"111 Centre on Biological Computing and Artificial Intelligence" , Dalian University (DLU)

Advanced Artificial Intelligence Technologies and Applications

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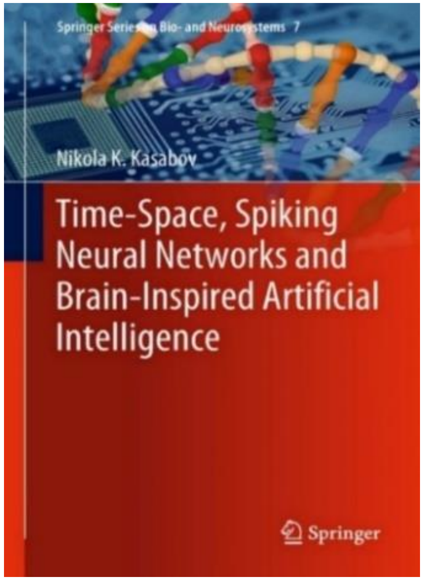
Advanced Artificial Intelligence Technologies and Applications

1. AI and the evolution of its principles. Evolving processes in Time and Space (Ch1, 3-19)
2. From Data and Information to Knowledge. Fuzzy logic. (Ch1,19-33 + extra reading)
3. Artificial neural networks - fundamentals. (Ch2, 39-48). Computational modelling with NN. Tut1: NeuCom.
4. Deep neural networks (Ch.2, 48-50 + extra reading).
5. Evolving connectionist systems (ECOS) (Ch2, 52-78). Tutorial 2: ECOS in NeuCom.
6. Deep learning and deep knowledge representation in the human brain (Ch3)
7. Spiking neural networks (Ch4). Evolving spiking neural networks (Ch5)
8. Brain-inspired SNN. NeuCube. (Ch.6). Tutorial 3: NeuCube software (IA)
9. Evolutionary and quantum inspired computation (Ch.7)
10. AI applications in health (Ch.8-11)
11. AI applications for computer vision (Ch.12,13)
12. AI for brain-computer interfaces (BCI) (Ch.14)
13. AI for language modelling. ChatBots (extra reading)
14. AI in bioinformatics and neuroinformatics (Ch15,16, 17,18)
15. AI applications for multisensory environmental data (Ch.19)
16. AI in finance and economics (Ch19)
17. Neuromorphic hardware and neurocomputers (Ch20).



Course book: N.Kasabov, Time-Space, Spiking Neural Networks and Brain-Inspired Artificial Intelligence Springer, 2019, https://www.springer.com/gp/book/9783662577134

Additional materials: https://www.knowledgeengineering.ai/china

N. Kasabov Foundations of Neural Networks, Fuzzy Systems, and Knowledge Engineering, MIT Press, 1996.
ZOOM link for all lectures: https://us05web.zoom.us/j/4658730662?pwd=eFN0eHRCN3o4K0FaZ0lqQmN1UUgydz09

Lecture 5.

Evolving connectionist systems (ECOS)

(Ch2, 52-78). Tutorial 2 on ECOS in NeuCom

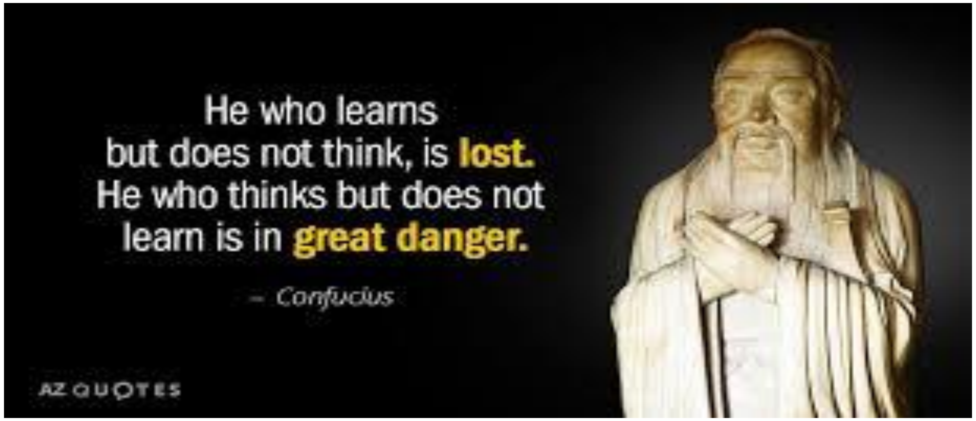
1. The strive for learning and knowledge in science
2. Principles of ECOS
3. EFuNN (Evolving fuzzy neural network) and ECF (evolving classification function)
4. DENFIS (Dynamic evolving neuro-fuzzy inference system)

5. Developing ECOS applications in NeuCom (Tutorial 2, Ms Iman AbouHassan)

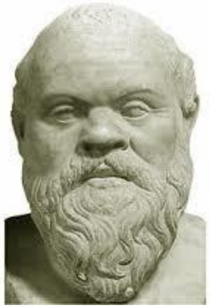
6. Questions for individual work

1. The strive for learning and knowledge

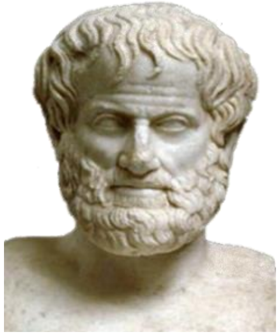
Confucius (551-479 BC)



Socrates (399 BC) "*An unexamined life is not worth living….One thing only I know, and that is that I know nothing…*



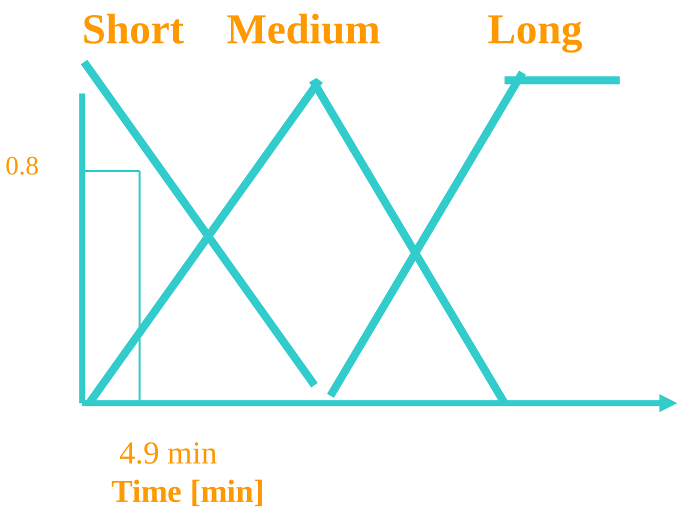
Aristotle (384-322 BC, e*pistemology: The* study of particular phenomena which leads to the articulation of new knowledge (rules, formulas).



Fuzzy logic and fuzzy knowledge

- Fuzzy logic (1965) represents information uncertainties and tolerance in a linguistic form (Lotfi Zadeh (1920-2018)
  - fuzzy rules, containing fuzzy propositions;
  - fuzzy inference
- Fuzzy propositions can have truth values between true (1) and false (0), e.g. the proposition "washing time is short" is true to a degree of 0.8 if the time is 4.9 min, where *Short* is represented as a *fuzzy set* with its *membership function*
- Fuzzy rules can be used to represent human knowledge and reasoning, e.g.

  "IF wash load is small THEN washing time is short".
- Fuzzy inference systems: Calculate outputs based on inpu data an a set of fuzzy rules
- Contributions from: T.Yamakawa, L.Koczy, I.Rudash and many others



Fuzzy rules can be learned in NN and extracted as new knowledge, which is the goal of the ECOS development.

2. ECOS principles (section 2.3)

- Evolving Connectionist Systems (ECOS) are systems that **develop their structure, their functionality and their internal knowledge representation** through continuous learning from data and interaction with the environment.
-
- ECOS can also evolve through generations of populations using evolutionary computation, but the focus of the tutorial is on the adaptive learning and improvement of each individual system.
- The learning process can be: on-line, off-line, incremental, supervised, unsupervised, active, sleep/dream, etc.
- Evolving features, e.g. incremental feature selection
- The emphasis though is on the knowledge engineering aspect of the systems, ie how to represent human knowledge in a system and to extract interpretable information that can be turned into knowledge.

N. Kasabov (2007), Evolving Connectionist Systems: The Knowledge Engineering Approach (2nd ed.), Springer-Verlag, London, England, 2007.

Learning methods in ECOS

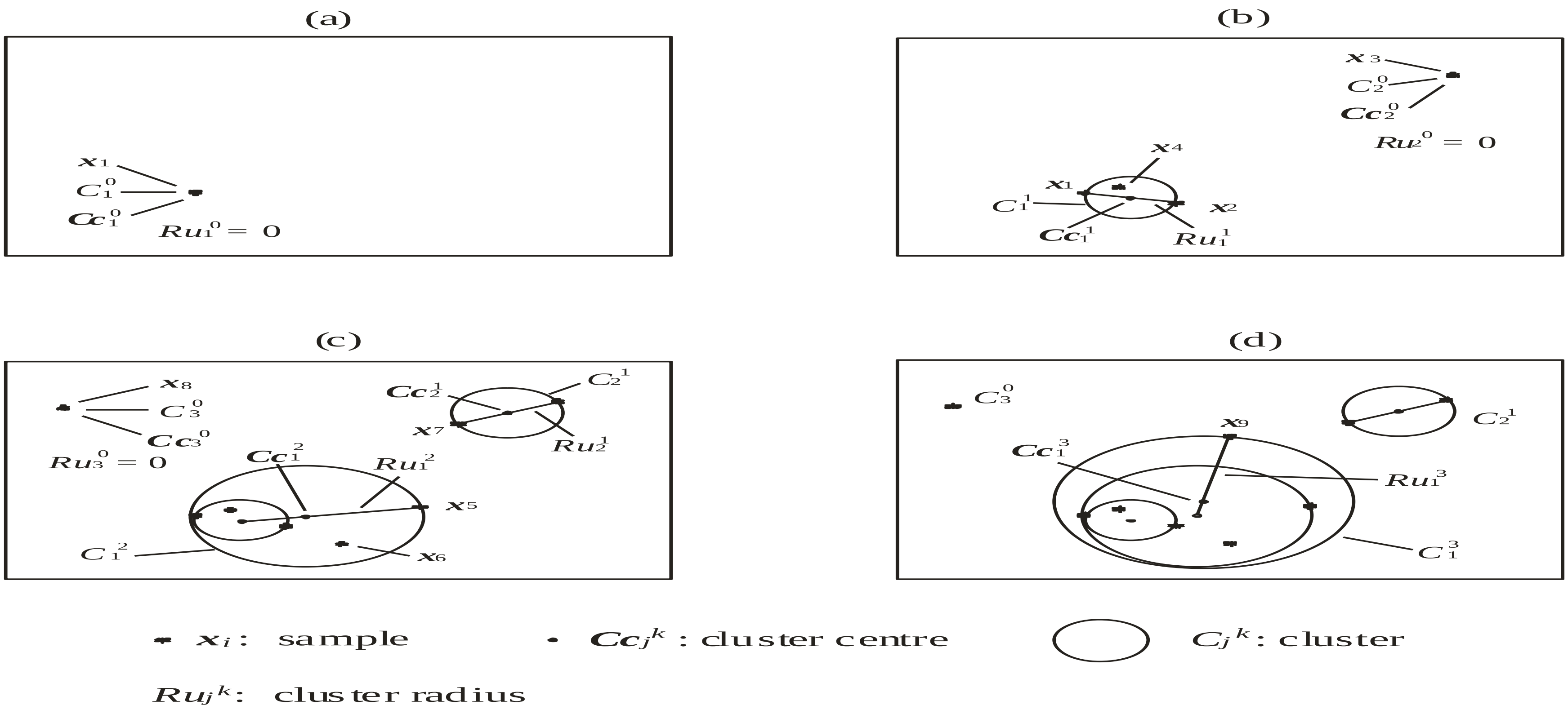
- Batch-mode learning: A model is created on existing data for all existing tasks and not adapted to new data or new tasks.

- Incremental learning (IL): A model is created on existing data for existing tasks and it can continuously learn new data for the same tasks or/and new tasks.

- Transfer learning (TL): A type of IL, where a model is created on existing data for existing tasks and it can continuously learn new data and new tasks by partially utilising previously learned knowledge.

- Knowledge transfer: The partial transfer of knowledge learned in a system from data at one period of time ("old" knowledge), to the knowledge learned in the system from data at a next period of time ("new" knowledge).

Local learning based on clustering of input (or input-output) vectors and learning local models



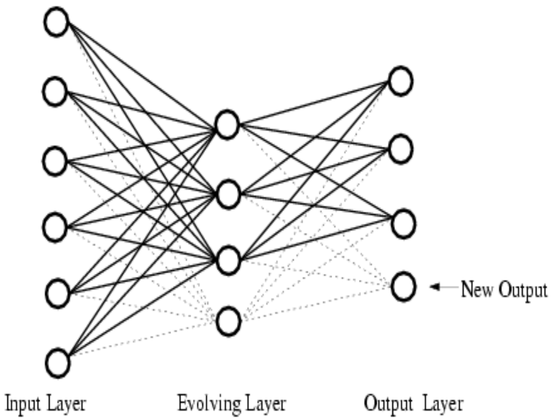
An evolving clustering process using ECM with consecutive examples x1 to x9 in a 2D space (Kasabov and Song, DENFIS, IEEE Tr FS, 2002)

Simple ECOS (section2.4, Box 2.4)

- Hidden nodes evolve, starting from no nodes at all.
- Each hidden node is a cluster center.
- Clusters grow in radius and shrink through a learning algorithm
- Each hidden node represents a local model (a rule) that associates an input cluster with an output function, e.g. a constant label, a linear function, a non-linear function, etc
- If a new input vector belongs to a cluster to certain degree, than the corresponding local model applies, otherwise – m of the closest models are used to calculate the output.
- Incremental **supervised clustering** with new input vectors **x**
- First layer of connections: $W1(r_j(t+1))=W1(r_j(t)) + lj.\ D(\mathbf{x}, W1(r_j(t)))$
- Second layer: $W2(r_j(t+1)) = W2(r_j(t)) + lj.\ (\mathbf{y} - A2).\ A1(r_j(t))$,

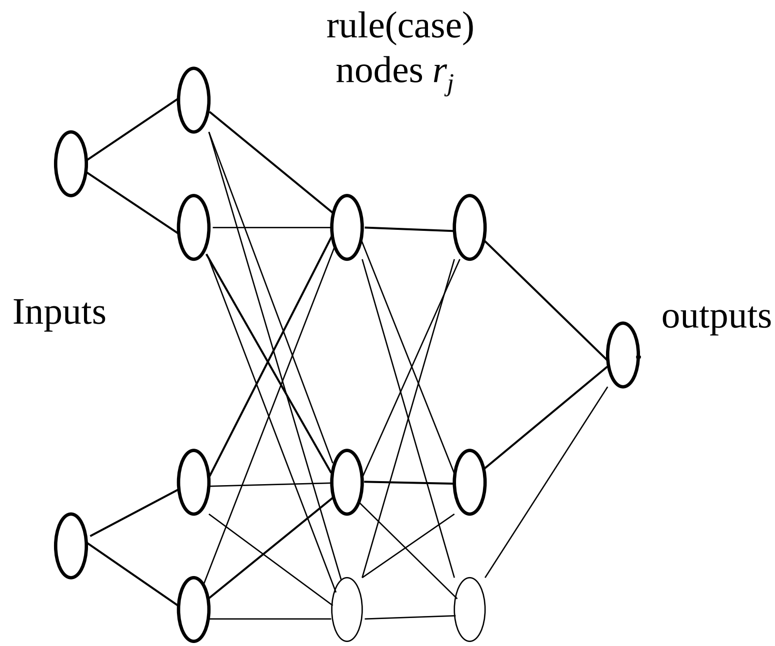
where: r_j is the jth rule node (hidden node); D – distance; A2=f2(W2.A1) is the activation vector of the output neurons when **x** is presented;

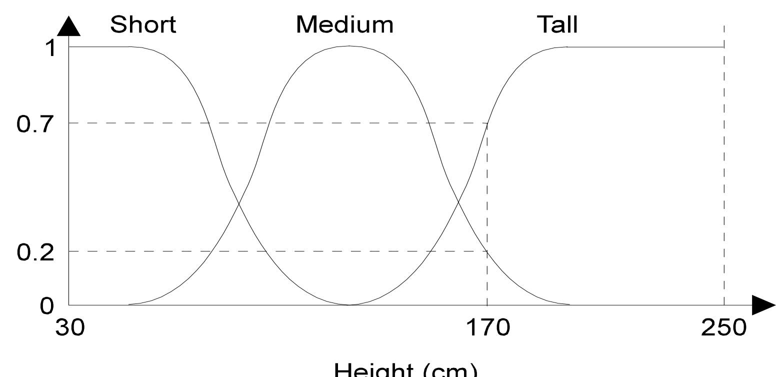
- $A1(r_j(t)) = f2(D(W1(r_j(t)), \mathbf{x}))$ is the activation of the rule node $r_j(t)$;
- a simple linear function can be used for f1 and f2, e.g. $A1(rj(t)) = 1 - D(W1(r_j(t)), \mathbf{x})$;
- lj is the current learning rate of the rule node r_j calculated for example as $lj = 1/Nex(r_j)$, where $Nex(r_j)$ is the number of examples associated with rule node r_j.



3. **Evolving fuzzy neural networks (EFuNN)**

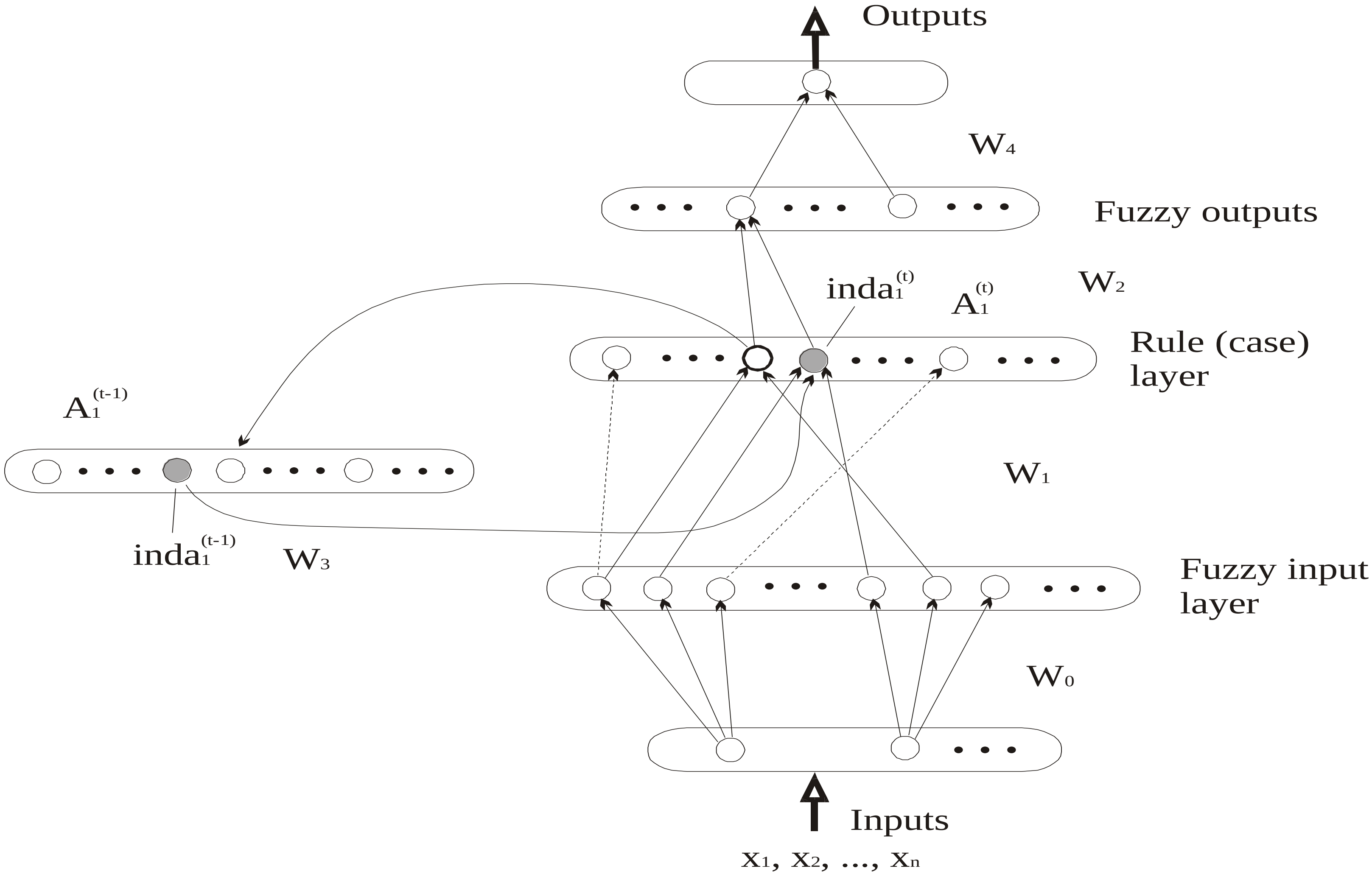
- Hidden nodes evolve, starting from no nodes at all to capture clusters of input data in a *supervised way, e.g. data from the same class are clustered together* .
- Each hidden node is a cluster center.
- Clusters grow in radius and shrink through a learning algorithm
- Each hidden node represents a local model (a rule) that associates an input cluster with an output function, e.g. a constant label, a linear function, a non-linear function, etc
- If a new input vector belongs to a cluster to certain degree, than the corresponding local model applies, otherwise – m of the closest models are used to calculate the output.
- As a general case input and/or output variables can be fuzzy or non-fuzzy (crisp)
- ECF – evolving classifier function – no output MF, only input MF.
- ECF parameters: Rmax, Rmin, #input MF (e.g. 1,2,3,...), m-of-n (e.g. 1,2,3,..), #iterations for training (e.g. 1,2,3, …





N. Kasabov (2001), Evolving Fuzzy Neural Networks for On-Line Supervised/ Unsupervised, Knowledge–Based Learning. IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics, **6** (vol.31), 2001, pp. 902-918.

An EFuNN architecture with a feedback connection



EFuNN

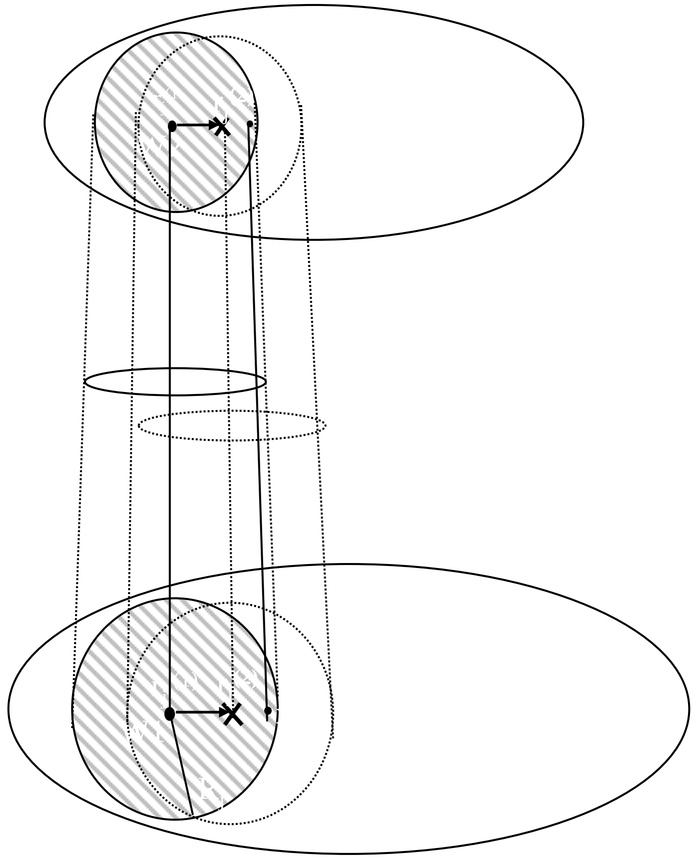
- Incremental supervised clustering
- First layer of connections:

  $W1(r_j(t+1))=W1\ (r_j(t)) + lj.\ D\ (W1(r_j(t))\ ,\ \mathbf{x}f)$
- Second layer:

  $W2\ (r_j(t+1)\ ) = W2(r_j(t)) + lj.\ (A2 - \mathbf{y}f).\ A1(r_j(t))$,

  where:

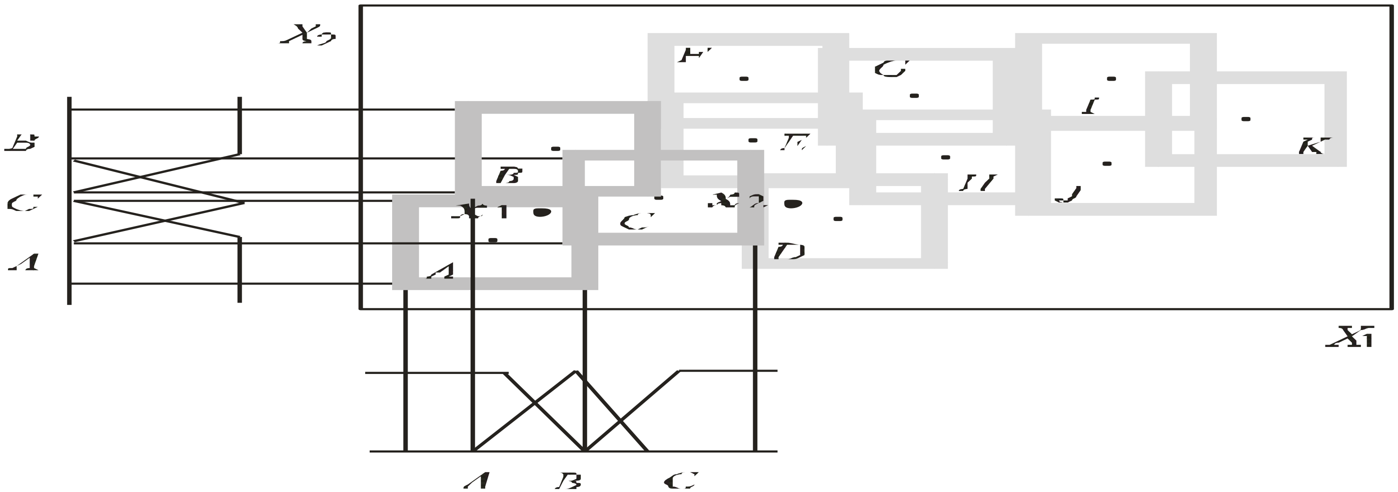
- r_j is the jth rule node (hidden node);
- D – distance – fuzzy or Euclidean (normalised)
- A2=f2(W2.A1) is the activation vector of the fuzzy output neurons in the EFuNN structure when **x** is presented;
- $A1(r_j(t)) = f2\ (D\ (W1\ (r_j(t))\ ,\ xf))$ is the activation of the rule node r_j (t); a simple linear function can be used for f1 and f2, e.g. $A1(rj(t)) = 1 - D\ (W1\ (r_j(t))\ ,\ \mathbf{x}f))$;
- lj is the current learning rate of the rule node r_j calculated for example as $lj = 1/\ Nex(r_j)$, where $Nex(r_j)$ is the number of examples associated with rule node r_j.



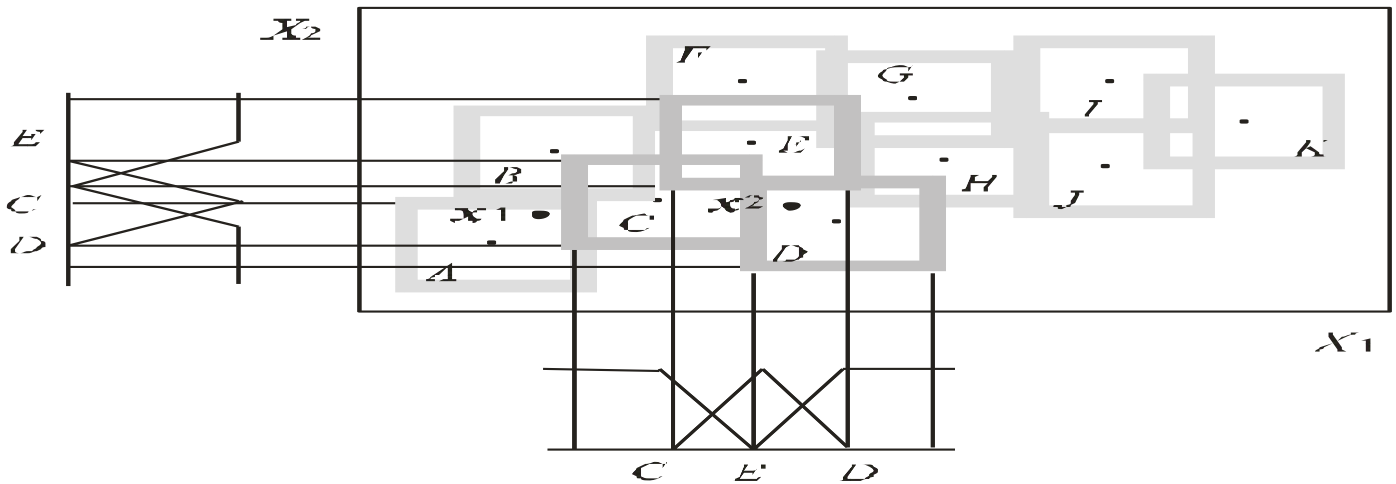
4. DENFIS

Learning and Inference in DENFIS

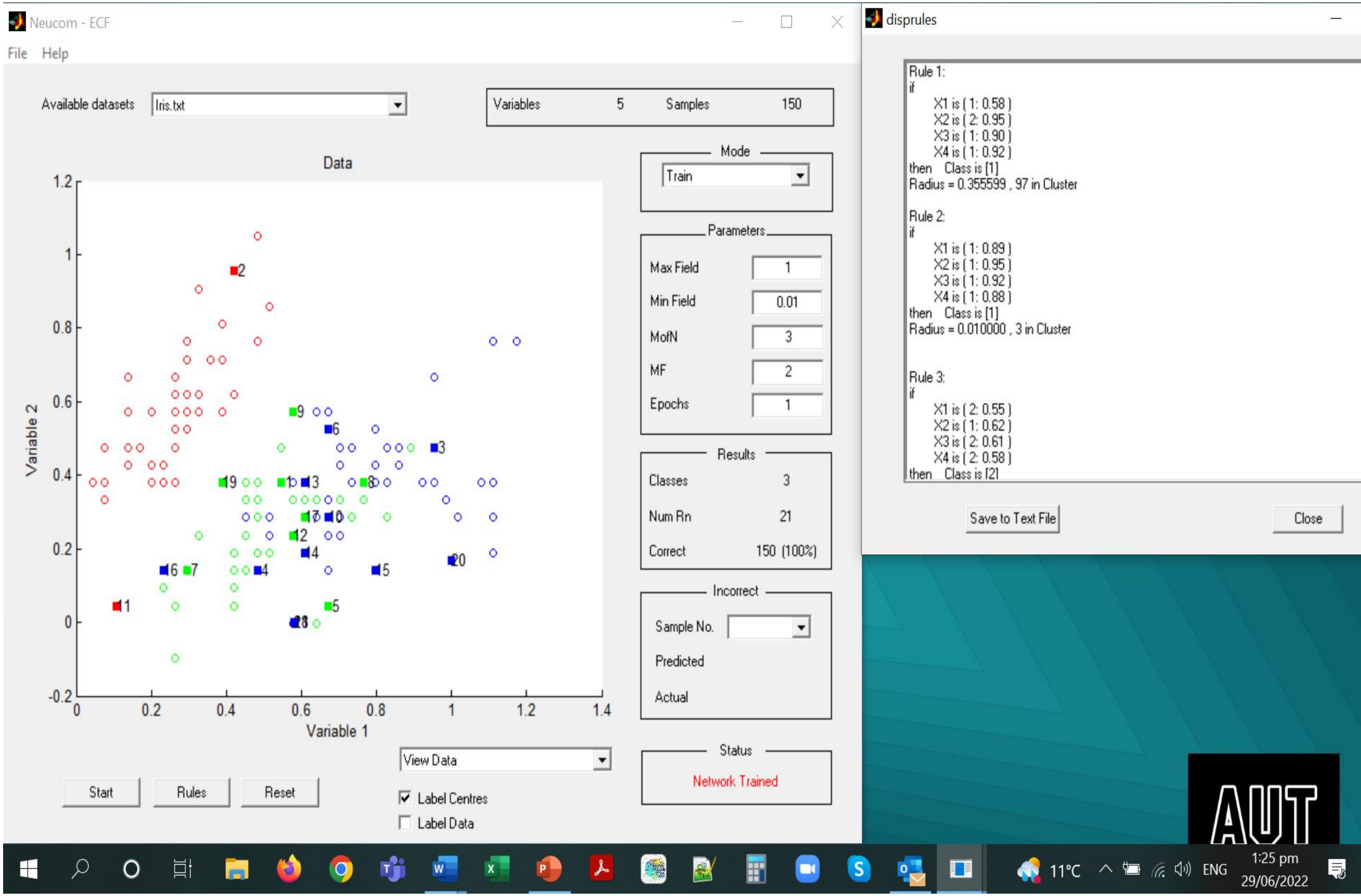
(a) Fuzzy rule group 1 for a DENFIS



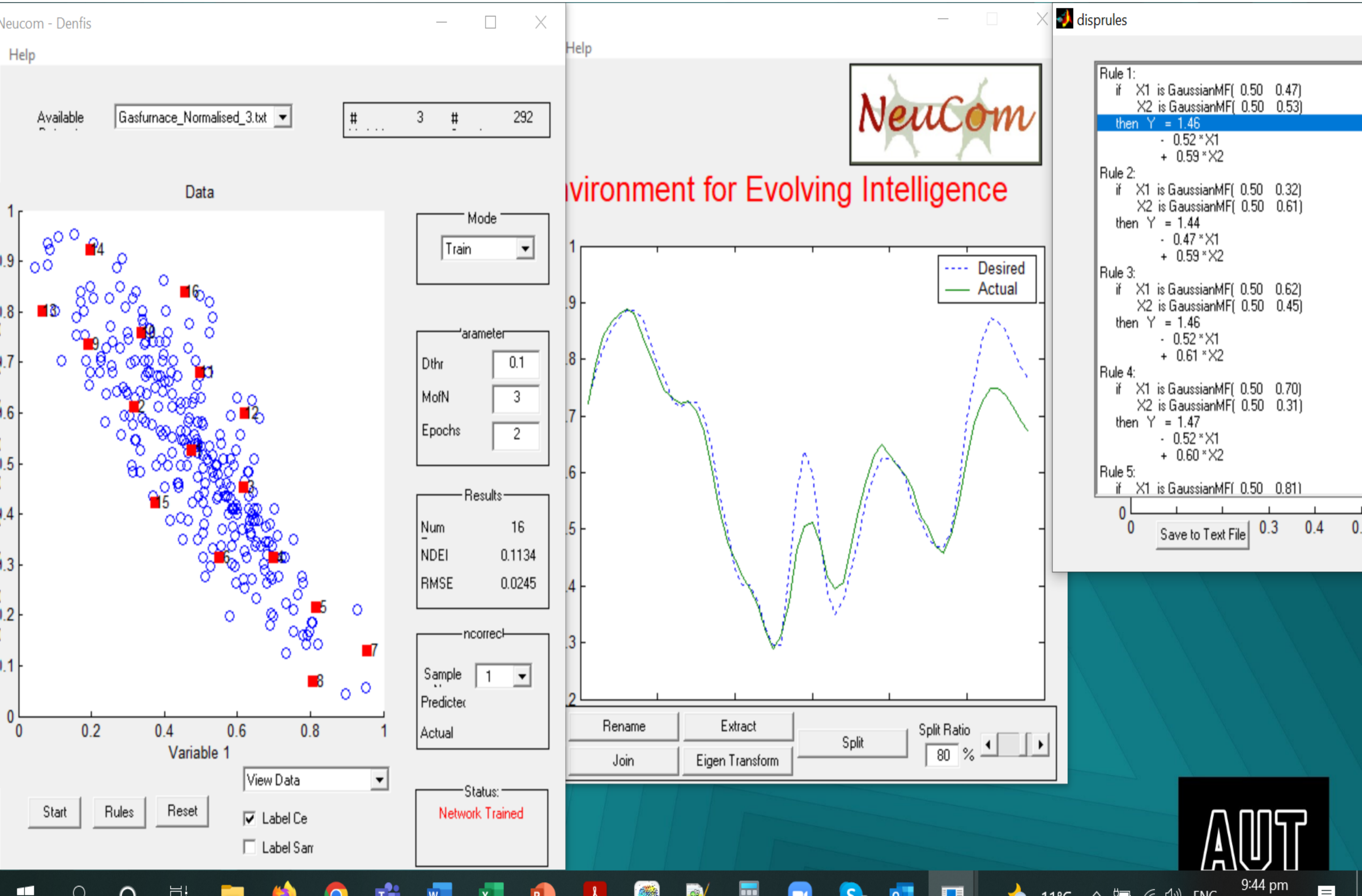
(b) Fuzzy rule group 2 for a DENFIS



Evolving rule extraction from a trained EFuNN



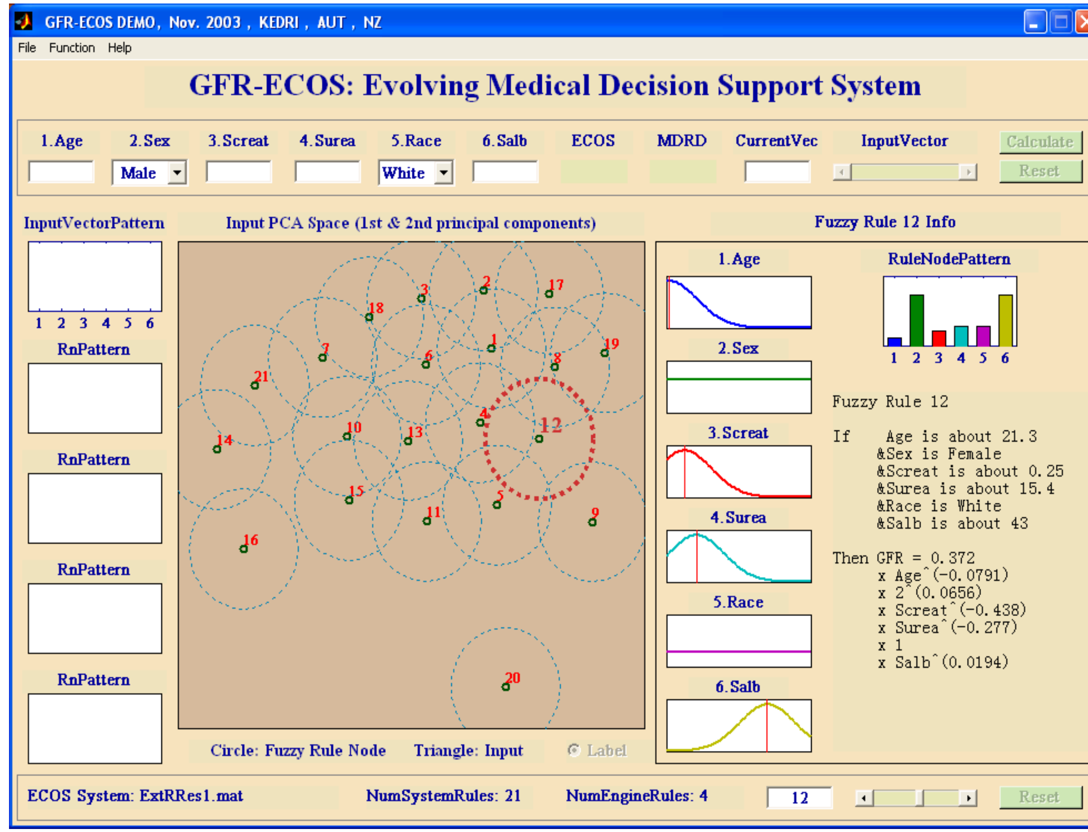
During IL rules can be extracted at each phase of learning and they overlap (TL)



Example: Local, adaptive GFR Renal Function Evaluation System based on DENFIS – Fig.2.18

Marshal, Song, Ma, McDonell and Kasabov, Kidney International, May 2005)

- A real data set from a medical institution is used here for experimental analysis (M. Marshal et al, 2005) The data set has 447 samples, collected at hospitals in New Zealand and Australia.
- Each of the records includes six variables (inputs):
  - age,
  - gender,
  - serum creatinine,
  - serum albumin,
  - race and
  - blood urea nitrogen concentrations,
  - output - the glomerular filtration rate value (GFR).

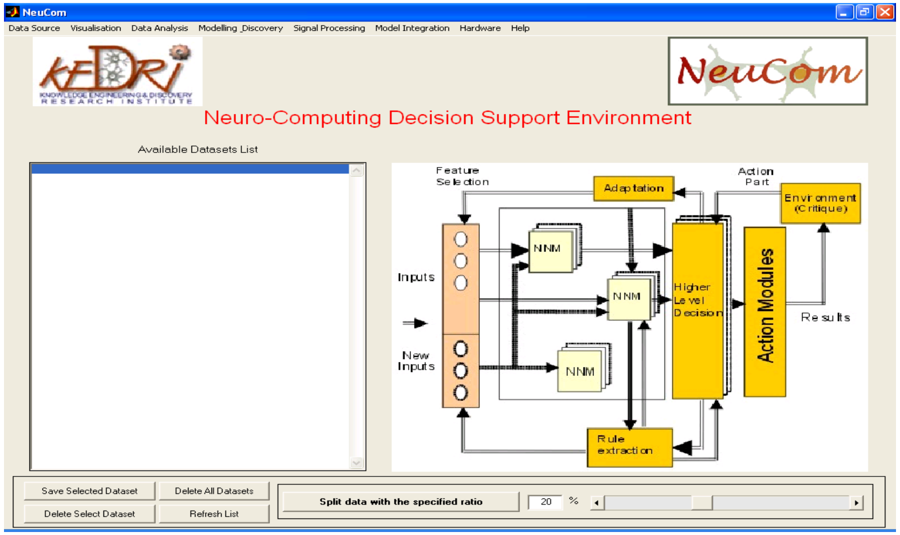


5. Developing ECOS Applications in NeuCom (www.theneucom.com) (Tutorial by Ms Iman AbouHassan)

Computational modelling with NN:

- Data preparation;
- Feature ranking and feature selection;
- NN methods for classification;
- NN methods for regression (time series prediction);
- NN methods for explanation (rule extraction; knowledge discovery);

- NeuCom is a generic environment, that incorporates 60 traditional and new techniques for intelligent data analysis and the creation of intelligent systems
- A free copy available for education and research from: www.theneucom.com



Course References

1. N.Kasabov, Time-Space, Spiking Neural Networks and Brain-Inspired AI, Springer 2019 (course book).
2. N. Kasabov Foundations of Neural Networks, Fuzzy Systems, and Knowledge Engineering, MIT Press, 1996 (additional reading)
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16. Kasabov, Nikola; Tan, Yongyao Tan; Doborjeh, Maryam; Tu, Enmei; Yang, Jie (2023): Transfer Learning of Fuzzy Spatio-Temporal Rules in the NeuCube Brain-Inspired Spiking Neural Network: A Case Study on EEG Spatio-temporal Data. TechRxiv. Preprint. https://techrxiv.org), https://doi.org/10.36227/techrxiv.21781103.v1, licence CC BY 4.0)
17. Nikola K. Kasabov, Iman AbouHassan, Vinayak G.M. Jagtap, Parag Kulkarni, Spiking neural networks for predictive and explainable modelling of multimodal streaming data on the Case Study of Financial Time Series Data and on-line news, SREP, Nature, pre-print on the Research Square, DOI: https://doi.org/10.21203/rs.3.rs-2262084/v1, licence CC BY 4.0,

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6. Questions, exercises, assignments and project work

1. What are the main principles of ECOS?
2. What is the EFuNN and how rules can be extracted from data?
3. What is DENFIS and how rules can be extracted from data?
4. How do you develop an ECOS application in NeuCom?

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