Introduction to Learning Classifier Systems

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Outline

- Introduction
- Machine Learning & Classification
- Paradigms of LCS
- Knowledge representations
- Real-world examples
- Recent trends
- Summary

Introduction

- Learning Classifier Systems (LCS) are one of the major families of techniques that apply evolutionary computation to machine learning tasks
  - **Machine learning**: How to construct programs that automatically learn from experience [Mitchell, 1997]
- LCS are almost as ancient as GAs, Holland made one of the first proposals

Introduction

- Paradigms of LCS
  - The Pittsburgh approach [Smith, 80]
  - The Michigan approach [Holland & Reitman, 78]
  - The Iterative Rule Learning approach [Venturini, 93]
- Knowledge representations
  - All the initial approaches were rule-based
  - In recent years several knowledge representations have been used in the LCS field: decision trees, synthetic prototypes, etc.

Machine Learning and classification

- A more formal definition of machine learning and some examples [Mitchell, 1997]
  - 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 at tasks in *T*, as measured by *P*, improves with experience *E*
  - How does this definition translate to real life?

Machine Learning and classification

- A checkers learning problem
  - Task *T*: playing checkers
  - Performance measure *P*: percent of games won against opponents
  - Training experience *E*: playing practice games against itself

Machine Learning and classification

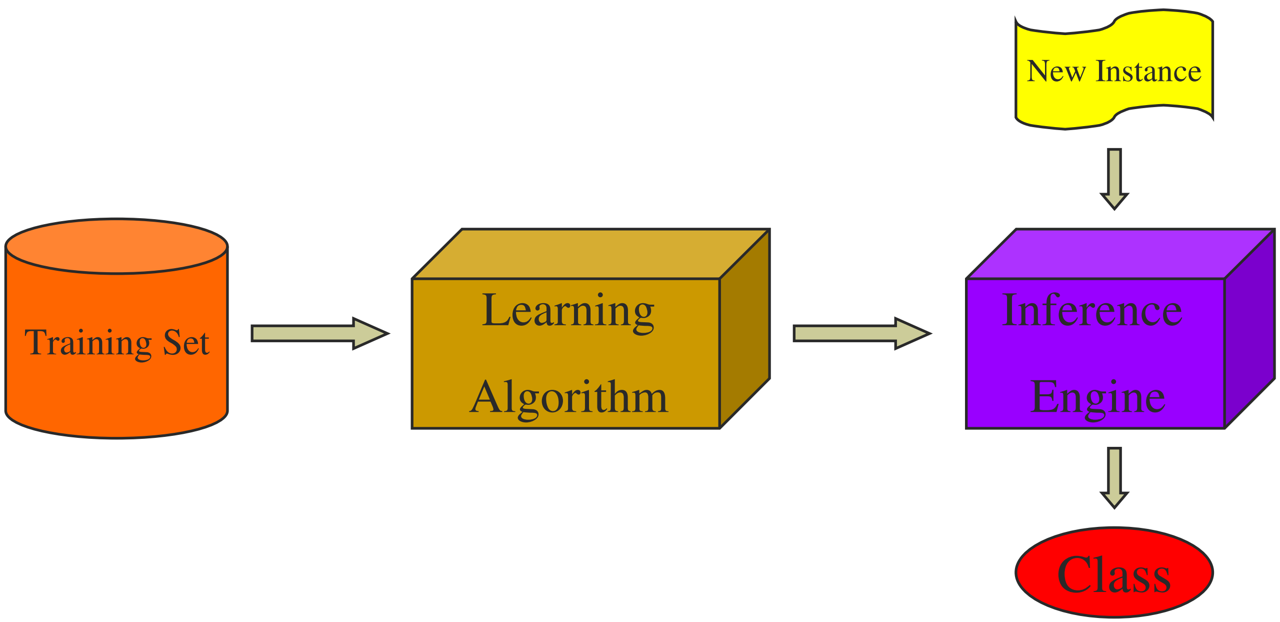
- A handwriting recognition learning problem
  - Task *T*: recognizing and classifying handwritten words withing images
  - Performance measure *P*: percent of words correctly identified
  - Training experience *E*: a database of handwritten words with given classifications

Machine Learning and classification

- A robot driving learning problem
  - Task *T*: driving on public four-lane highways using vision sensors
  - Performance measure *P*: average distance traveled before an error (as judged by human overseer)
  - Training experience *E*: a sequence of images and steering commands recorded while observing a human driver

Machine Learning and classification

- **Classification task**: Learning how to label correctly new instances from a domain based on a set of previously labeled instances

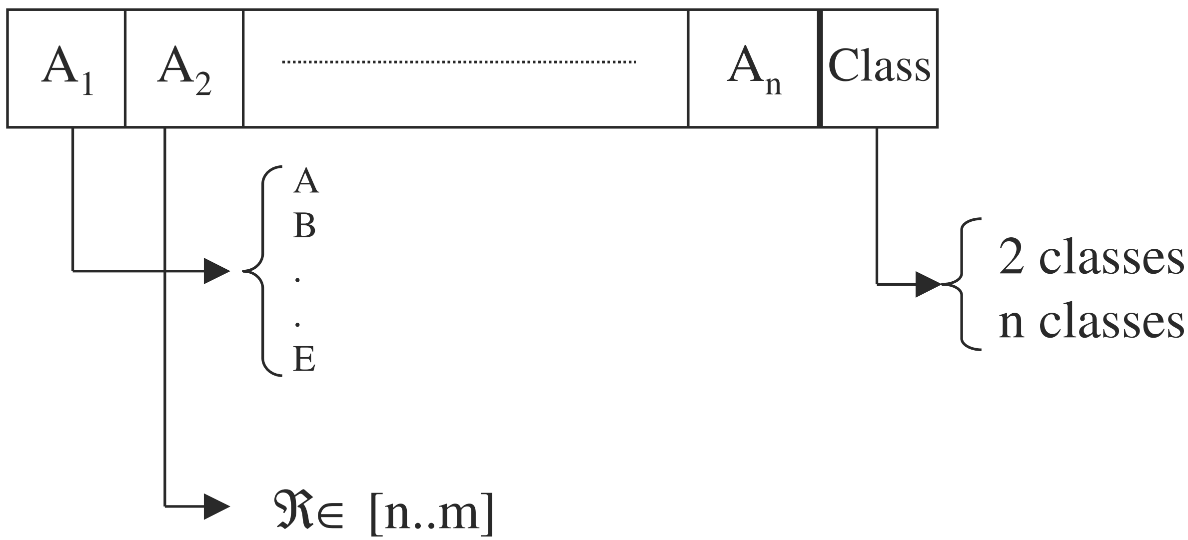


Machine Learning and classification

- Instance: individual, independent example of the domain that has to be learned
- Instances have regular structure:
  - Fixed number of attributes: features that characterize an instance
  - A class: a label belonging to a finite and discrete domain
- Attributes can be of diverse type
  - Nominal: discrete and finite variable
  - Integer
  - Continuous

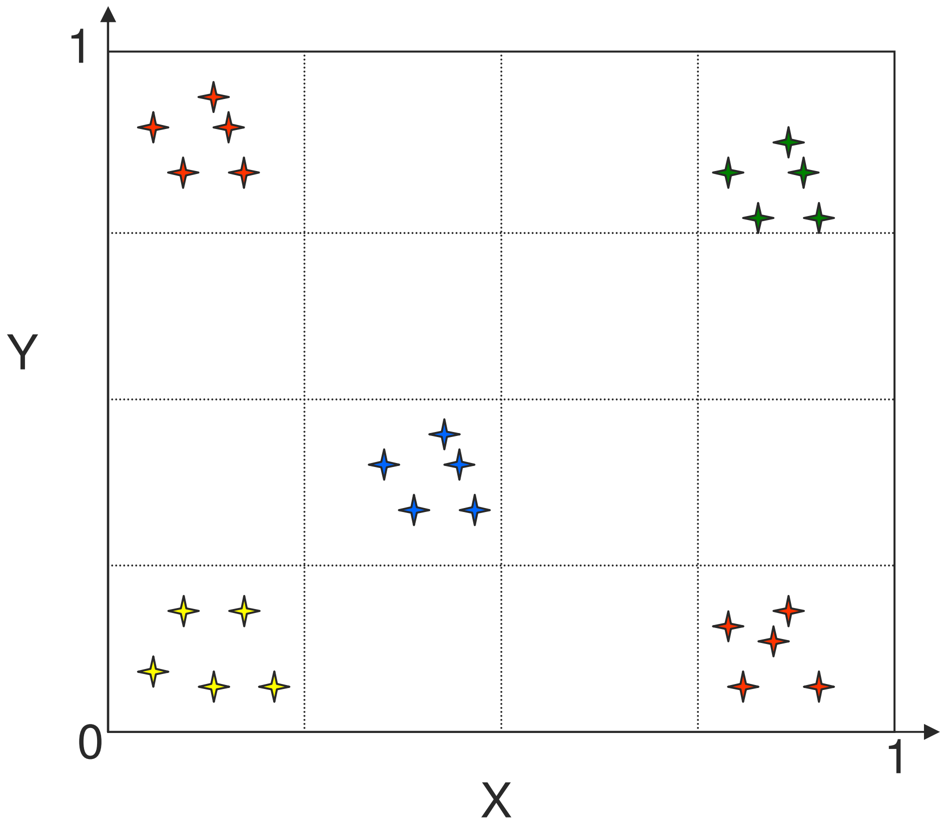
Machine Learning and classification

- Instance



- Goal of classification is to learn how to predict the class of an instance from its attributes

Machine Learning and classification



Instance: (X,Y||Colour)

1: If (X<0.25 and Y>0.75) or
(X>0.75 and Y<0.25) then →

2: If (X>0.75 and Y>0.75) then →

3: If (X<0.25 and Y<0.25) then →

4: If (X ∈ [0,25,0,50] and
Y ∈ [0.25,0.50]) then →

4': Everything else then →

Paradigms of LCS

- Paradigms of LCS
  - The Pittsburgh approach [Smith, 80]
  - The Michigan approach [Holland & Reitman, 78]
  - The Iterative Rule Learning approach [Venturini, 93]

Paradigms of LCS

- The Pittsburgh approach
  - This approach is the closest one to the standard concept of GA
  - Each individual is a complete solution to the classification problem
  - Traditionally this means that each individual is a variable-length set of rules
  - GABIL [De Jong & Spears, 93] is a well-known representative of this approach

Paradigms of LCS

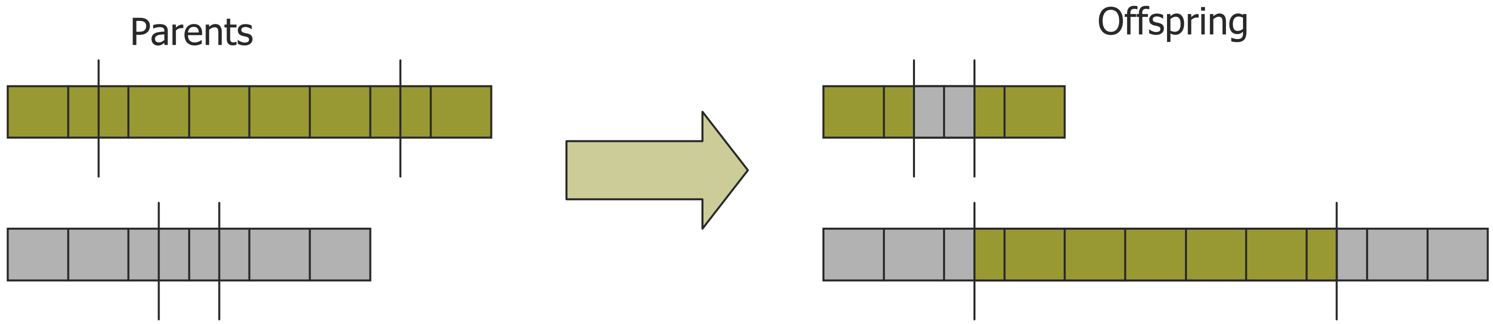
- Pittsburgh approach
  - More than one rule could be used to classify a given instance
  - **Match process**: deciding which rule is used in these cases
  - An usual approach is that individuals are interpreted as a decision list [Rivest, 87]: an ordered rule set

1	2	3	4	5	6	7	8

Instance 1 matches rules 2, 3 and 7 → Rule 2 will be used
Instance 2 matches rules 1 and 8 → Rule 1 will be used
Instance 3 matches rule 8 → Rule 8 will be used
Instance 4 matches no rules → Instance 4 will not be classified

Paradigms of LCS

- Pittsburgh approach
  - Crossover operator



  - Mutation operator: classic GA mutation of bit inversion

Paradigms of LCS

- Pittsburgh approach
  - Evaluation process of an individual:
    - *NumExamples=0*
    - *CorrectExamples=0*
    - **For** each example in training set
      - NumExamples++
      - Determine first rule that matches training example
      - **If** class of rule is the same as class of instance
        - CorrectExamples++
    - Fitness=(CorrectExamples/NumExamples)^2

Paradigms of LCS

- In the other two approaches each individual is a rule
- What happens usually in the evolutionary process of a GA?
  - All individuals converge towards a single solution
- Our solution is a set of rules. Therefore we need some mechanism to guarantee that we generate all of them.
- Each approach uses a different method for that

Paradigms of LCS

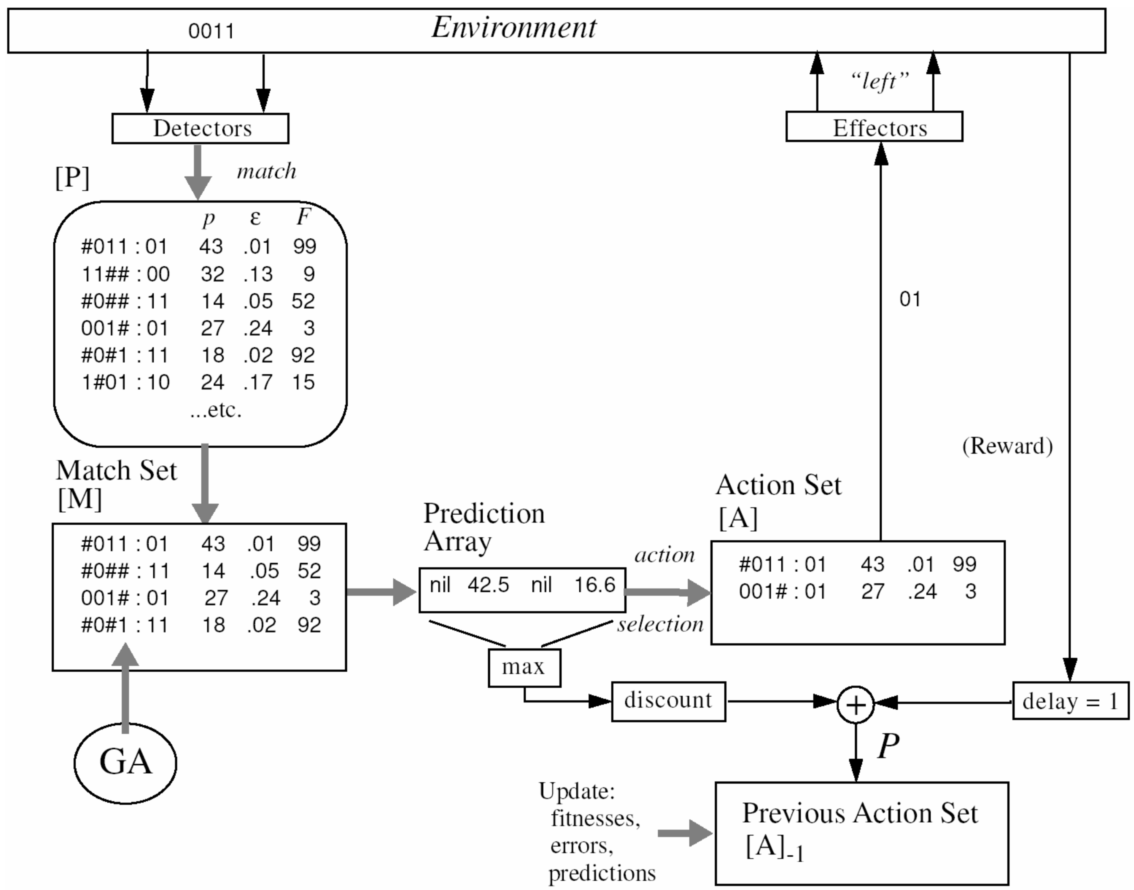
- The Michigan approach
  - Each individual (classifier) is a single rule
  - The whole population cooperates to solve the classification problem
  - A reinforcement learning system is used to identify the good rules
  - A GA is used to explore the search space for more rules
  - XCS [Wilson, 95] is the most well-known Michigan LCS

Paradigms of LCS

- The Michigan approach
  - What is Reinforcement Learning?
    - “a way of programming agents by reward and punishment without needing to specify how the task is to be achieved” [Kaelbling, Littman, & Moore, 96]
    - Rules will be evaluated example by example, receiving a positive/negative reward
    - Rule fitness will be update incrementally with this reward
    - After enough trials, good rules should have high fitness

Paradigms of LCS

- Working cycle

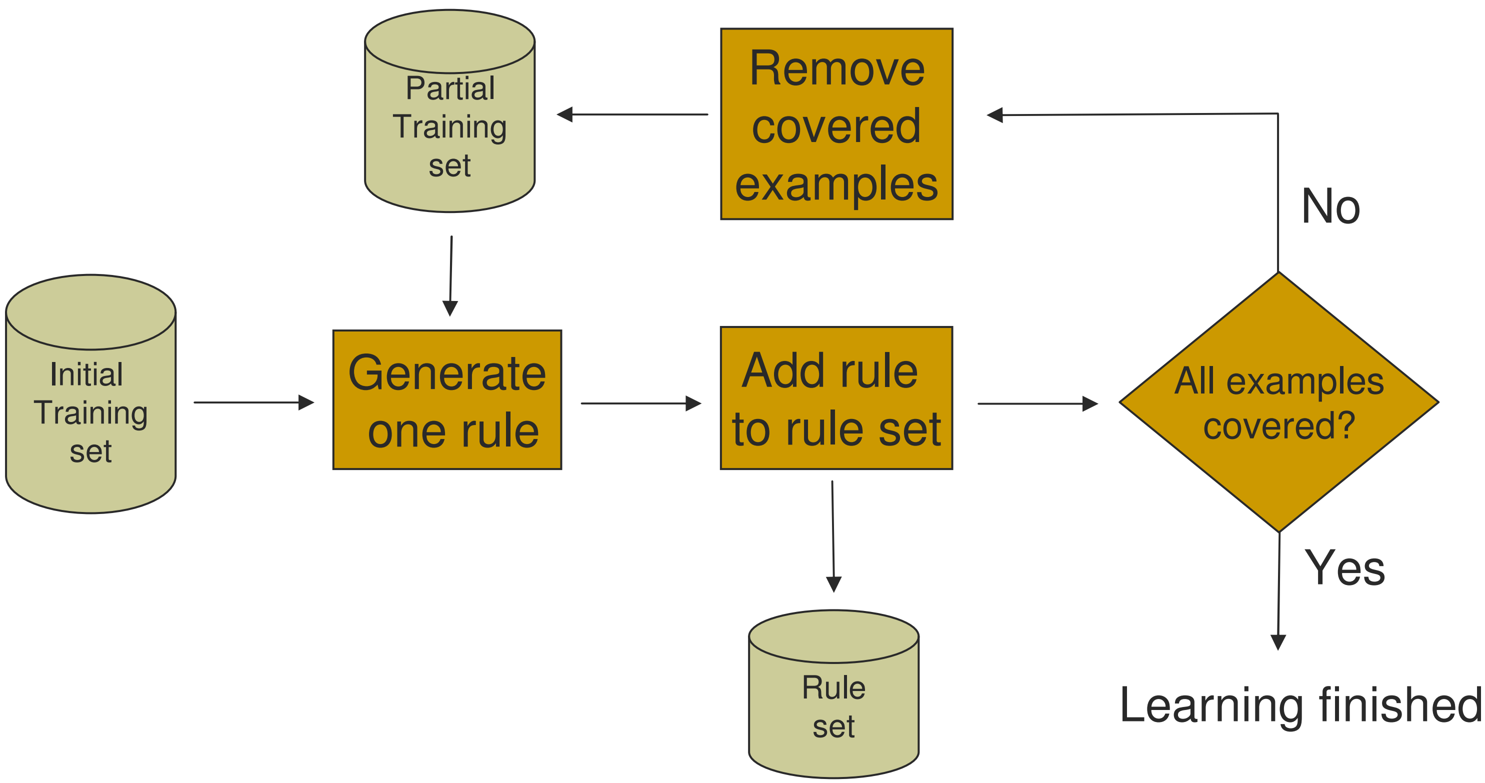


Paradigms of LCS

- The Iterative Rule Learning approach
  - Each individual is a single rule
  - Individuals compete as in a standard GA → A single GA run generates one rule
  - The GA is run iteratively to learn all rules that solve the problem
  - Instances already covered by previous rules are removed from the training set of the next iteration

Paradigms of LCS

- The Iterative Rule Learning approach
  - Also known as separate-and-conquer



Paradigms of LCS

- The Iterative Rule Learning approach
  - HIDER System [Aguilar, Riquelme & Toro, 03]
    1. **Input:** Examples
    2. RuleSet = Ø
    3. **While** |Examples| > 0
       1. Rule = Run GA with Examples
       2. RuleSet = RuleSet **U** Rule
       3. Examples = Examples \ Covered(Rule)
    4. **EndWhile**
    5. **Output**: RuleSet
  - Fitness uses accuracy + generality measure
    - Generality: rule covering as much examples as possible

Knowledge representations

- Knowledge representations
  - For nominal attributes
    - Ternary representation
    - GABIL representation
  - For real-valued attributes
    - Decision tree
    - Synthetic prototypes
    - Others

Knowledge representations

- Representation of XCS for binary problems: ternary representation
  - Ternary alphabet {0,1,#}
  - If A_1=0 and A_2=1 and A_3 is irrelevant → class 0

$$\boxed{01\#|0}$$

  - For non-binary nominal attributes:
    - {0,1, 2, …, n,#}
  - Crossover and mutation act as in a classic GA

Knowledge representations

- Representation of GABIL for nominal attributes
  - Predicate $\rightarrow$ Class
  - Predicate: Conjunctive Normal Form (CNF)
    $(A_1=V_1^1 \vee .. \vee A_1=V_1^n) \wedge ..... \wedge (A_n=V_n^2 \vee .. \vee A_n=V_n^m)$
    - A_i : ***i****th* *a*ttribute
    - V_i^j : ***j****th* *v*alue of the **i***th* attribute
  - The rules can be mapped into a binary string
    1100|0010|1001|1
  - Usual crossover and mutation

Knowledge representations

- Representation of GABIL for nominal attributes
  - 2 Variables:
    - Sky = {clear, partially cloudy, dark clouds}
    - Pressure = {Low, Medium, High}
  - 2 Classes: {no rain, rain}
  - Rule: If [sky is (partially cloudy or has dark clouds)] and [pressure is low] then predict rain
  - Genotype: “011|100|1”

Knowledge representations

- Representation of XCS for real-valued attributes: real-valued interval
  - XCSR [Wilson, 99]
    - Interval is codified with two variables: center & spread: [center, spread] → [center-spread,center+spread]
    - Rule for the colours example:
      - [0.125,0.125]|[0.125,0.125]|
    - Usual crossover
    - Mutation adds or substracts a small quantity from the genes

Knowledge representations

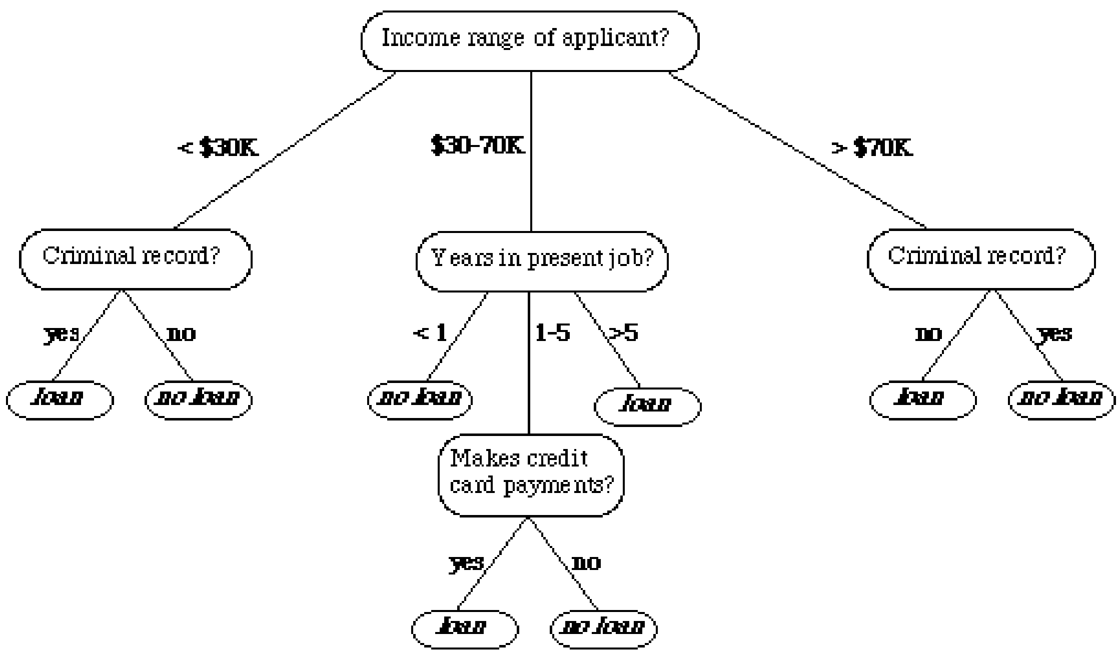
- Representation of XCS for real-valued attributes: real-valued interval
  - UBR [Stone & Bull, 03]
    - Interval is codified with two variables: lower & upper bound: [lower, upper]
    - The variable with lowest value is the lower bound, the variable with higher value is the upper bound
      - [0,0.25]|[0.25,0]|

Knowledge representations

- Pittsburgh representations for real-valued attributes:
  - Rule-based: Adaptive Discretization Intervals (ADI) representation [Bacardit, 04]
    - Intervals in ADI are build using as possible bounds the cut-points proposed by a discretization algorithm
    - Search bias promotes maximally general intervals
    - Several discretization algorithms are used at the same time in order to choose correctly the appropiate method for each domain

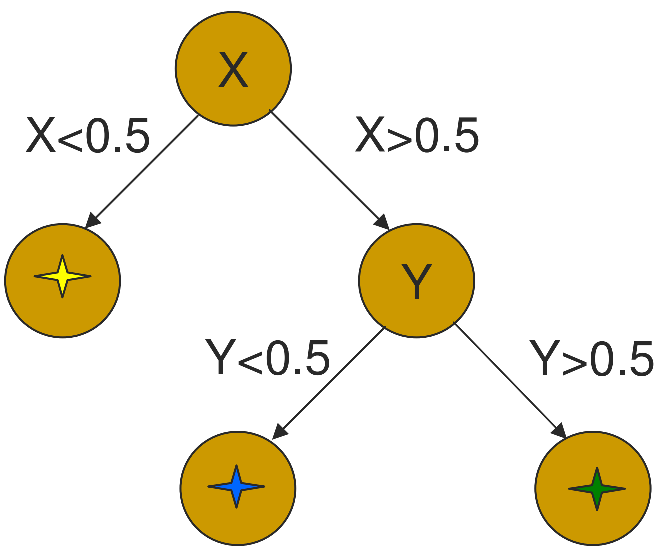
Knowledge representations

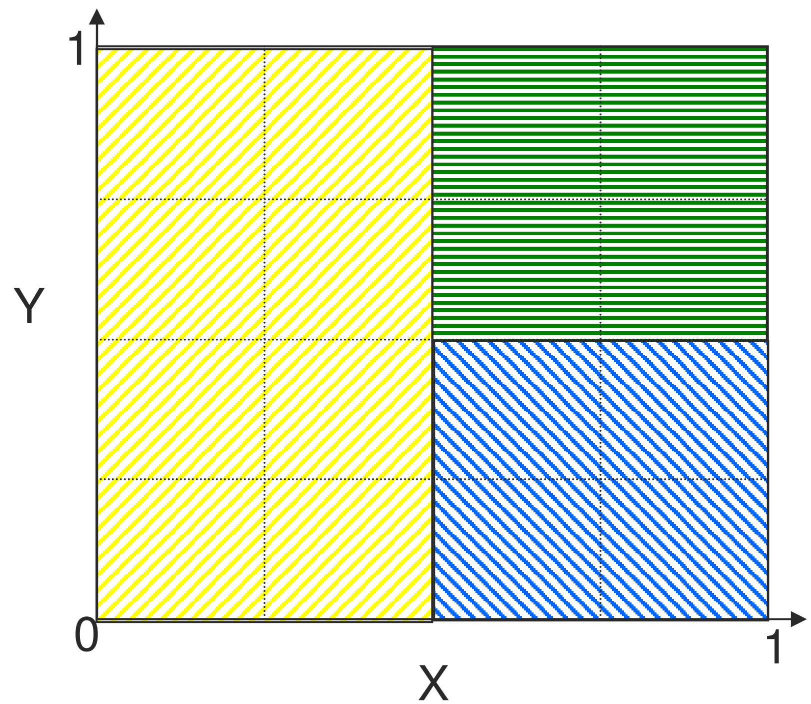
- Pittsburgh representations for real-valued attributes:
  - Decision trees [Llorà, 02]
    - Nodes in the trees can use orthogonal or oblique criteria



Knowledge representations

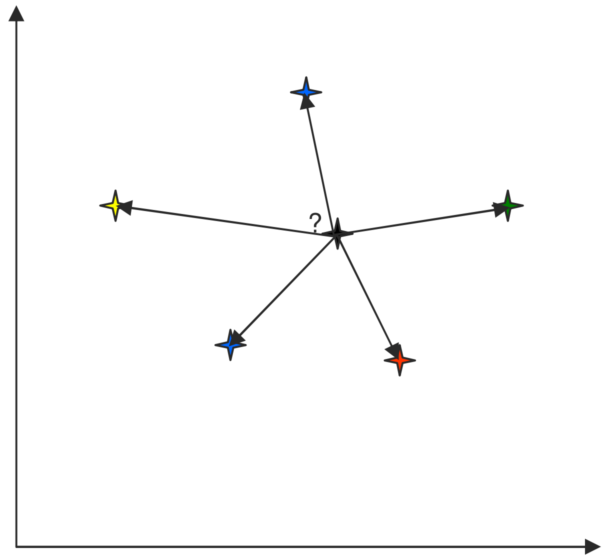
- Pittsburgh representations for real-valued attributes:
  - Orthogonal decision tree





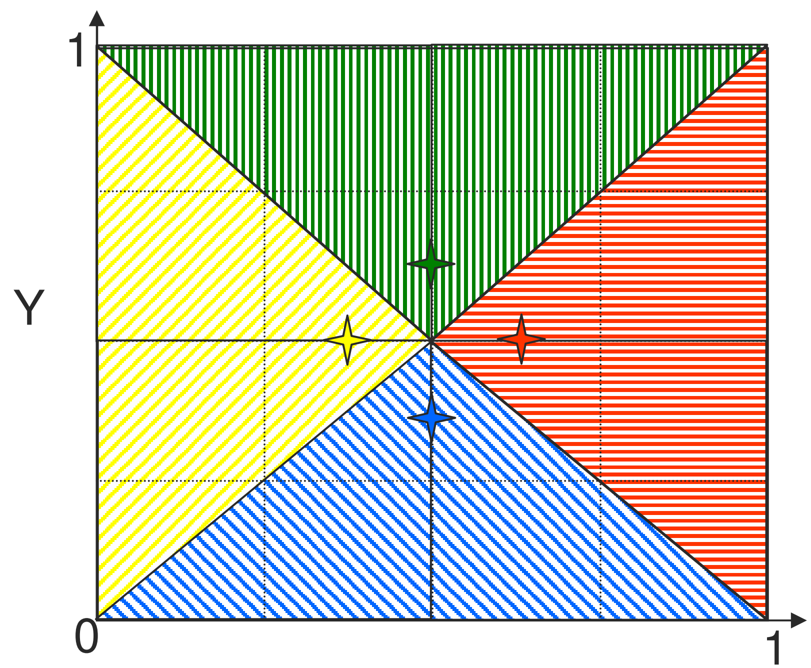
Knowledge representations

- Pittsburgh representations for real-valued attributes
  - Synthetic prototypes [Llorà, 02]
    - Each individual is a set of synthetic instances
    - These instances are used as the core of a nearest-neighbor classifier



- Pittsburgh representations for real-valued attributes
  - Synthetic prototypes

1. (-0.125,0,yellow)
2. (0.125,0,red)
3. (0,-0.125,blue)
4. (0,0.125,green)



Real-world applications

- Generating control rules for a fighter aircraft [Smith et. al., 00]
  - Using Michigan LCS
  - Learning aircraft maneuvers
  - Input information:
    - Airspeed, altitude, aircraft angle, …
  - Actions (classes):
    - Rudder angle and speed

Real-world applications

- Predicting the mill temperature (range of temperatures) in a aluminium plate mill [Browne & Bacardit, 04]
  - The Pittsburgh approach was used
  - A press is used to level raw aluminium into a thin sheet that can be coiled
  - The aluminium temperature should be within some operational limits
  - Temperature is predicted from around 60 input sensors

Real-world applications

- Medical domains: Generation of epidemiologic hypothesis [Holmes, 96]
  - Predicting if a pacient has a disease based on their degree of exposure to certain factors
  - In this domain the difference between false positives and false negatives is important

Recent trends

- Develop a theoretical framework of the behavior of each kind of LCS
  - These models are intended to allow the user to adjust the LCS in a principled way to guarantee success
  - Convert LCS into an engineering tool

Recent trends

- New kinds of knowledge representations, specially non-linear ones
  - Making sure that the representation has enough expressive power to model successfully the domain

Recent trends

- Development of exploration mechanism that can go beyond the classic crossover and mutation operators
  - It is known that these classic exploration mechanisms have limitations, specially in identifying the structure of the problem
  - If the algorithm learns this structure, it can explore more efficiently and find better solutions

Summary

- This talk was a brief overview of the Learning Classifier Systems area: EC techniques applied to Machine Learning
- Description of the three main paradigms
  - Pittsburgh
  - Michigan
  - Iterative rule learning

Summary

- Description of several knowledge representations
  - Rule based
    - Nominal attributes
    - Continuous attributes
  - Decision trees
  - Synthetic prototypes

Summary

- Applications to real-world domains
  - Medical
  - Industrial
  - Military
- Recent trends
  - Explore better
  - Model the problem better
  - Understand better