Machine Learning Unit 4

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Unit 4: Hybrid Computational Intelligence

- Constituents of computational intelligence
- Possible hybridization of constituents of computational intelligence
 - Neuro-Fuzzy Systems,
 - Neuro-Genetic Systems and
 - Neuro-Fuzzy-Genetic systems
- Applications of computational intelligence system in real life

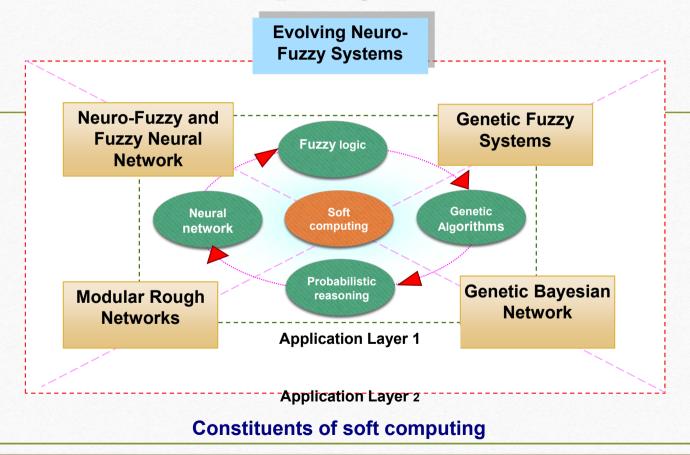
Unit 4: Hard Computing and Soft Computing

- Traditional and formal computing techniques that **does not tolerate** imprecision, fuzziness, incompleteness and approximation.
- Hard computing systems (supported thru AI) do not resembles biological processes efficiently.
- Soft computing techniques **resemble biological processes more closely** than traditional formal techniques that are largely based on logical systems, such as predicate logic, or rely heavily on computer-aided numerical analysis..

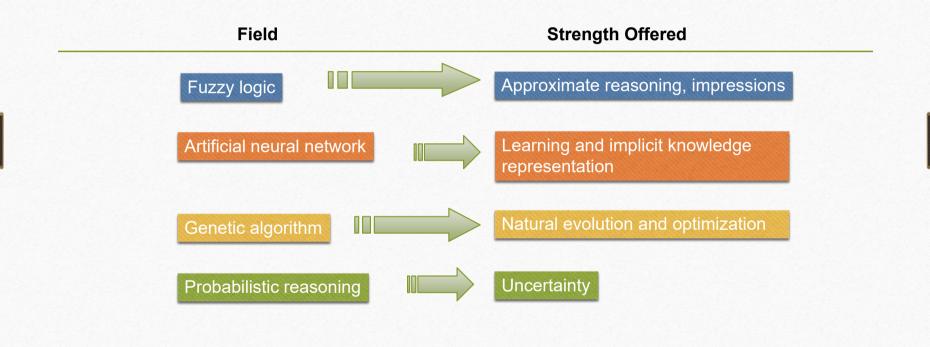
Unit 4: Hard Computing and Soft Computing

Traditionalhard computing	Computational intelligence-based (soft) computing
 Traditional, formal, and conventional techniques 	Informal and non-conventional techniques
 Requires and handlesprecise and complete data while input, output, and processing 	 Can handle ambiguous data as well as data with partial, vague, and imprecision content
Applicability is less flexible and rigid	Applicable in a highly flexible way to real- life complex problems
Resembles mechanical procedures very well	Resembles biological processes very well
Based on binary logic and crisp set/logic theory	Based on approximate reasoning, multi- valued logic, self-learning, and evolutionary approach
Generally performs sequential or linear computations	Can perform sequential as well parallel computations
 Results are precise and the aim is to obtain optimum results 	 Provides approximate, good, and acceptable results

Constituents of Soft Computing



Constituents of Soft Computing



Neuro-Fuzzy Systems

To take benefits of fuzzy logic-based systems and artificial neural networks simultaneously neuro-fuzzy hybridization is called. An artificial neural network takes normalized and crisp (non-fuzzy) data for various parameters based on which decision is learned. However, there are situations where data may be incomplete, vague, and uncertain. Here, fuzzy membership functions can be used as an interface to the neural network. The membership functions vaguely interact with users, deal with uncertainty, and take fuzzy data in order to make the data understandable by the back end neural network. There are many ways how a neuro-fuzzy hybridization is achieved. Some of the popular ways are enlisted below.

Neuro-Fuzzy Systems

- As an interface to a base neural network, to convert vague data into crisp data while providing input to a neural network. Similarly, crisp output is converted into natural, user-friendly, and vague output;
- The output of the neural network can be fine-tuned with the help of a fuzzy rule-based system; such fine-tuning can facilitate the addition of explanation and reasoning into the neural network;
- The activation function of a neural network can be fuzzy;
- Weights of connections in a neural network can be fuzzy;
- The error determining functions can be fuzzy for backpropagation algorithm;
- Fuzzy rules, membership functions, or other parameters of the fuzzy system can be learned via a neural network;
- etc.

Fuzzy – Genetic Systems

- Fuzzy-genetic systems hybridize fuzzy logic for uncertainty management, approximate reasoning, and managing vague inputs/outputs; and genetic algorithms for optimization, evolution searching, and other possible evolutionary benefits. The most popular use of genetic-fuzzy hybridization is to evolve fuzzy rules from a given set of a few rules, called seed rules set. The following are the major objectives of the genetic-fuzzy hybridization.
- To evolve fuzzy rules or component of fuzzy logic-based systems;
- To evolve strong membership functions and other parameters to employ fuzzy systems including testing (genetic learning of fuzzy components);
- Genetic adaptive fuzzy inference technique and inference engine parameters;
- Fuzzy genetic operators such as fuzzy crossover, fuzzy mutation, and other application-specific genetic operators;
- The fine-tuning output of fuzzy rule-based systems with genetic algorithms;
- etc.

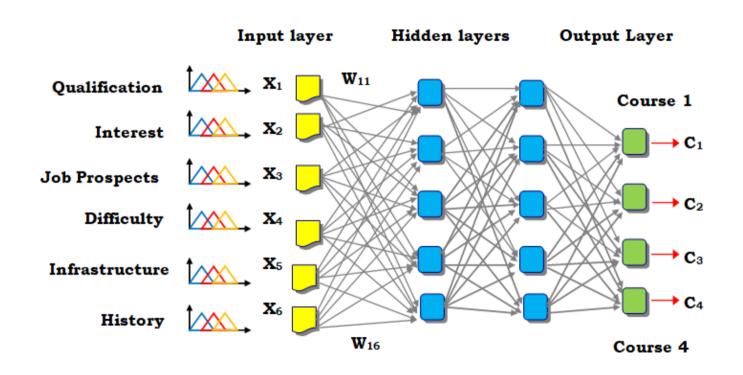
Neuro-Genetic Systems

- Learning capability and evolutionary advantages are combined in the case of the neuro-genetic system. The neuro-genetic system can be hybridized by accommodating two computational intelligenceconstituents, artificial neural network, and genetic algorithms. Major and popular uses of such a neuro-genetic system are to evolve the design of a neural network with the help of evolutionary algorithms or to learn genetic systems related parameters such as fitness function through a neural network. The following are the major possibilities of such hybridization.
- Topology and design of neural network can be evolved by a genetic algorithm;
- Solutions learned by a neural network can be further evolved by a genetic algorithm; however, this type of hybridization is less useful, as neural networks used to provide limited results;
- Learning rate, rate of momentum, level of tolerance, etc. neural network control parameters can be learned by a neural network;
- A neural network can be used to evaluate fitness functions used by the genetic algorithms component;
- etc.

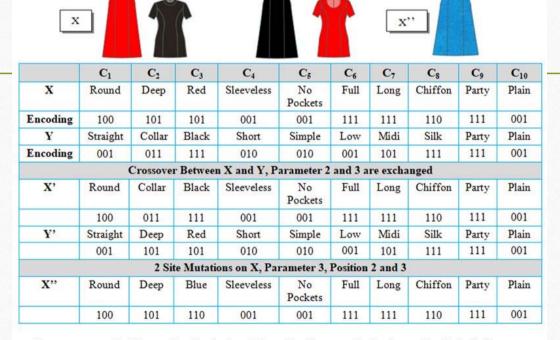
Other Hybrid Systems

Often, there is a requirement of combining more than two constituents of computational intelligenceto take multi-folded advantages of the constituents. For example, evolving topologies of neuro-fuzzy systems, selflearning (by ANN) of a fuzzy fitness function for a genetic algorithm, etc. requires the three computational intelligence constituents namely artificial neural network, genetic algorithms, and fuzzy logic-based systems. Application domain for such multi-folded hybridization can be face reorganization, crowd behavior monitoring, cybercrime monitoring & security in eCommerce transactions, multiple intelligence modeling, advisory systems, etc.

Example 1: Neuro Fuzzy System for Course Selection



Example 2:
Fuzzy –
Genetic
System for
Fashion
Design



Components: C₁: Shape, C₂: Neck, C₃: Color, C₄: Sleeves, C₅: Pockets, C₆: Embellishment, C₇: Length /Waist, C₈: Material, C₉: Style, C₁₀: Print

Example 3 Crop Advisory

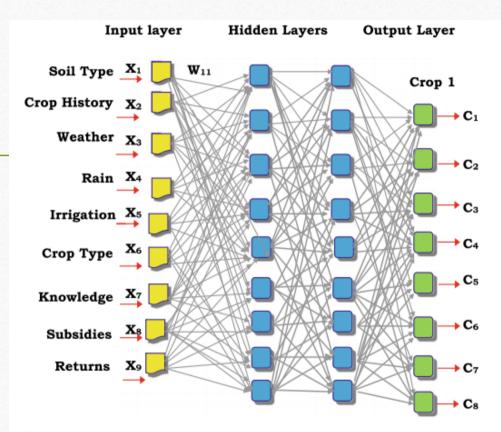
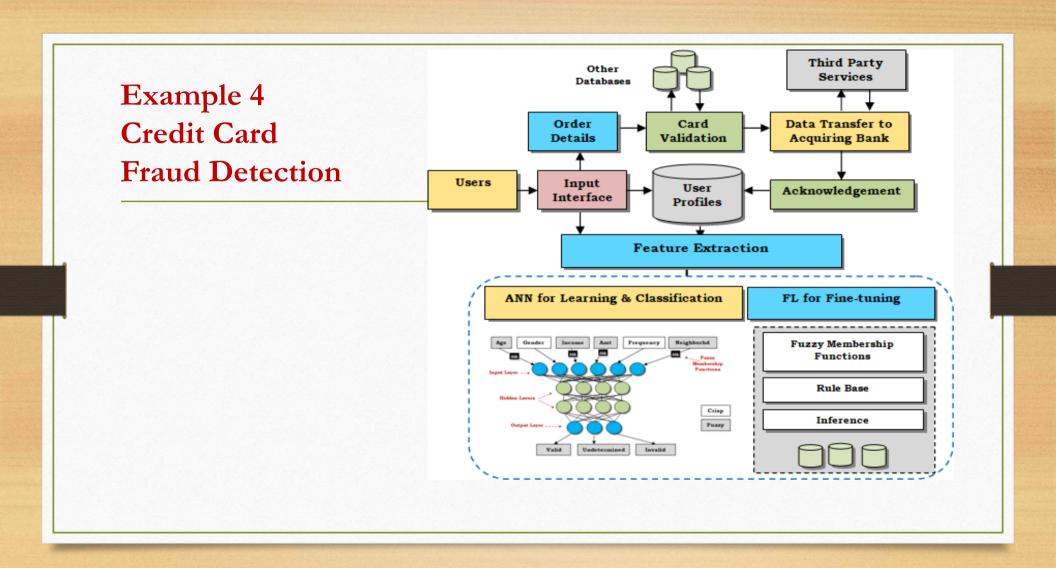
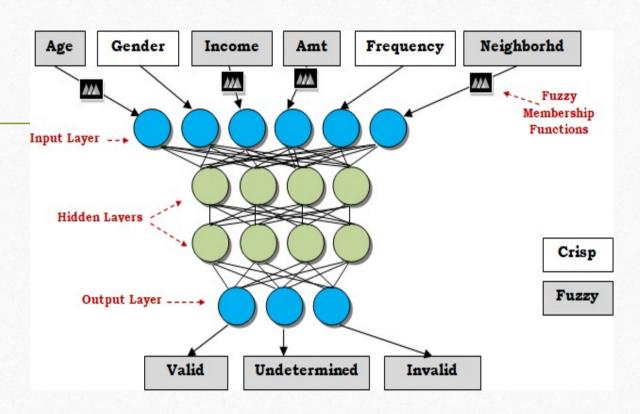
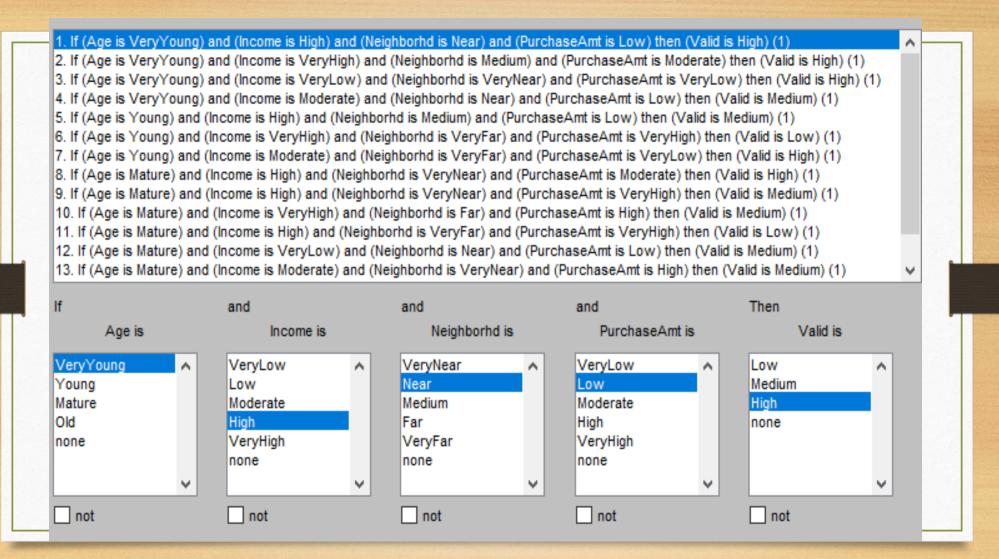


Fig. 4.9 Neural network for agriculture advisory system

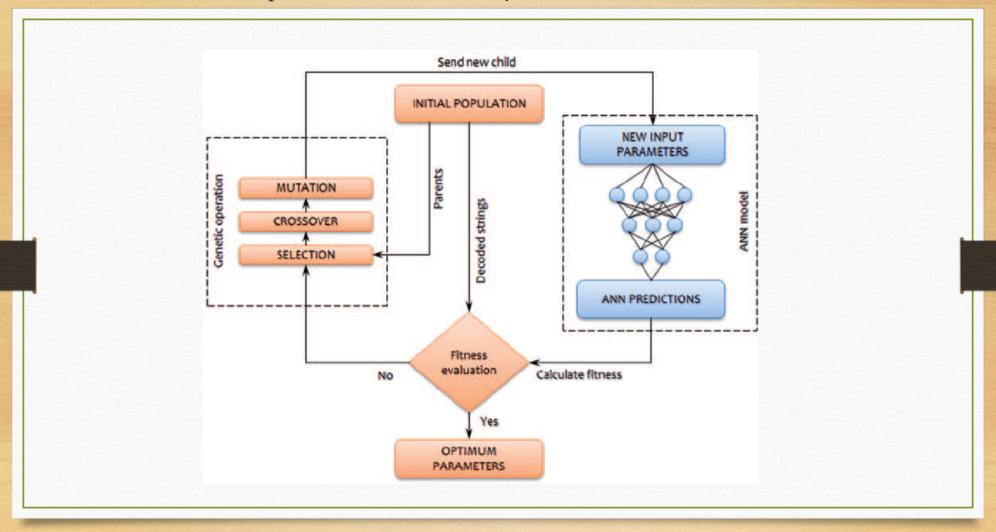


Example 4 Credit Card Fraud Detection





Example 5: Neuro-Genetic System



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