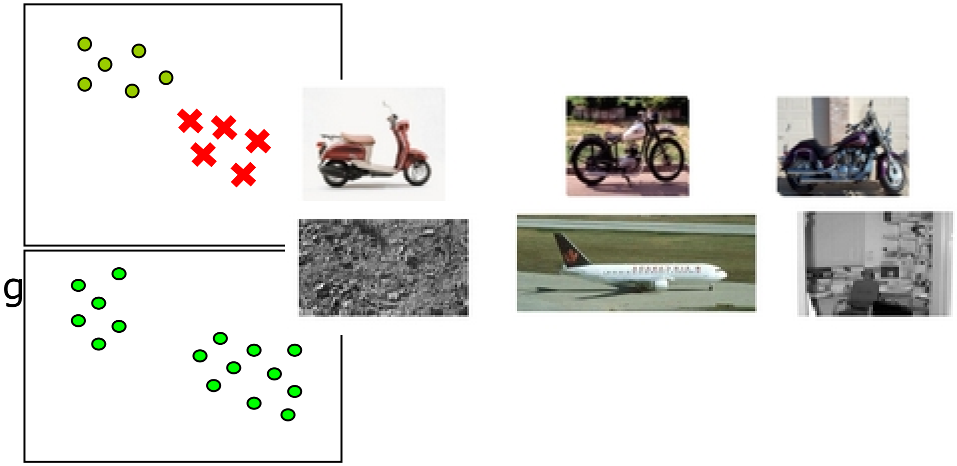
- Typology
  - Based on their aim (goal)
    - ISs for prediction
      - Aim: predict the output for a new input based on a previously learned model
      - Eg. predicting sales of a product for a time in the future based on price, calendar month, region, average income
    - ISs for regression
      - Aim: estimation of the (uni or multi - variable) function shape based on a previously learned model
      - Eg.: estimate the function that models the edge of a surface
    - ISs for classification
      - Aim: classify an object into one or more – known or unknown - categories based on their characteristics
      - Eg.: diagnostic systems for cancer: malign or benign or normal
    - ISs for planning
      - Aim: generate a sequence of optimal actions for performing a task
      - Eg.: planning the moves of a robot from a position to a source of energy



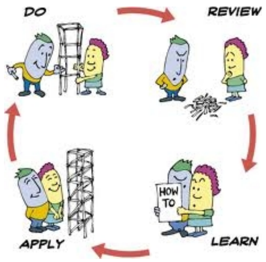


Intelligent systems – Machine Learning (ML)

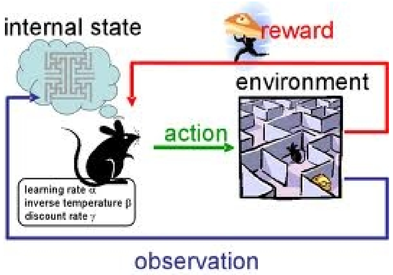
- Typology
  - Based on the experience learned during training process
    - ISs with supervised learning
    - ISs with unsupervised learning



    - ISs with active learning



    - ISs with reinforcement learning



Intelligent systems – Machine Learning (ML)

- Typology
  - Based on algorithm
    - **Decision trees**
    - Artificial Neural Networks
    - Evolutionary algorithms
    - Support Vector Machines
    - Hidden Markov Models

Intelligent systems – decision trees (DT)

- Decision trees (DT s)
  - Aim
  - Definition
  - Solved problems
  - Example
  - Process
  - Tools
  - Advantages and limits

Intelligent systems – decision trees (DT)

- Aim
  - Divide a collection of articles in smaller sets by successively applying some decision rules → asking more questions
    - Each question is addressed based on the answer of the previous question
  - Elements are characterized by non-metric information
- Definition
  - Decision tree
    - A special graph → bi-colour and oriented tree
    - Contains three node types:
      - Decision nodes → possibilities of decider (a test on an attribute of item that must be classified)
      - Hazard nodes → random events outside the control of decider (exam results, therapy consequences)
      - Result nodes → final states that have a utility or a label
    - Decision and hazard nodes alternate on the tree levels
    - Result nodes → leaf (terminal nodes)
    - (oriented) Edges of the tree consequences of decisions (can be probabilistic)
  - Each internal node corresponds to an attribute
  - Each branch under a node (attribute) corresponds to the value of that attribute
  - Each leaf corresponds to a class

Intelligent systems – decision trees (DT)

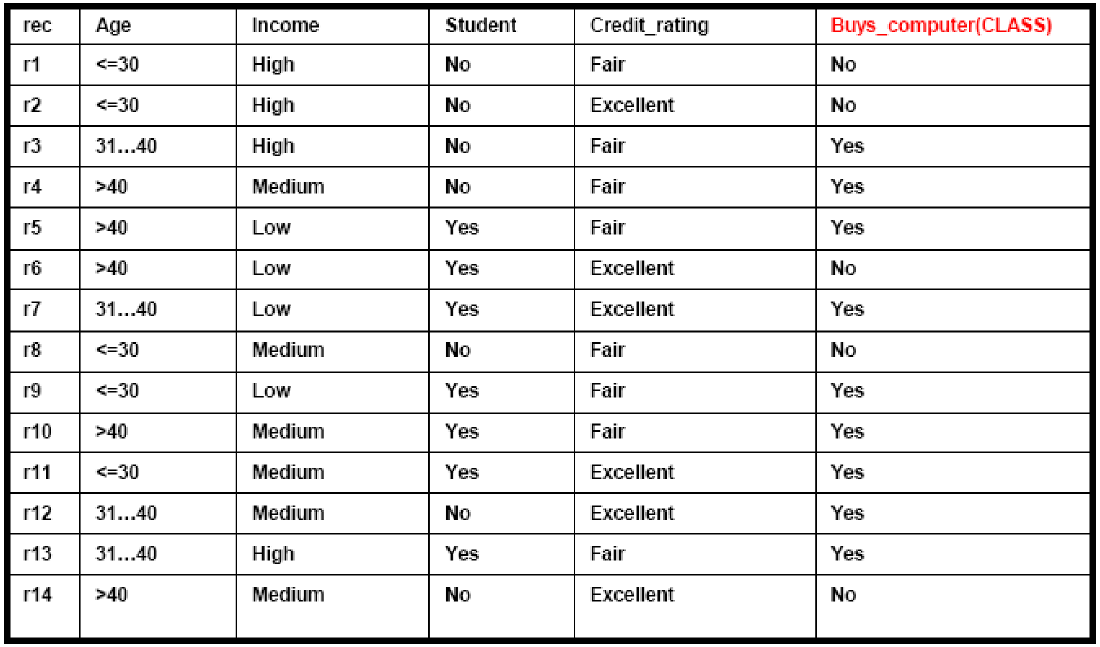
- Problems solved by DTs
    - Problem’s instances are represented by a fixed number of attributes, each attribute having a finite number of values
    - Objective function takes discrete values
    - DT represents a dis-junction of more conjunctions, each conjunction being “attribute a_i has value v_j”
    - Training data could contain errors
    - Training data could be incomplete
        - Some data have not all attributes

    - Classification problem
        - Binary classification
            - Instances are [(attribute$_{ij}$, value*ij*), class$_i$, i=1,2,...,n, j=1,2,...,m, classi taking 2 values]
        - Multi-class (k-class)
            - Instances are [(attribute$_{ij}$, value$_{ij}$), class$_i$, i=1,2,...,n, j=1,2,...,m, classi taking *k* values]

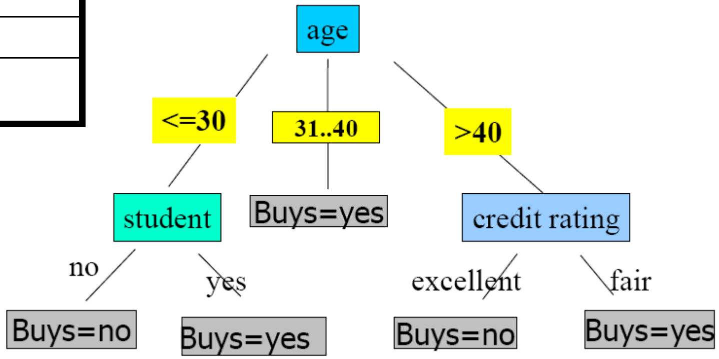
    - Regression problems
        - DTs are constructed in a similar manner to those of classification problems, but instead to label each node by the label of a class, each node has associated a real value or a function that depends on the inputs of that node
        - Input space is split in decision regions by parallel cuttings to Ox and Oy
        - Discrete outputs are transformed in continuous functions
        - Quality of problem solving
            - Prediction error (square or absolute)

Intelligent systems – decision trees (DT)

- Example

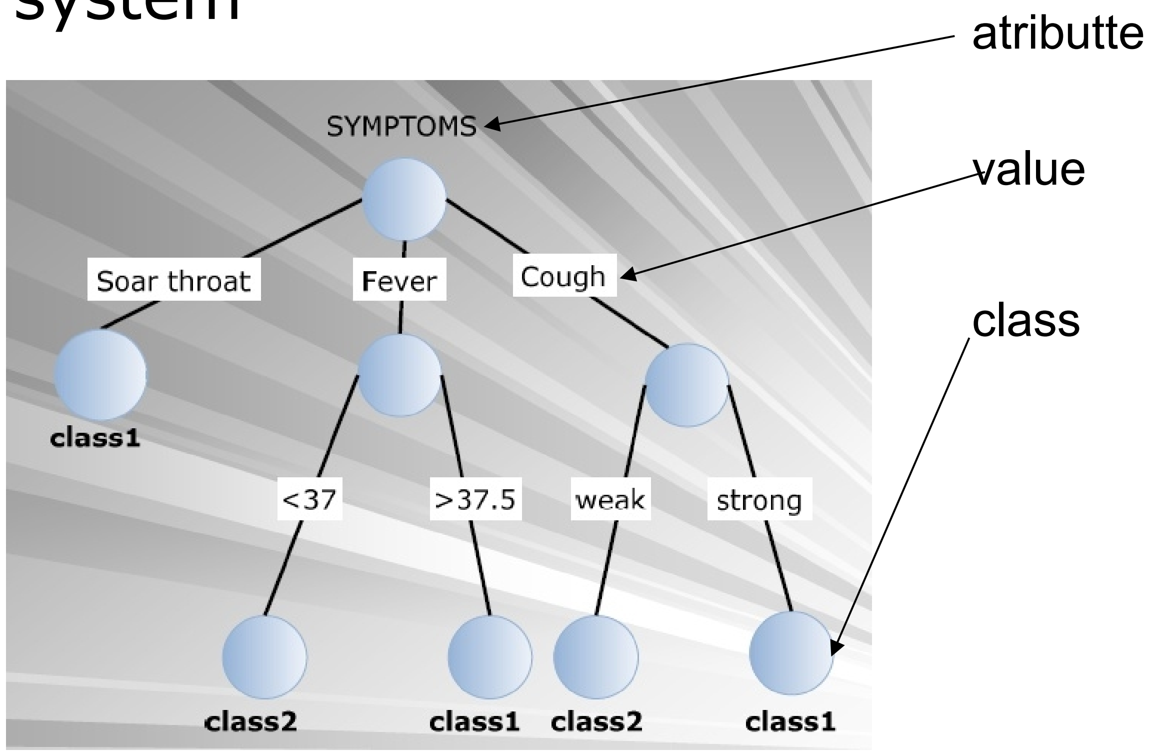


rec	Age	Income	Student	Credit_rating	Buys_computer(CLASS)
r1	<=30	High	No	Fair	No
r2	<=30	High	No	Excellent	No
r3	31…40	High	No	Fair	Yes
r4	>40	Medium	No	Fair	Yes
r5	>40	Low	Yes	Fair	Yes
r6	>40	Low	Yes	Excellent	No
r7	31…40	Low	Yes	Excellent	Yes
r8	<=30	Medium	No	Fair	No
r9	<=30	Low	Yes	Fair	Yes
r10	>40	Medium	Yes	Fair	Yes
r11	<=30	Medium	Yes	Excellent	Yes
r12	31…40	Medium	No	Excellent	Yes
r13	31…40	High	Yes	Fair	Yes
r14	>40	Medium	No	Excellent	No



Intelligent systems – decision trees (DT)

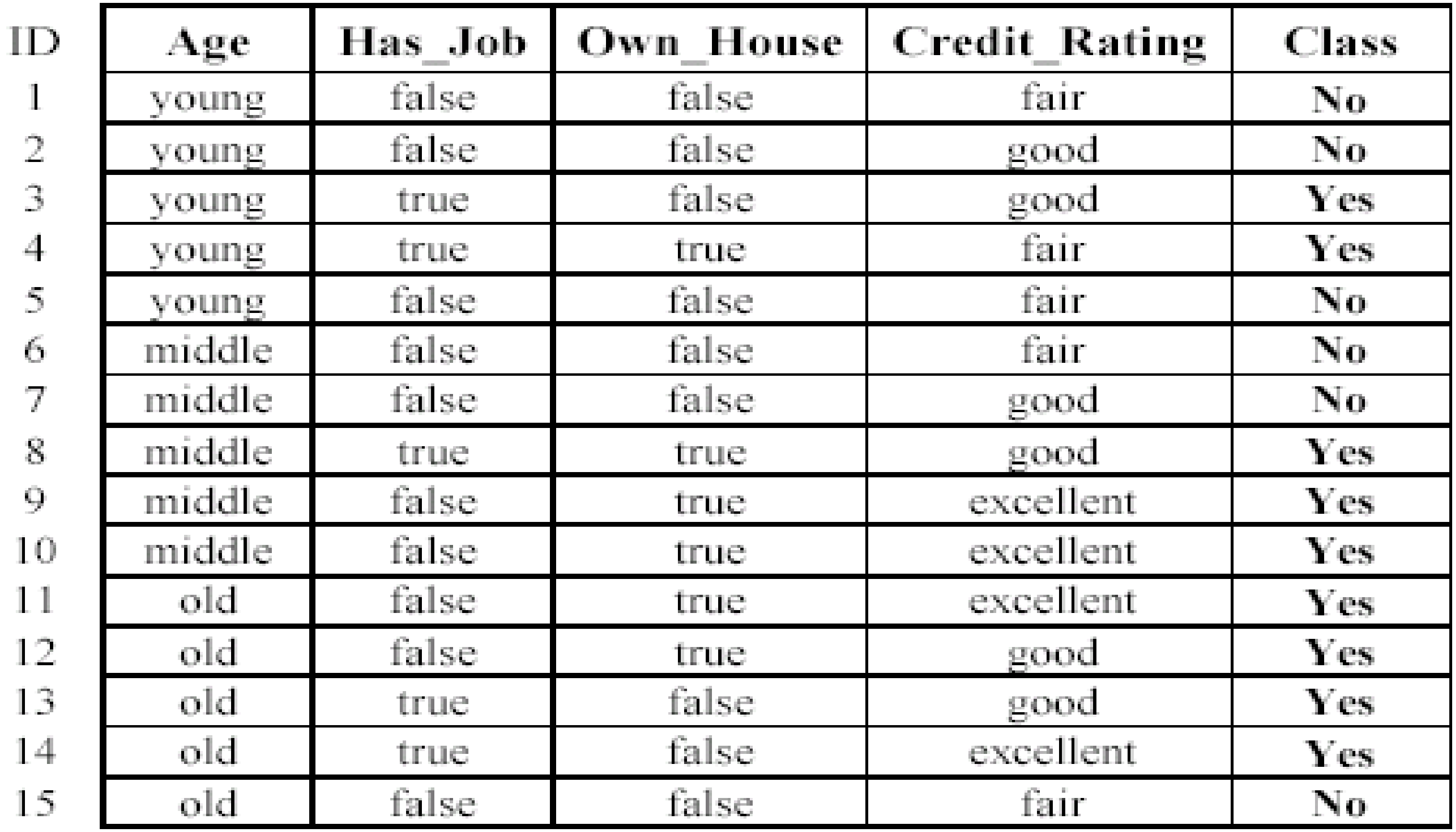
- Example
  - Medical system



Intelligent systems – decision trees (DT)

- Example
  - Credits

Approved or not



ID	Age	Has_Job	Own_House	Credit_Rating	Class
1	young	false	false	fair	No
2	young	false	false	good	No
3	young	true	false	good	Yes
4	young	true	true	fair	Yes
5	young	false	false	fair	No
6	middle	false	false	fair	No
7	middle	false	false	good	No
8	middle	true	true	good	Yes
9	middle	false	true	excellent	Yes
10	middle	false	true	excellent	Yes
11	old	false	true	excellent	Yes
12	old	false	true	good	Yes
13	old	true	false	good	Yes
14	old	true	false	excellent	Yes
15	old	false	false	fair	No

Intelligent systems – decision trees (DT)

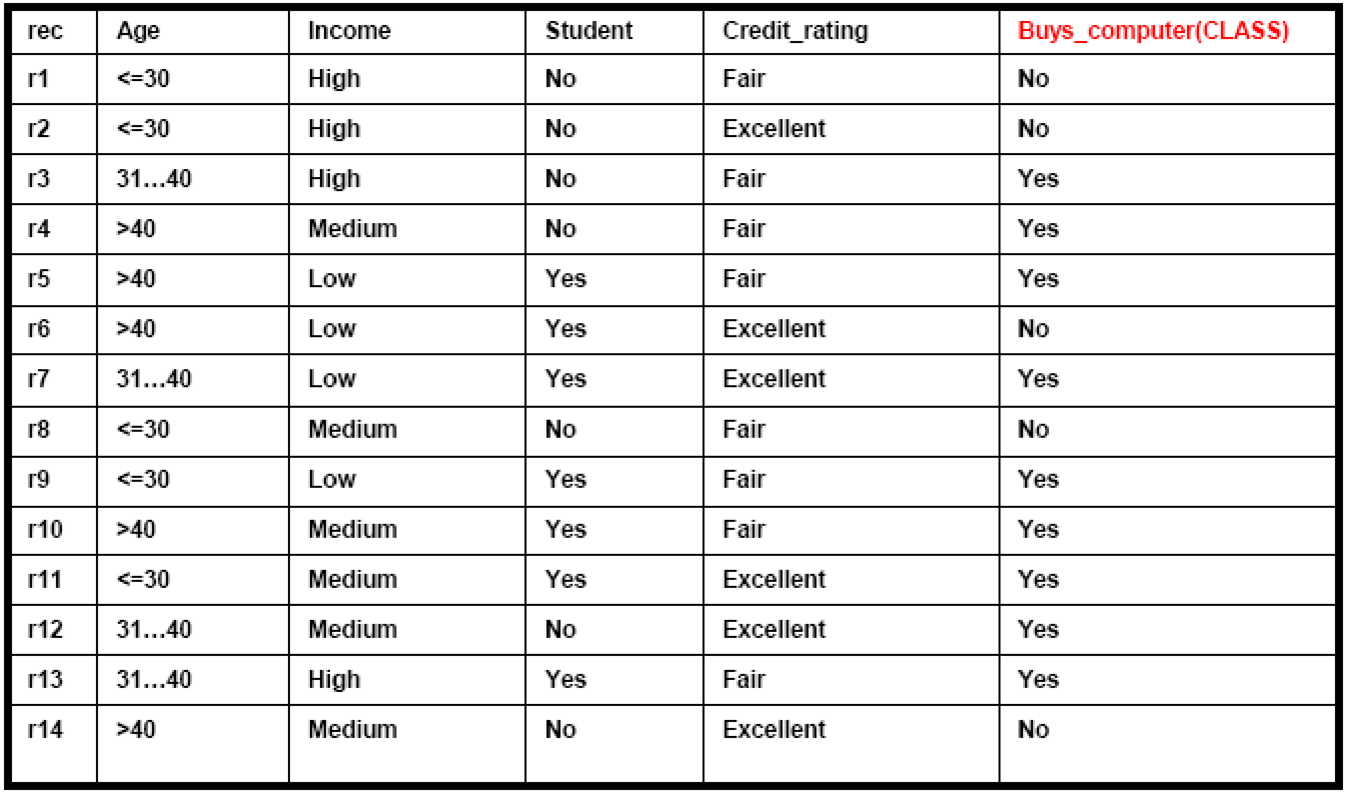
- Process
  - Tree construction (induction)
    - Based on training data
    - Works bottom-up or top-down (splitting)
  - Using the tree as a problem solver
    - All decisions performed along a path from the root to a leaf form a rule
    - Rules from DT are used for labeling new data
  - Pruning
    - Identify and move/eliminate branches that reflect noise or exceptions

Intelligent systems – decision trees (DT)

- Process → Tree construction (induction)
  - Split the training data into subsets based on the characteristics of data
    - A node → Question related to a property
    - Branches of a node → possible answers to the question of the node
    - Initially, all examples are located in the root
      - An attribute gives the root ant its values give the branches
    - On next levels, examples are partitioned based on their attributes → order of attributes
      - For each node, an attribute is (recursively) chosen – its values → branches
    - Splitting → greedy decision making
  - Iterative process
    - Stop conditions
      - All examples from a node belong to the same class → node is a leaf and is labeled by *class*$_i$
      - There are no examples → node becomes a leaf and is labeled by the majority class of training data
      - There are no attributes

Intelligent systems – decision trees (DT)

- Process → Tree construction (induction)
  - Example



rec	Age	Income	Student	Credit_rating	Buys_computer(CLASS)
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r2	<=30	High	No	Excellent	No
r3	31…40	High	No	Fair	Yes
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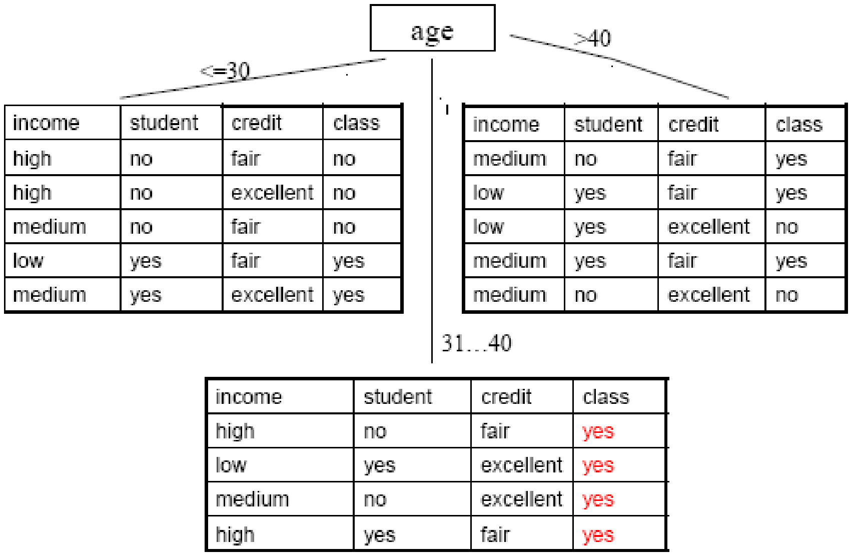
r5	>40	Low	Yes	Fair	Yes
r6	>40	Low	Yes	Excellent	No
r7	31…40	Low	Yes	Excellent	Yes
r8	<=30	Medium	No	Fair	No
r9	<=30	Low	Yes	Fair	Yes
r10	>40	Medium	Yes	Fair	Yes
r11	<=30	Medium	Yes	Excellent	Yes
r12	31…40	Medium	No	Excellent	Yes
r13	31…40	High	Yes	Fair	Yes
r14	>40	Medium	No	Excellent	No

Intelligent systems – decision trees (DT)

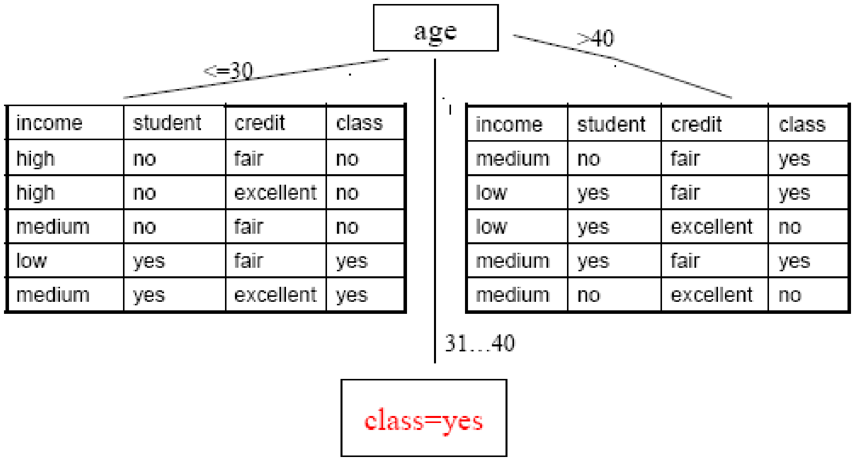
- Process → Tree construction (induction)
  - Example
    - Attribute *age* is selected for the root



income	student	credit	class
high	no	fair	no
high	no	excellent	no
medium	no	fair	no
low	yes	fair	yes
medium	yes	excellent	yes

income	student	credit	class
medium	no	fair	yes
low	yes	fair	yes
low	yes	excellent	no
medium	yes	fair	yes
medium	no	excellent	no

income	student	credit	class
high	no	fair	yes
low	yes	excellent	yes
medium	no	excellent	yes
high	yes	fair	yes

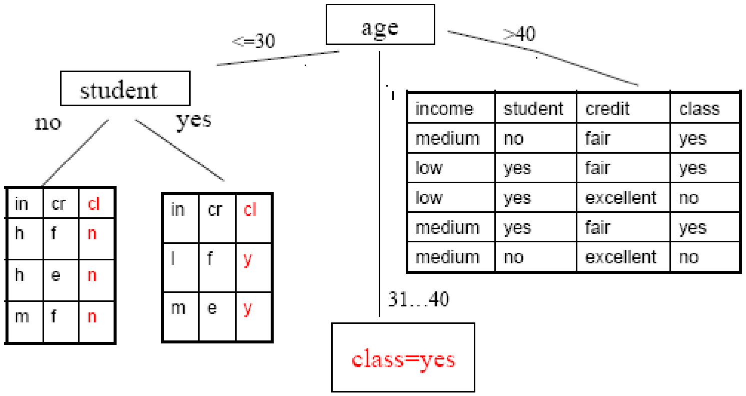


income	student	credit	class
high	no	fair	no
high	no	excellent	no
medium	no	fair	no
low	yes	fair	yes
medium	yes	excellent	yes

income	student	credit	class
medium	no	fair	yes
low	yes	fair	yes
low	yes	excellent	no
medium	yes	fair	yes
medium	no	excellent	no

Intelligent systems – decision trees (DT)

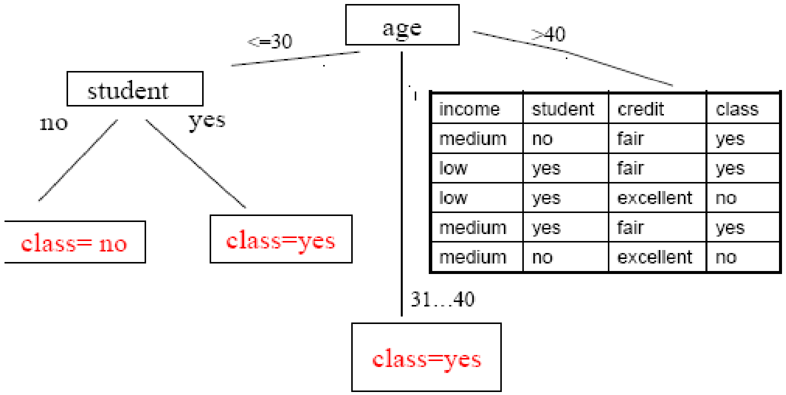
- Process → Tree construction (induction)
  - Example
    - Attribute *age* is selected for the root
    - Attribute *student* is selected on branch *age <=30*



in	cr	cl
h	f	n
h	e	n
m	f	n

in	cr	cl
l	f	y
m	e	y

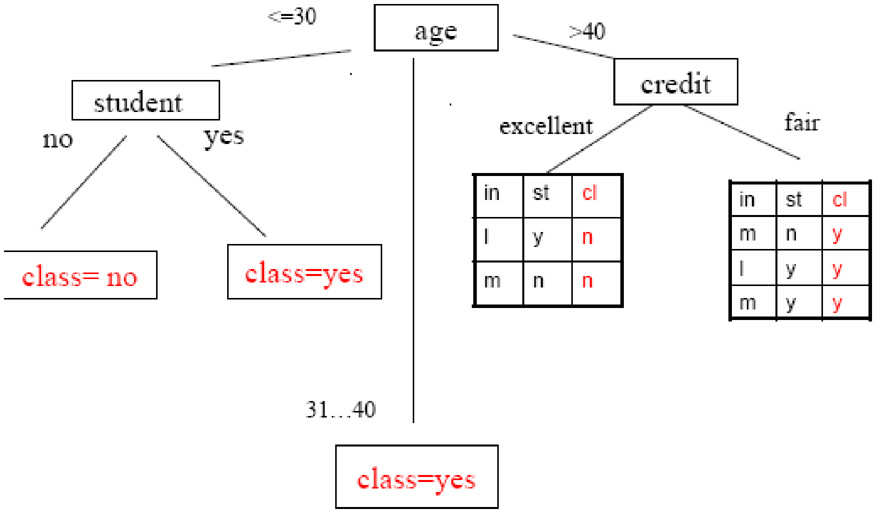
income	student	credit	class
medium	no	fair	yes
low	yes	fair	yes
low	yes	excellent	no
medium	yes	fair	yes
medium	no	excellent	no



income	student	credit	class
medium	no	fair	yes
low	yes	fair	yes
low	yes	excellent	no
medium	yes	fair	yes
medium	no	excellent	no

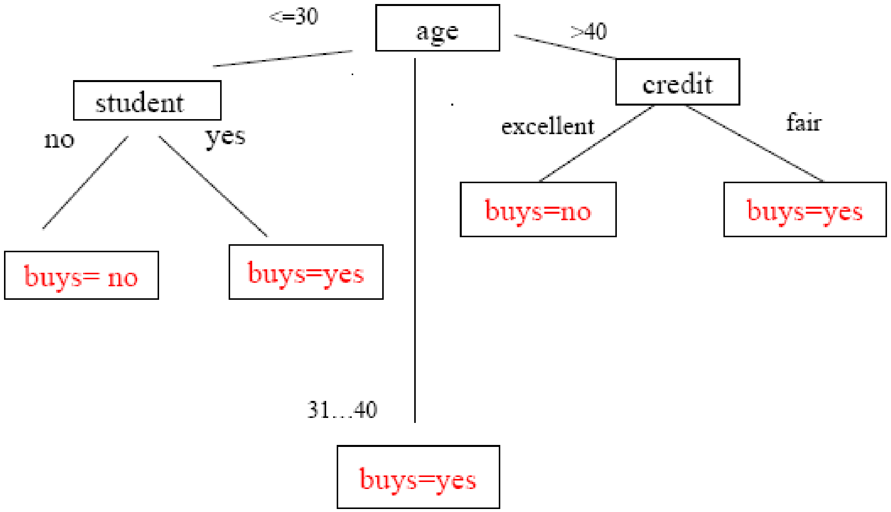
Intelligent systems – decision trees (DT)

- Process → Tree construction (induction)
  - Example
    - Attribute *age* is selected for the root
    - Attribute *student* is selected on branch *age <=30*
    - Attribute *credit* is selected on branch *age > 40*



in	st	cl
l	y	n
m	n	n

in	st	cl
m	n	y
l	y	y
m	y	y



Intelligent systems – decision trees (DT)

- Process → tree construction → ID3/C4.5 algorithm
  - Greedy, recursive, top-down, divide-and-conquer

```
generate(D, A){  //D – a partitioning of training data, A – list of attributes
      create a new node N
      if examples from D belong to a single class C then
      node N becomes a leaf and is labeled by C
      return node N
      else
      if A=∅ then
          node N becomes a leaf and is labeled by majority class of D
          return node N
      else
          separation_attribute = AttributeSelection(D, A)
          label node N by separation_attribute
          for all possible values vj of separation_attribute
              let Dj – set of examples from D that have separation_attribute=vj
              if Dj =∅ then
                          add a leaf (to node N) labeled by majority class of D
              else
                   add a node (to node N) return by generate(Dj, A–separation_attribute)
         return node N
}
```

Intelligent systems – decision trees (DT)

- Process → tree construction → ID3/C4.5 algorithm
    - AttributeSelection(D,A) → select the attribute that corresponds to a node (root or internal node)
        - Random
        - Attribute with the fewest/most values
        - Based on a pre-established order
            - Information gain
            - Gain rate
            - Gini index
            - Distance between partitions created by the attribute

Intelligent systems – decision trees (DT)

- Process → tree construction → ID3/C4.5 algorithm → Attribute Selection
  - Information gain
    - An impurity measure
      - 0 (minim) – if all examples belong to the same class
      - 1 (maxim) – if examples are uniform distributed over classes
    - Based on data entropy
      - Expected number of bits required by coding the class of an element from data
      - Binary classification (2 classes): $E(S) = – p_+log_2p_+ – p_-log_2p_,$ where
        - p_+ - proportion of positive examples in dataset S
        - p_- - proportion of negative examples in dataset S
      - Multi-class classification: $E(S) = \sum_{i=1, 2, …, k} – p_ilog_2p_i$ – data entropy related to target attribute (output attribute), where
        - p_i – proportion of examples from class *i* in dataset S
    - Information gain of an attribute
      - How the elimination of attribute *a* reduces the dataset’s entropy
      - $Gain(S, a) = E(S) - \sum_{v \in valori(a)} |S_v| / |S| E(S_v)$
      - $\sum_{v \in values(a)} |S_v| / |S| E(S_v)$ – expected information

Intelligent systems – decision trees (DT)

Process → tree construction → ID3/C4.5 algorithm → Attribute Selection

- Information gain
  - Example

	a1	a2	a3	Clasa
d1	mare	roșu	cerc	clasa 1
d2	mic	roșu	pătrat	clasa 2
d3	mic	roșu	cerc	clasa 1
d4	mare	albastru	cerc	clasa 2

$S = \{d1, d2, d3, d4\}$ ➔ $p_+= 2 / 4$, $p_-= 2 / 4$ ➔ $E(S) = - p_+\log_2 p_+ – p_-\log_2 p_- = 1$

$S_{v=mare} = \{d1, d4\}$ ➔ $p_+ = ½$, $p_- = ½$ ➔ $E(S_{v=mare}) = 1$

$S_{v=mic} = \{d2, d3\}$ ➔ $p_+ = ½$, $p_- = ½$ ➔ $E(S_{v=mic}) = 1$

$S_{v=rosu} = \{d1, d2, d3\}$ ➔ p+ = 2/3, p- = 1/3 ➔ $E(S_{v=rosu}) = 0.923$

$S_{v=albastru} = \{d4\}$ ➔ p+ = 0, p- = 1 ➔ $E(S_{v=albastru}) = 0$

$S_{v=cerc} = \{d1, d3, d4\}$ ➔ p+ = 2/3, p- = 1/3 ➔ $E(S_{v=cerc}) = 0.923$

$S_{v=patrat} = \{d2\}$ ➔ p+ = 0, p- = 1 ➔ $E(S_{v=patrat}) = 0$

$Gain(S, a) = E(S) - \sum_{v \: є \: values(a)} |S_v| / |S| \: E(S_v)$

$Gain(S, a_1) = 1 – (|S_{v=mare}| / |S| \: E(S_{v=mare}) + |S_{v=mic}| / |S| \: E(S_{v=mic})) = 1 – (2/4 * 1 + 2/4 * 1) = 0$

$Gain(S, a_2) = 1 – (|S_{v=rosu}| / |S| \: E(S_{v=rosu}) + |S_{v=albastru}| / |S| \: E(S_{v=albastru})) = 1 – (3/4 * 0.923 + 1/4 * 0) = 0.307$

$Gain(S, a_3) = 1 – (|S_{v=cerc}| / |S| \: E(S_{v=cerc}) + |S_{v=patrat}| / |S| \: E(S_{v=patrat})) = 1 – (3/4 * 0.923 + 1/4 * 0) = 0.307$

Intelligent systems – decision trees (DT)

- Process → tree construction → ID3/C4.5 algorithm → Attribute Selection
  - Gain rate
    - Penalises an attribute by integrating a new term – *split information* – that depends on spreading degree and on uniformity degree of separation
      - *Split information* – entropy related to possible values of attribute a
      - Sv – proportion of examples from dataset S that have attribute a with value v

Intelligent systems – decision trees (DT)

- Process
  - Tree construction
  - Using the tree as a problem solver
    - Main idea
      - Extract the rules from the constructed tree
        - IF *age* = *"<=30"* AND *student* = *"no"* THEN *buys_computer* = *"no"*
        - IF *age* = *"<=30"* AND *student* = *"yes"* THEN *buys_computer* = *"yes"*
        - IF *age* = *"31…40"* THEN *buys_computer* = *"yes"*
        - IF *age* = *">40"* AND *credit_rating* = *"excellent"* THEN *buys_computer* = *"no"*
        - IF *age* = *">40"* AND *credit_rating* = *"fair"* THEN *buys_computer* = *"yes"*
      - Use the rules for classifying the test data (new data)
        - Let x a data without class → rules can be written as predicates
        - IF *age(x, <=30)* AND *student(x, no)* THEN *buys_computer (x, no)*
        - IF *age(x, <=30)* AND *student (x, yes)* THEN *buys_computer (x, yes)*

Intelligent systems – decision trees (DT)

- Process
  - Tree construction
  - Using the tree as a problem solver
    - Difficulties
      - *Underfitting* → DT constructed on training data is to simple → large classification error during training and testing
      - *Overfitting* → DT constructed on training data match the training data, but it ca not generalize new data
    - Solutions
      - Pruning → remove some branches (un - useful, redundant) → small tree
      - Cross-validation

Intelligent systems – decision trees (DT)

- Process
  - Tree construction
  - Using the tree as a problem solver
  - Pruning
    - Why?
      - After the DT is constructed, classification rules are extracted in order to represent the knowledge as if-then rules (easy to understand)
      - A rule is create by traversing the DT from root to a leaf
      - Each pair (attribute, value) – (node, edge) – is a conjunction in the premise of the rule (if part), except the last node of the path that is a leaf and represents the consequence (output, then part) of the rule
    - Typology
      - *pre-pruning*
        - Increasing the tree is stopped during construction by stopping the division of nodes that become leaf labeled by majority class of examples from that node
      - *post-pruning*
        - After the DT is constructed, eliminate the branches of some nodes that become leaf → classification error reduces (on testing data)

Intelligent systems – decision trees (DT)

- Tools
  - http://webdocs.cs.ualberta.ca/~aixplore/learning/DecisionTrees/Applet/DecisionTreeApplet.html
  - WEKA → J48
  - http://id3alg.altervista.org/
  - http://www.rulequest.com/Personal/c4.5r8.tar.gz
- Biblio
  - http://www.public.asu.edu/~kirkwood/DAStuff/decisiontrees/index.html

Intelligent systems – decision trees (DT)

- Advantages
  - Easy to understand and interpret
  - Can use nominal or categorized data
  - Decision logic can be easy followed (rules are visible)
  - Works better with large data

- Disadvantages
  - Instability → change the training data
  - Complexity → representation
  - Difficult to use
  - The DT construction is expensive
  - The DT construction requires a lot of information

Intelligent systems – decision trees (DT)

- Difficulties
  - There can be more trees
    - To small
    - With a better accuracy (easy to be read and with good performances)
    - Identify the best tree → NP-problem
  - Select the best tree
    - Heuristic algorithms
    - ID3 → the smallest tree
      - Occam theorem: "always choose the simplest explanation"
  - Continuous attributes
    - Range splitting
      - How many intervals?
      - How large intervals?
  - To large trees
    - Pre - pruning → stops to construct the tree earlier
    - Post-pruning → remove some branches

Review

- Automatic learning systems
  - Machine Learning – ML
    - Supervised learning → annotated train data (by label from a predefined set) and test data have to be annotated by using the learnt model (by one of the known labels)
    - Unsupervised learning → not-annotated train data; a labeling model has to be learnt in order to annotate the test data; the set of labels is unknown befor training
  - Systems
    - Decision trees
      - Each internal node → attribute
      - Each branch of a node (attribute) → value of that attribute
      - Each leaf → class (label) – contains all data from that class

Next lecture

A. Short introduction in Artificial Intelligence (AI)

A. Solving search problems
   A. Definition of search problems
   B. Search strategies
      A. Uninformed search strategies
      B. Informed search strategies
      C. Local search strategies (Hill Climbing, Simulated Annealing, Tabu Search, Evolutionary algorithms, PSO, ACO)
      D. Adversarial search strategies

C. **Intelligent systems**
   A. Rule-based systems in certain environments
   B. Rule-based systems in uncertain environments (Bayes, Fuzzy)
   C. **Learning systems**
      A. **Decision Trees**
      - **Artificial Neural Networks**
      A. Support Vector Machines
      - Evolutionary algorithms
   D. Hybrid systems

Next lecture – useful information

- Chapter VI (19) of *S. Russell, P. Norvig, Artificial Intelligence: A Modern Approach, Prentice Hall, 1995*
- Chapter 8 of *Adrian A. Hopgood, Intelligent Systems for Engineers and Scientists, CRC Press, 2001*
- Chapters 12 and 13 of *C. Groşan, A. Abraham, Intelligent Systems: A Modern Approach, Springer, 2011*
- Chapter V of *D. J. C. MacKey, Information Theory, Inference and Learning Algorithms, Cambridge University Press, 2003*
- Chapter 4 of *T. M. Mitchell, Machine Learning, McGraw-Hill Science, 1997*

- Presented information have been inspired from different bibliographic sources, but also from past AI lectures taught by:
  - PhD. Assoc. Prof. Mihai Oltean – www.cs.ubbcluj.ro/~moltean
  - PhD. Assoc. Prof. Crina Groșan - www.cs.ubbcluj.ro/~cgrosan
  - PhD. Prof. Horia F. Pop - www.cs.ubbcluj.ro/~hfpop