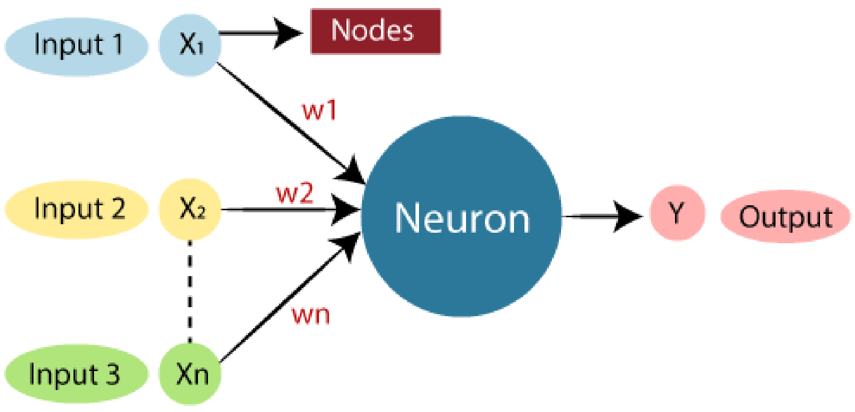
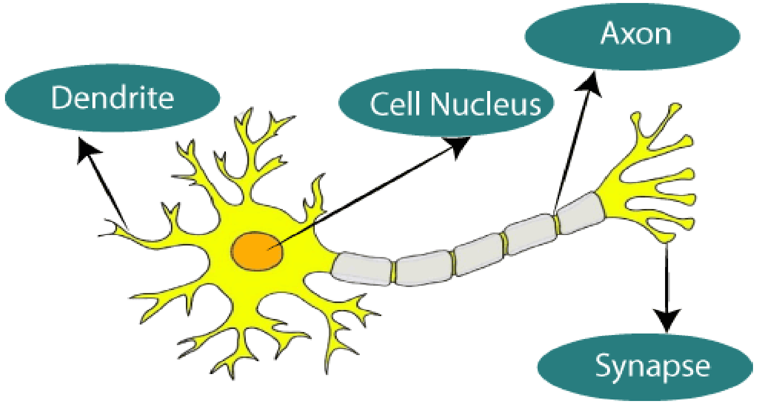
Artificial Neural Networks

- ANN is composed of input and output layers, and one or more hidden layers containing many interconnected neurons.
- ANN is a machine learning process that uses interconnected neurons in a layered structure similar to the human brain.
- ANN is a universal computational model that mimics the human brain in its main function of adaptive learning.
- ANN is an artificial intelligence technology that teaches computers to learn from data and make generalizations.

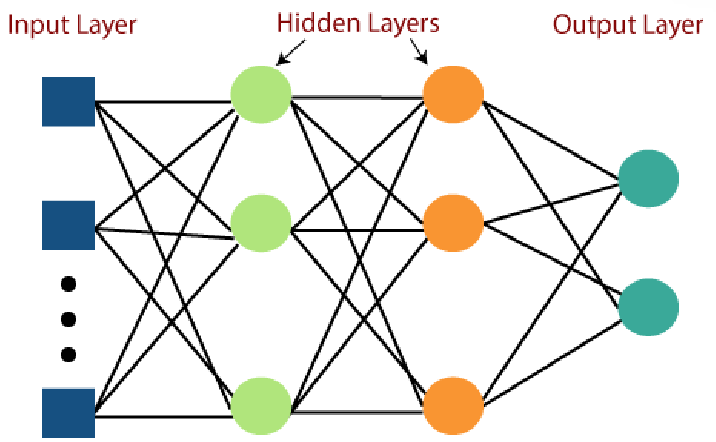


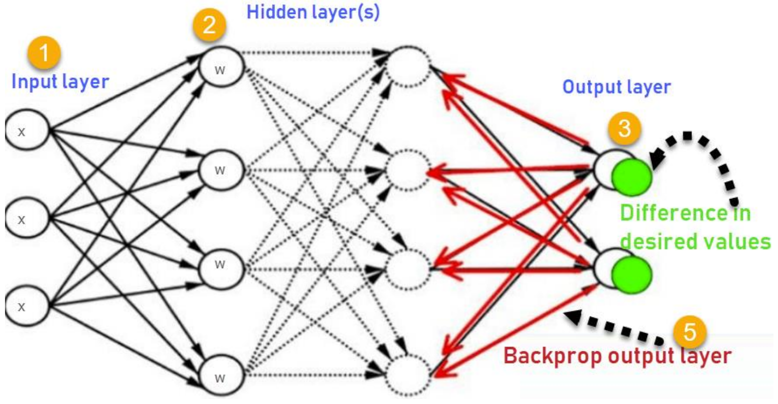


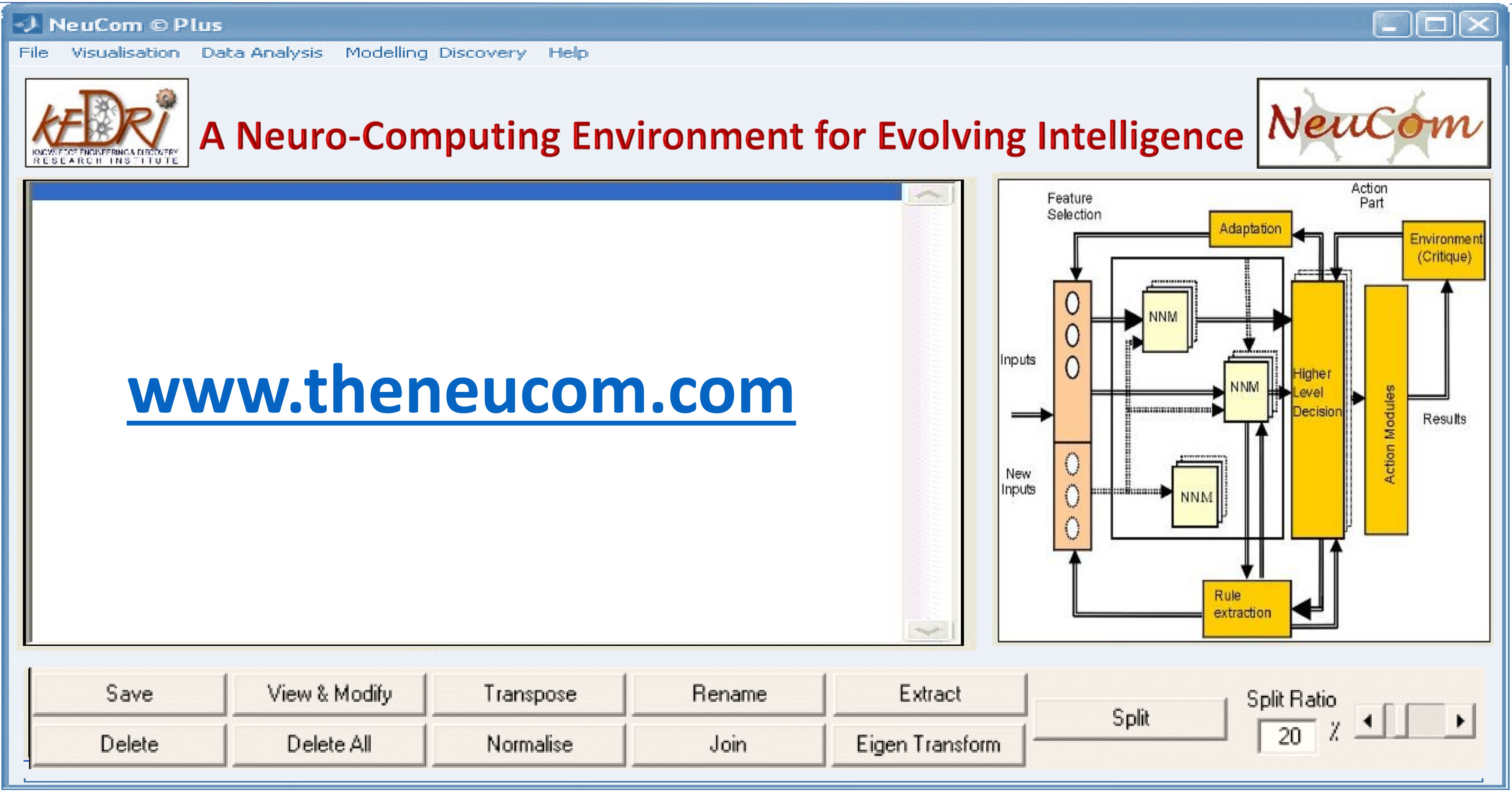
https://www.javatpoint.com/artificial-neural-network

Multi-Layer Perceptrons (MLP)

- MLP is a type of **Artificial Neural Network** that can learn a **non-linear function** that maps inputs to outputs based on a labeled training dataset.
- MLP is a **feed-forward network** that is trained using a **backpropagation** algorithm.
- MLP is a **deep learning** method that can be applied to a wide range of **supervised** learning problems, such as classification, regression, and pattern recognition
- MLP may learn to **discriminate** or approximate data based on the output labels, by **adjusting the weights** in the network during training to **minimize the difference** between predicted and actual output. After trained, MLP may be used to predict the output label for new input data.



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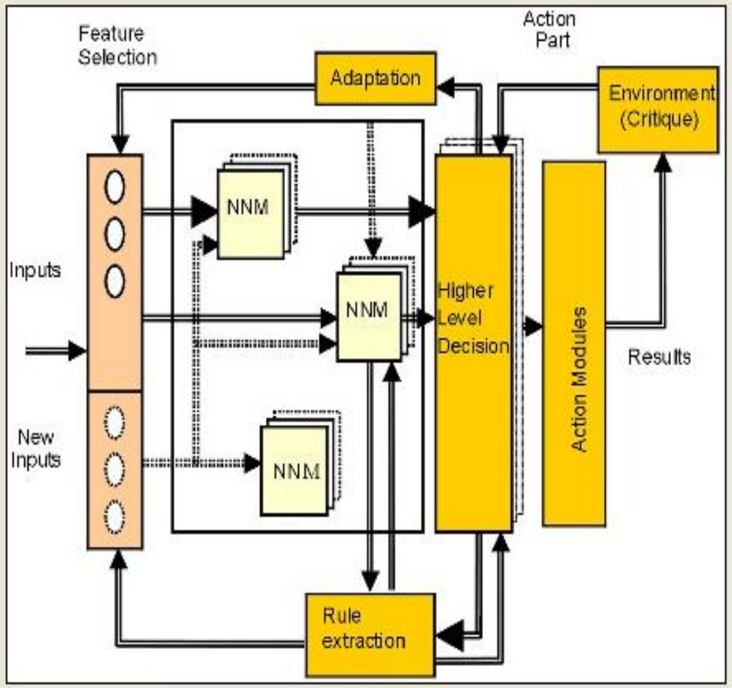
A Neuro-Computing Environment for Evolving Intelligence

- NeuCom is a generic modular open architecture for fast data analysis, fast model prototyping, data development, patterns learning, knowledge discovery, and visualization.
- NeuCom algorithms use traditional and novel techniques for intelligent data analysis and system development.
- NeuCom software provides computational methods for classification, regression, and pattern recognition.
- NeuCom is used worldwide, www.theneucom.com offers a free copy for research purposes.



Save | View & Modify | Transpose | Rename | Extract | Split | Split Ratio 20 %
Delete | Delete All | Normalise | Join | Eigen Transform

NeuCom Modules

- data collection
- data pre-processing
  - normalization
  - filling missing values, …
- data visualization
  - 2D
  - 3D
  - PCA
  - surface plot, …
- Data analysis
  - correlation
  - signal to noise ratio,
  - Clustering: k-means, hierarchical-, evolving-.
- modelling and rule discovery
  - classification
  - prediction
  - optimisation
  - Cross Validation
- Documentation and online help.

Modelling and Rule Discovery

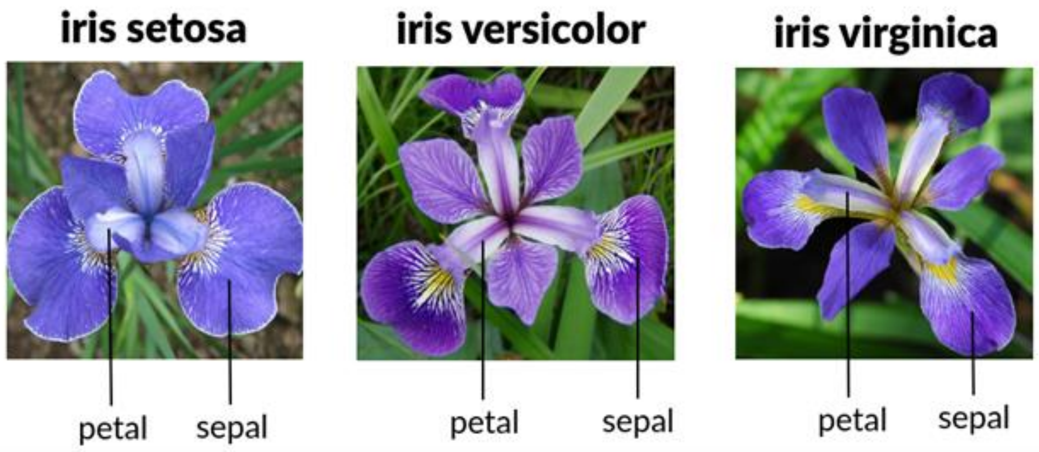
- **classification**
  - Traditional Statistical Methods
    - MLR Multiple Linear Regression
    - SVM Support Vector Machine
  - Classical Neural Network Methods
    - MLP Multi-Layer Perceptron
    - RBF Radial Basis Function
  - ECOS Evolving Connectionist Methods and Systems
    - ECF Evolving Classification Function
    - ECMC Evolving Clustering Method for Classification
- **prediction**
  - Traditional Statistical Methods
    - MLR Multiple Linear Regression
    - LR Logarithmic Regression
    - KNN K-Nearest Neighbour
  - Classical Neural Network Methods
    - MLP Multi-Layer Perceptron
    - RBF Radial Basis Function
  - ECOS Evolving Connectionist Methods and Systems
    - DENFIS Dynamic Evolving Neuro-Fuzzy Inference System
    - EFuNN Evolving Fuzzy Neural networks
- **parameter optimisation**
  - Genetic Algorithm
  - Generic Evolutionary Strategy
  - Genetic Algorithm for ECF optimization
  - Evolutionary Strategy for ECF optimization

MLP Classification Model: IRIS Flower Dataset

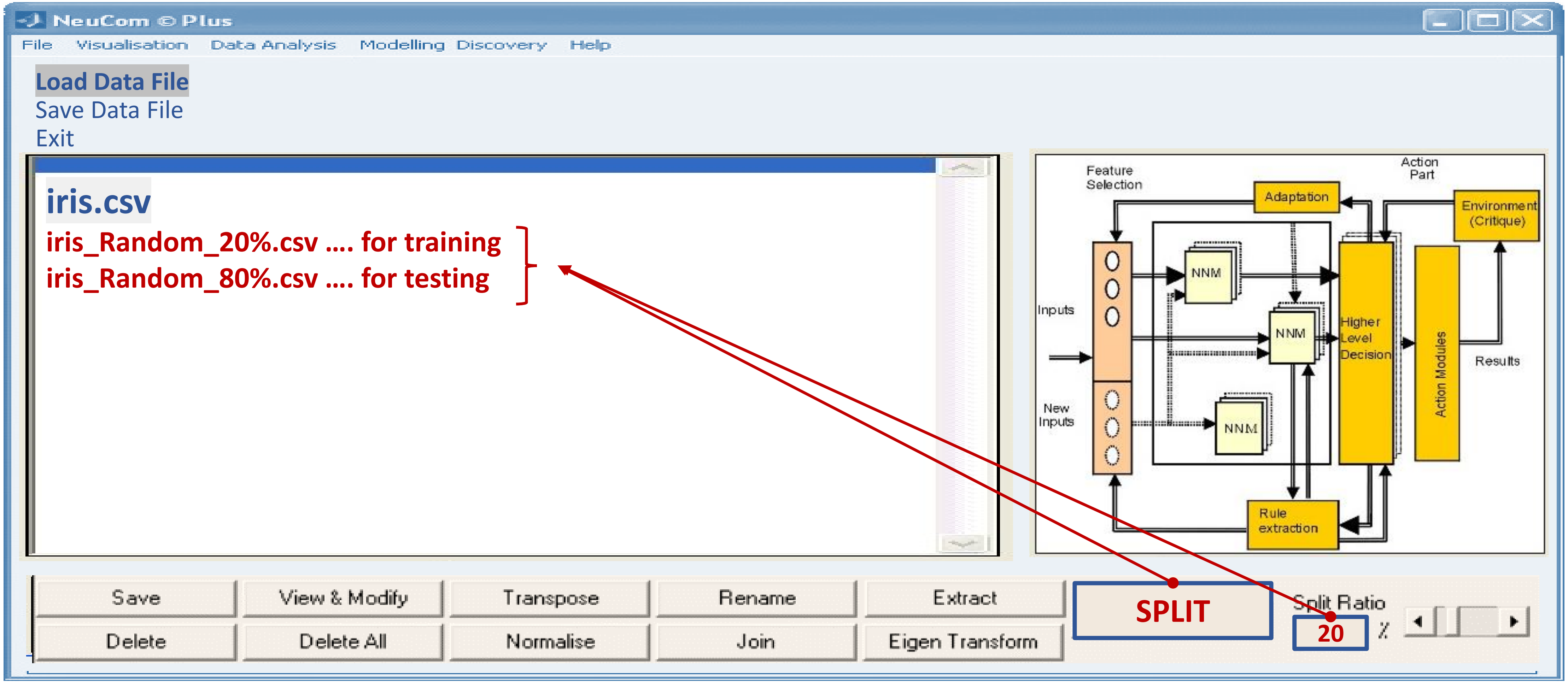
- The Iris flower dataset is widely used in machine learning and pattern recognition. It includes measurements of the sepal length/width and petal length/width of 150 samples of iris flowers, 50 samples from each of three different species: Iris setosa, Iris versicolor, and Iris virginica.
- Each sample in the dataset is labeled with the iris flower species, making this a supervised learning problem. The objective is to design an MLP model that can predict the species of an iris flower given its measurements.

MLP Classification Model: IRIS Flower Dataset

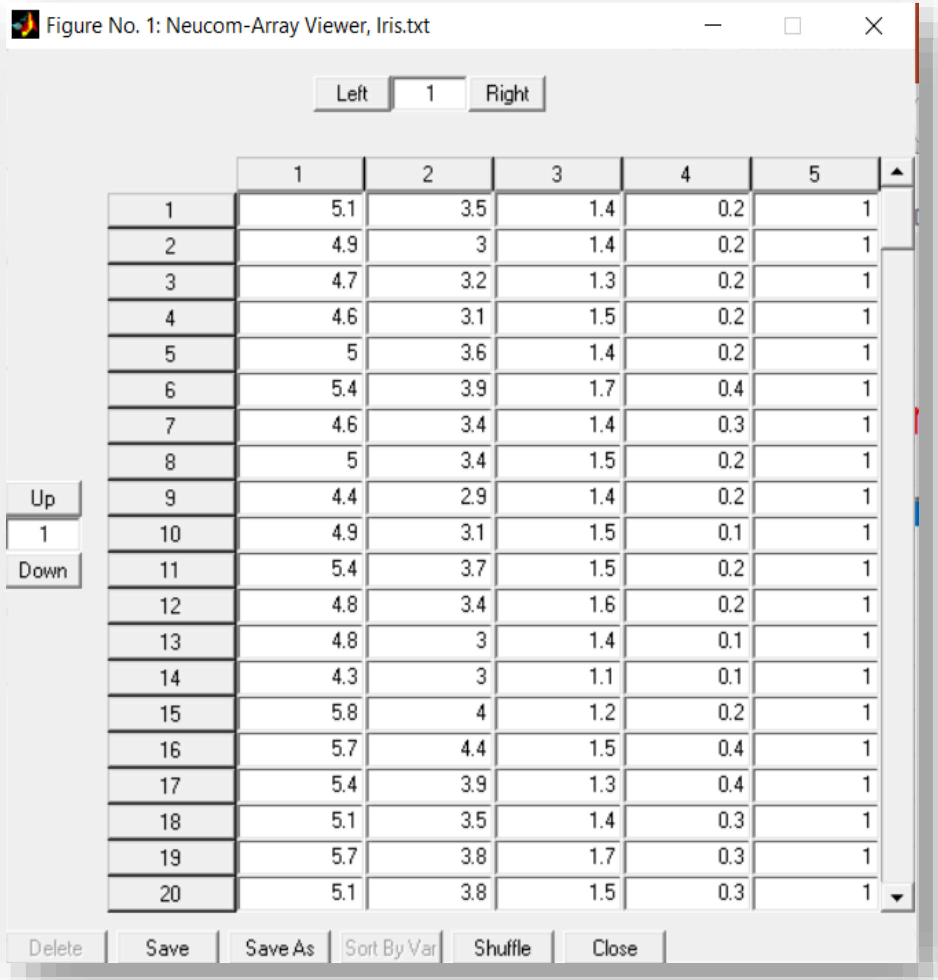
- Iris time series dataset consists of **150 iris plants.**
- **Four Features**: sepal length/width, petal length/width.
- **Three Classes**: Setosa, Versicolor, and Virginica.
- Iris dataset modelling for **classification.**
- Modelling method: **MLP**.
- Iris dataset **split** 20/80 training-learning ratio.



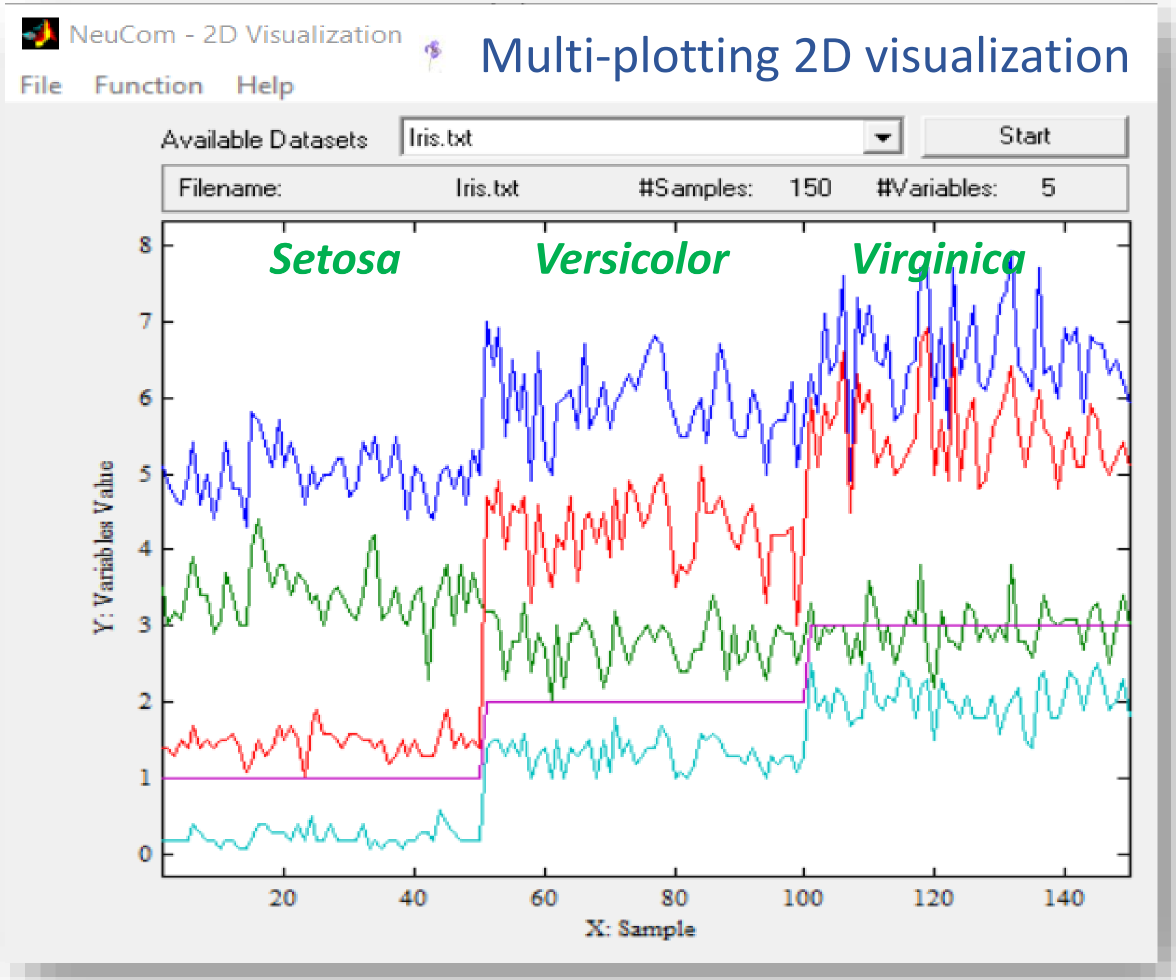
MLP Classification Model: Data Loading



MLP Classification Model: Input and Visualisation

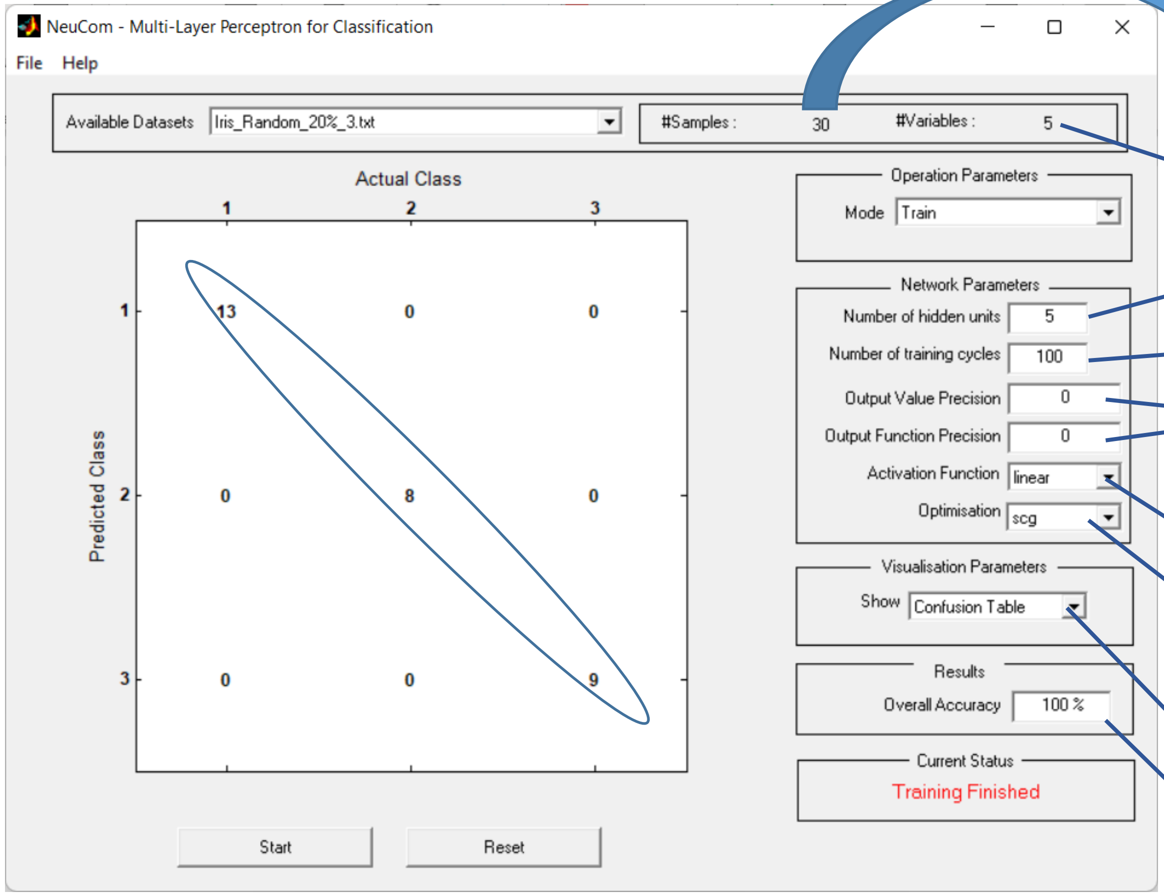


	1	2	3	4	5
1	5.1	3.5	1.4	0.2	1
2	4.9	3	1.4	0.2	1
3	4.7	3.2	1.3	0.2	1
4	4.6	3.1	1.5	0.2	1
5	5	3.6	1.4	0.2	1
6	5.4	3.9	1.7	0.4	1
7	4.6	3.4	1.4	0.3	1
8	5	3.4	1.5	0.2	1
9	4.4	2.9	1.4	0.2	1
10	4.9	3.1	1.5	0.1	1
11	5.4	3.7	1.5	0.2	1
12	4.8	3.4	1.6	0.2	1
13	4.8	3	1.4	0.1	1
14	4.3	3	1.1	0.1	1
15	5.8	4	1.2	0.2	1
16	5.7	4.4	1.5	0.4	1
17	5.4	3.9	1.3	0.4	1
18	5.1	3.5	1.4	0.3	1
19	5.7	3.8	1.7	0.3	1
20	5.1	3.8	1.5	0.3	1



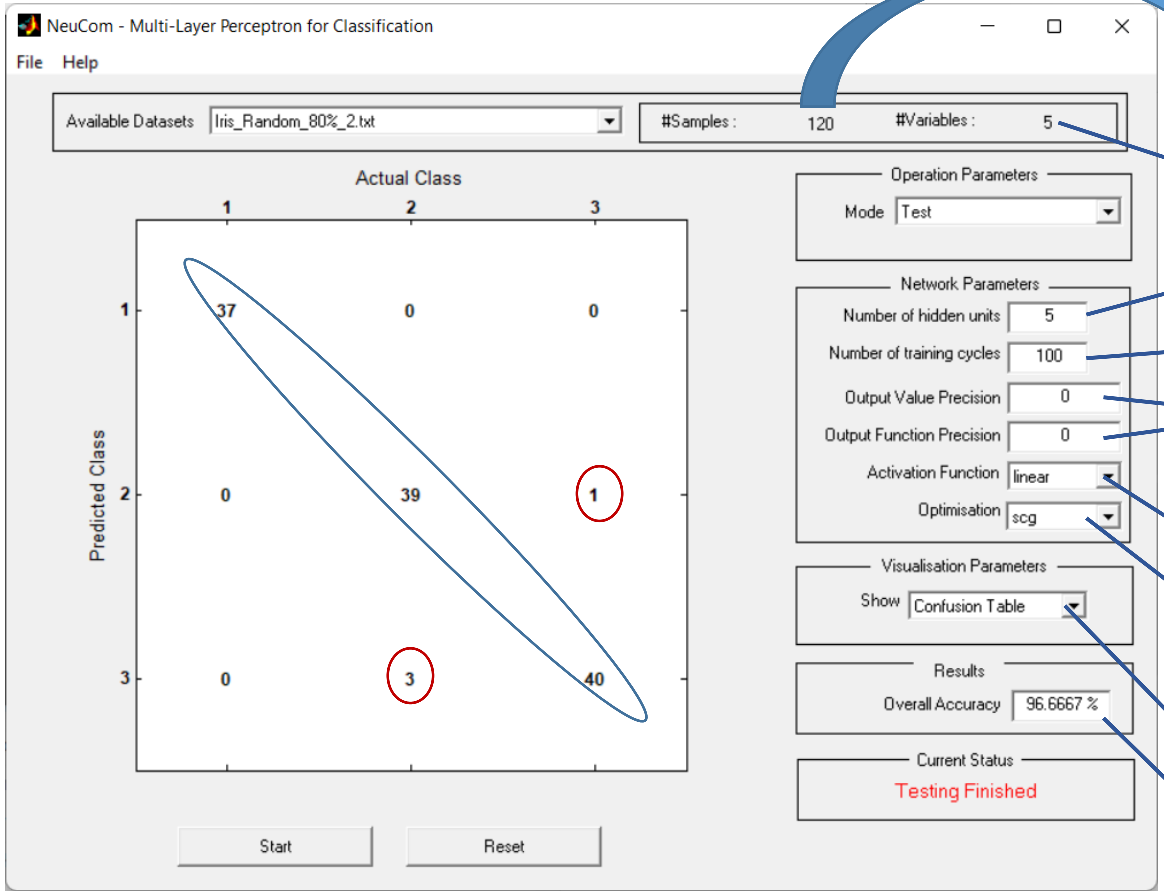
sepal_length
sepal_width
petal_length
petal_width

MLP Classification Model: Parameters, Modelling and Analysis



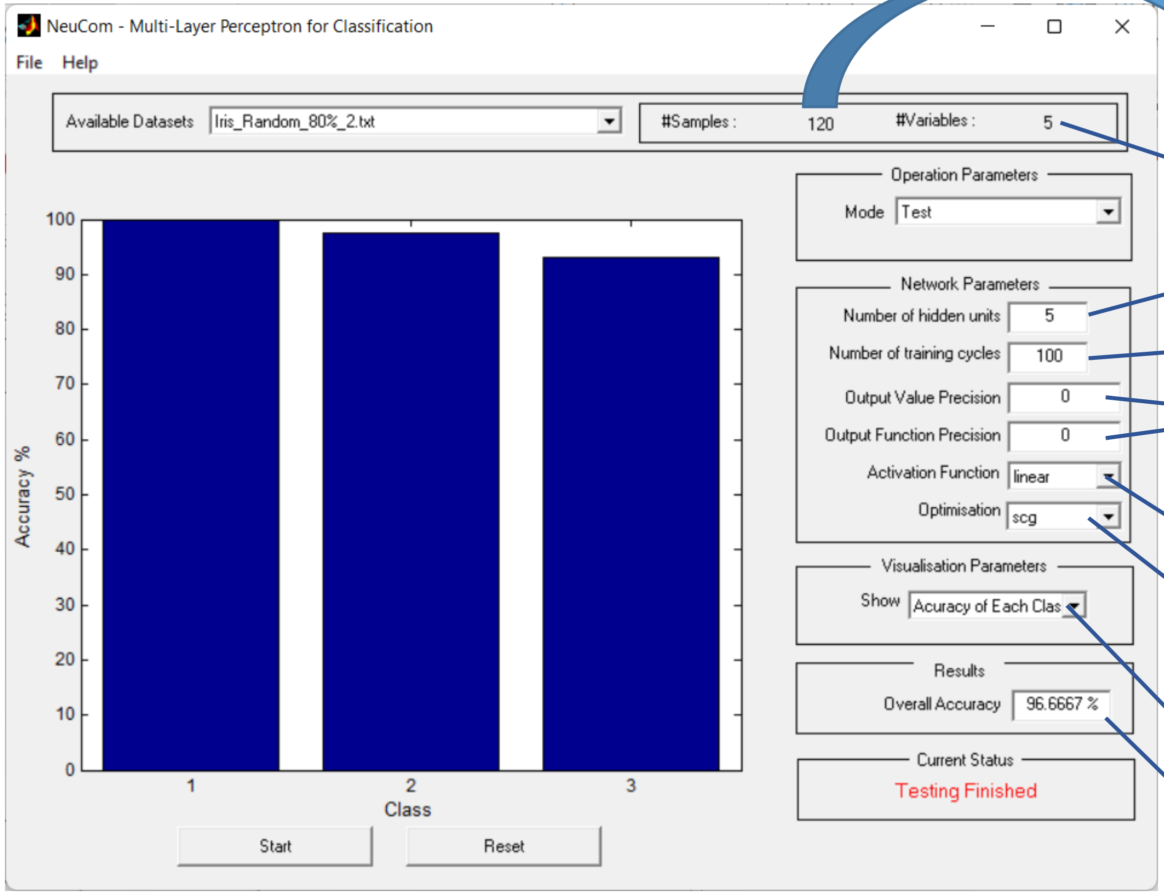
- Number of observations for training
- Number of inputs (4) and outputs (1 class)
- Specify number of hidden nodes
- Specify the max number of Iterations.
- Specify the absolute precision required for the output value & output function in both optimizations.
- MLP model uses linear output activation function
- MLP model uses scaled conjugate gradient optimization or quasi-newton optimization
- Confusion table; Accuracy for each class; and Learning rate.
- Overall Model's Accuracy.

MLP Classification Model: Parameters, Modelling and Analysis



- Number of observations for testing
- Same number of inputs (4) and outputs (1 class)
- Same number of hidden nodes
- Same max number of Iterations.
- Same absolute precision for output value & output function in both optimizations.
- MLP model uses linear output activation function
- MLP model uses scaled conjugate gradient optimization or quasi-newton optimization
- Confusion table; Accuracy for each class; and Learning rate.
- Overall Model's Accuracy = **97%**.

MLP Classification Model: Parameters, Modelling and Analysis

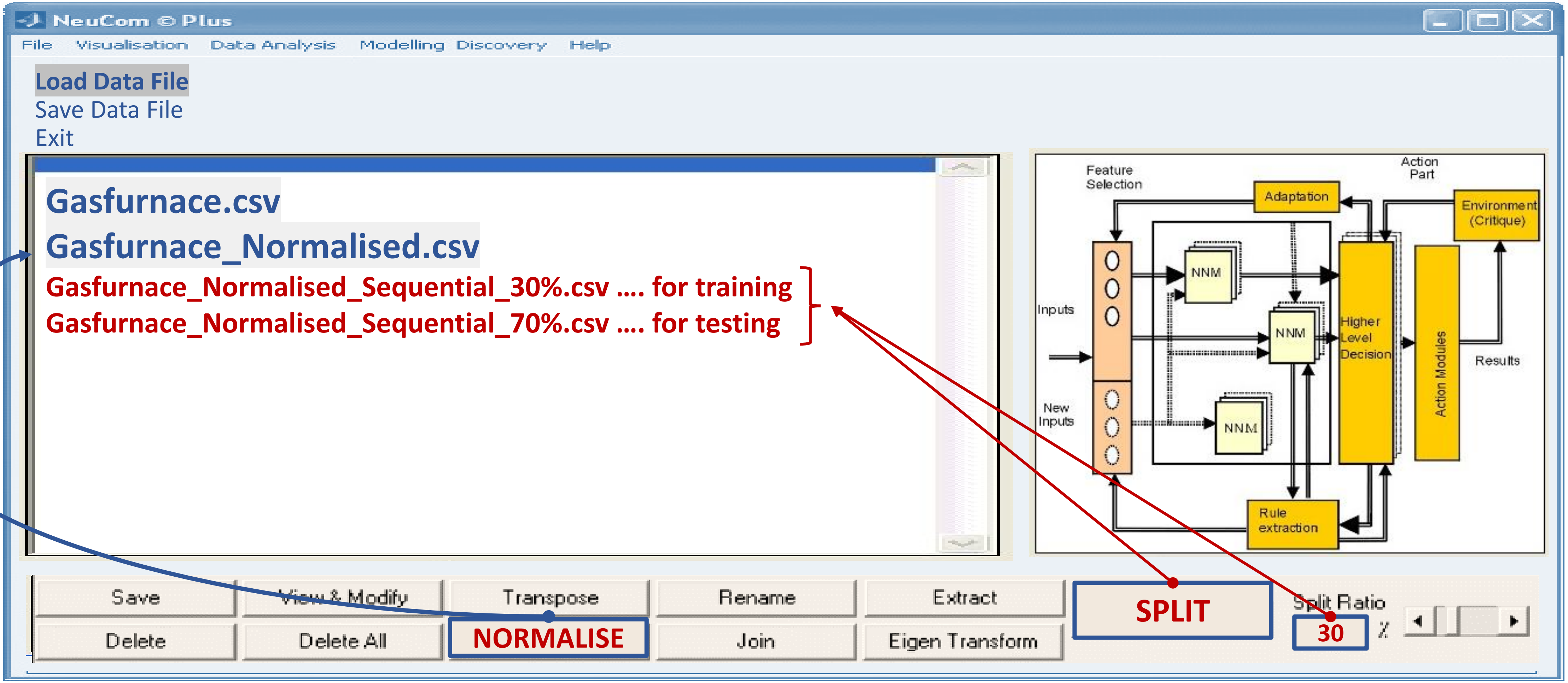


- Number of observations for testing
- Same number of inputs (4) and outputs (1 class)
- Same number of hidden nodes
- Same max number of Iterations.
- Same absolute precision for output value & output function in both optimizations.
- MLP model uses linear output activation function
- MLP model uses scaled conjugate gradient optimization or quasi-newton optimization
- Confusion table; Accuracy for each class; and Learning rate.
- Overall Model's Accuracy = 97%.

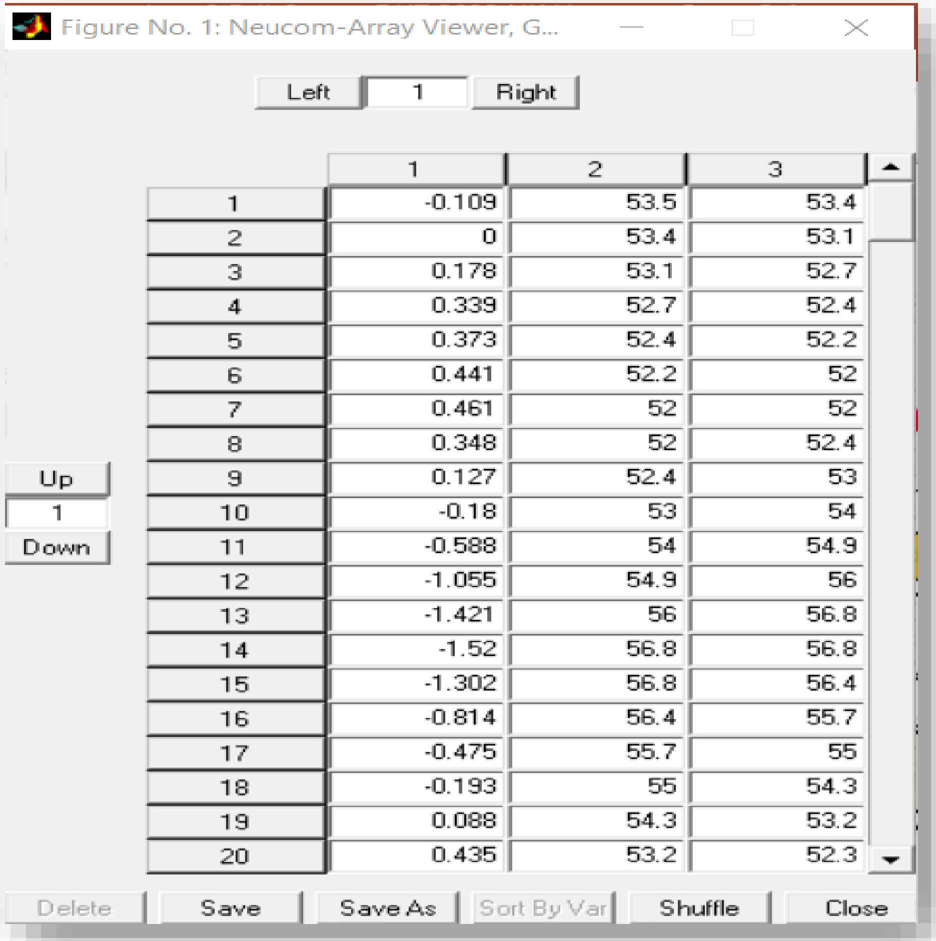
MLP Prediction Model: Gas Furnace Dataset

- The gas furnace dataset for time series analysis contains the gas rate and the percentage CO_2 in the gas.
- Gas furnace time series dataset consists of **292 observations.**
- **Two input features:** Methane and CO_2
- **One output feature:** $CO_2(t+1) = f\ (Methane(t-4), CO_2(t)\ , \varepsilon)$
- dataset modelling for **Prediction.**
- Modelling method: **MLP**.
- Gas furnace dataset **split** 30/70 training-learning ratio.

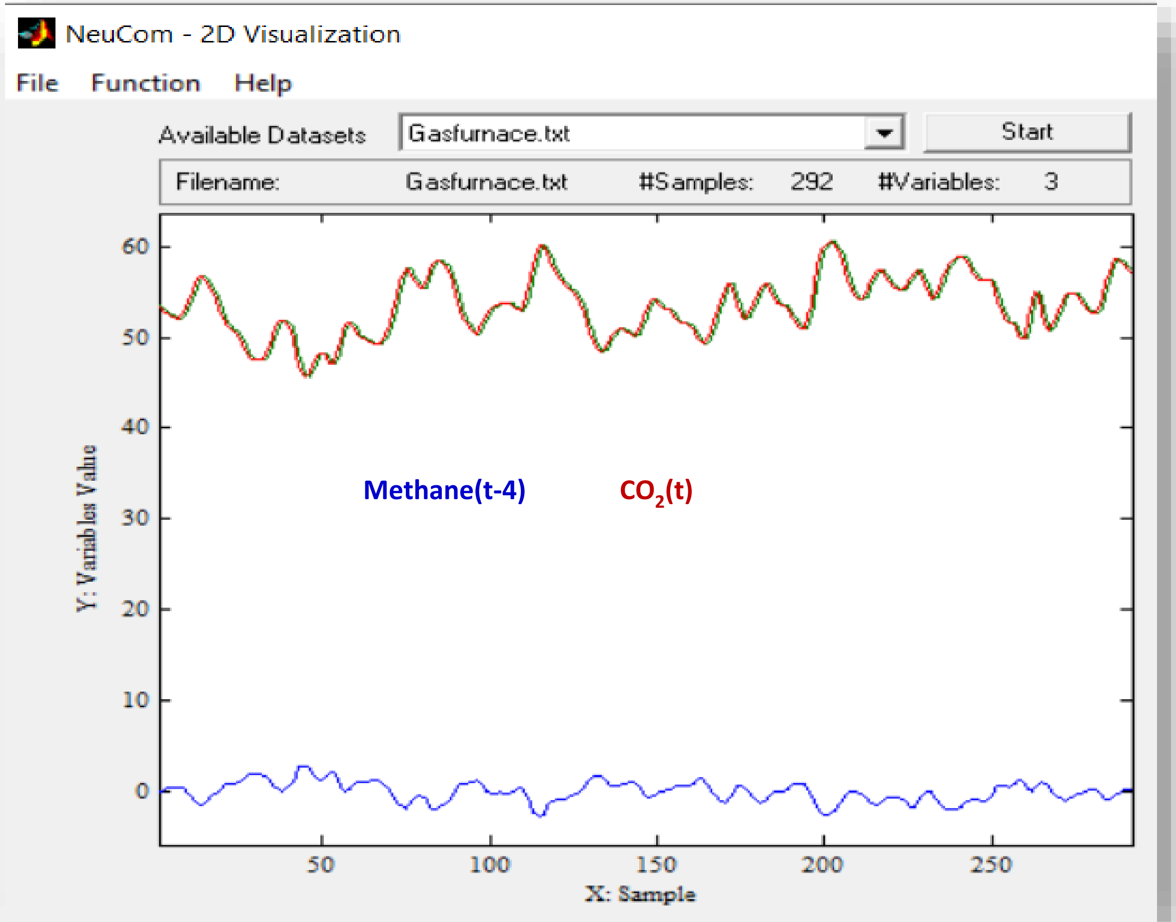
MLP Prediction Model : Data Loading



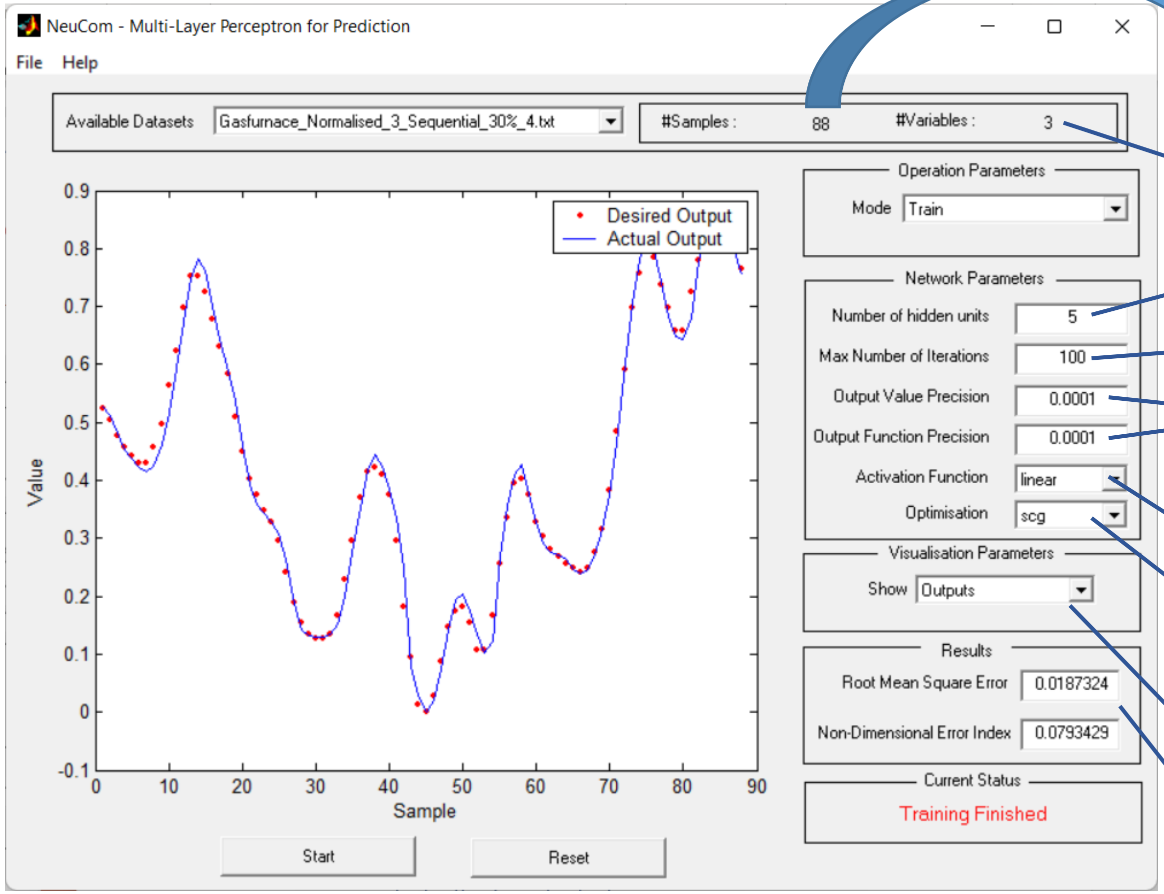
MLP Prediction Model: Input and Visualization



	1	2	3
1	-0.109	53.5	53.4
2	0	53.4	53.1
3	0.178	53.1	52.7
4	0.339	52.7	52.4
5	0.373	52.4	52.2
6	0.441	52.2	52
7	0.461	52	52
8	0.348	52	52.4
9	0.127	52.4	53
10	-0.18	53	54
11	-0.588	54	54.9
12	-1.055	54.9	56
13	-1.421	56	56.8
14	-1.52	56.8	56.8
15	-1.302	56.8	56.4
16	-0.814	56.4	55.7
17	-0.475	55.7	55
18	-0.193	55	54.3
19	0.088	54.3	53.2
20	0.435	53.2	52.3

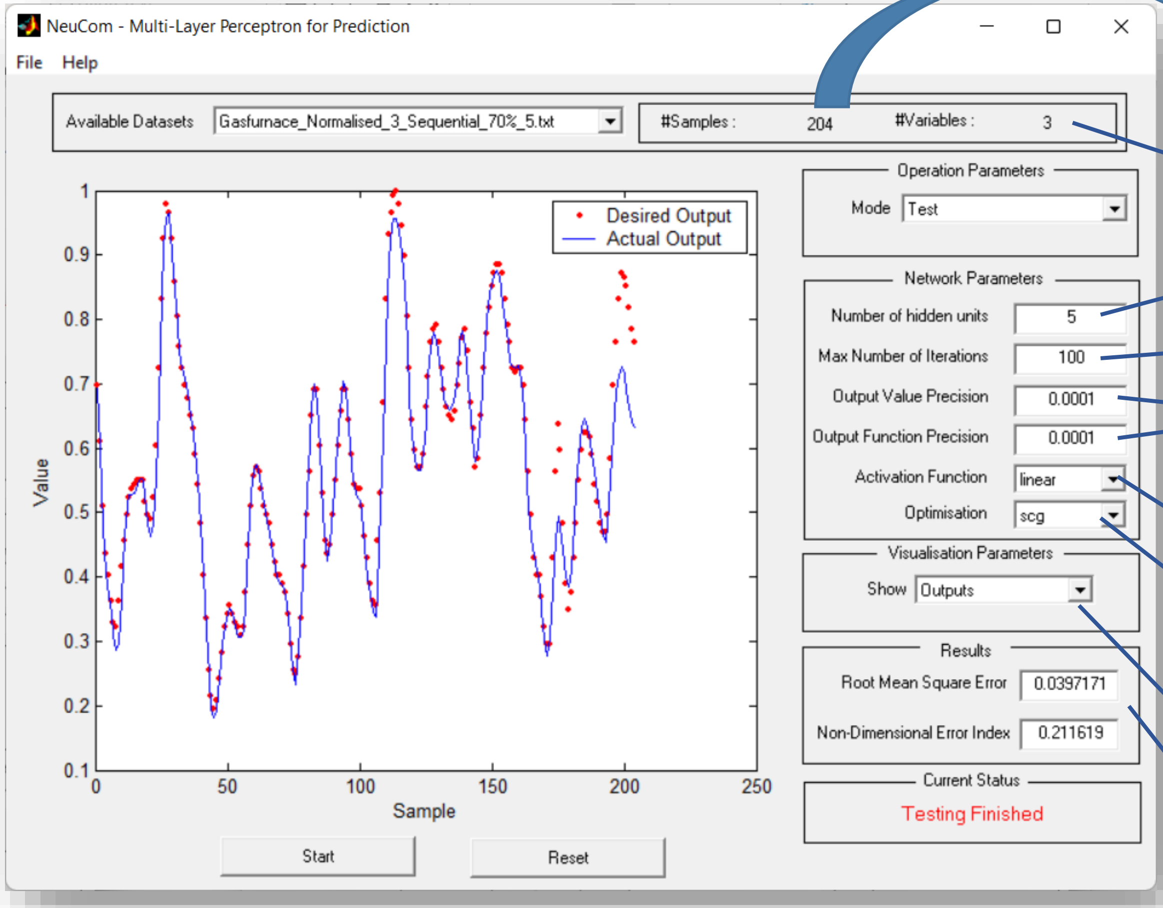


MLP Prediction Model: Parameters, Modelling and Analysis



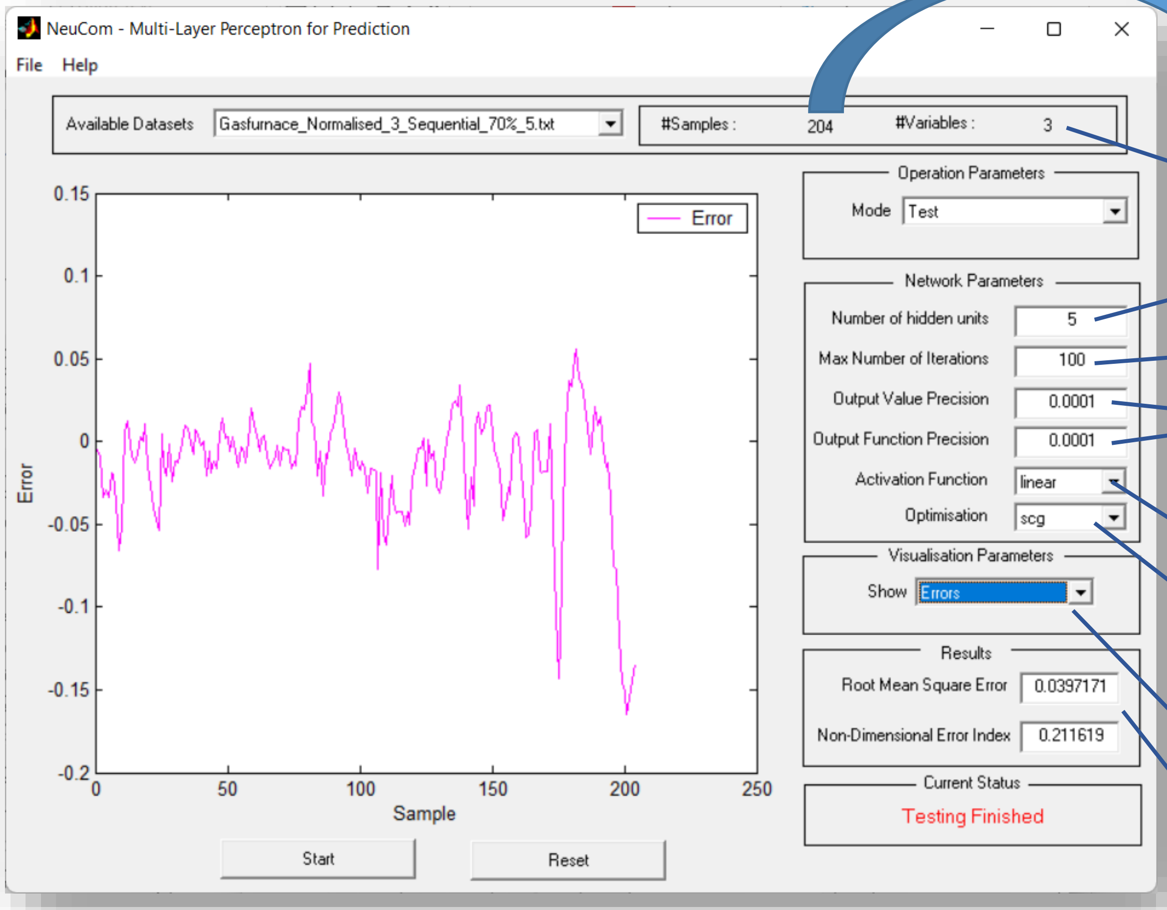
- Number of observations for training in normalized dataset.
- Number of inputs (2) and outputs (1)
- Specify number of hidden nodes
- Specify the max number of Iterations.
- Specify the absolute precision required for the output value & output function in both optimizations.
- MLP model uses linear output activation function
- MLP model uses scaled conjugate gradient optimization or quasi-newton optimization
- Outputs; Errors; and Learning rate.
- RMSE & NDEI defined as RMSE / StDev of the target series.

MLP Prediction Model: Parameters, Modelling and Analysis



- Number of observations for testing in normalized dataset.
- Same number of inputs (2) and outputs (1)
- Same number of hidden nodes
- Same max number of Iterations.
- Same absolute precision required for output value & output function in both optimizations.
- MLP model uses linear output activation function
- MLP model uses scaled conjugate gradient optimization or quasi-newton optimization
- Outputs; Errors; and Learning rate.
- RMSE = **4%**.

MLP Prediction Model: Parameters, Modelling and Analysis



- Number of observations for testing in normalized dataset.
- Same number of inputs (2) and outputs (1)
- Same number of hidden nodes
- Same max number of Iterations.
- Same absolute precision required for output value & output function in both optimizations.
- MLP model uses linear output activation function
- MLP model uses scaled conjugate gradient optimization or quasi-newton optimization
- Outputs; Errors; and Learning rate.
- RMSE = 4%.

References:

1. N.Kasabov, *Time-Space, Spiking Neural Networks and Brain-Inspired Artificial Intelligence*, Springer, 2019.
2. N.Kasabov, *Evolving connectionist systems: Methods and Applications in Bioinformatics, Brain study and intelligent machines*, Springer Verlag, London, New York, Heidelberg, 2002.
3. N.Kasabov, *Foundations of neural networks, fuzzy systems and knowledge engineering*, MIT Press, CA, MA, 1996.
4. Q. Song and N. Kasabov, *NFI- A neuro-fuzzy inference method for transductive reasoning*, IEEE Tr. Fuzzy Systems, in print, 2004.
5. R. Fisher, *The use of Multiple Measurements in Taxonomic Problems*, Annals Eugenics 7, 1936.

Assignment:

1. Download NeuCom.
2. Use the attached iris.csv to model MLP for classification.
    1. Use split ratio of 50/50 and check the accuracy.
    2. Change the number of training cycles to 50. check accuracy.
3. Use the attached gasfurnace.csv to model MLP for prediction.
    1. Use split ratio of 50/50 and check the accuracy.
    2. Change the number of hidden nodes to 10. check accuracy.
4. Email results to nkasabov@aut.ac.nz & iabouhassan@tu-sofia.bg


Thank you!