N3 – AI Revolution

- Neuroinformatics
- Neural networks
- Neurocomputing

N3-BG Seminar 10

Unleashing the Future Applications of Advanced Artificial Intelligence and Neural Networks in Economics and Finance

N3 – AI Revolution

https://www.knowledgeengineering.ai/seminars

Neuroinformatics, Neural networks and Neurocomputers for Brain-inspired AI: Challenges and Opportunities[1]

Challenges

1. Efficient Learning of Data.
2. Interpretability and Explainability.
3. Personalized Predictive Modeling and Profiling.
4. Multiple Modalities of Data.
5. Computational Complexity.
6. Energy Consumption.
7. Human-Machine Interaction.
8. Ethical Considerations and Regulation.
9. Global Challenges.

1- N.K. Kasabov, "Neuroinformatics, Neural Networks and Neurocomputers for Brain-inspired Computational Intelligence," 2023 IEEE 17th International Symposium on Applied Computational Intelligence and Informatics (SACI), Timisoara, Romania, 2023, pp. 13-14, doi: 10.1109/SACI58269. 2023.10158578.

Neuroinformatics, Neural Networks and Neurocomputers for Brain-inspired AI: Challenges and Opportunities

Opportunities

1. Neuroinformatics
2. Neural networks
3. Neurocomputers

Advances in Neuroinformatics, Neural networks, and Neurocomputers provide opportunities to address these challenges and understand how innovative research and technology will shape the future of artificial intelligence.

………. N3 - the AI revolution ……….

Neural Networks Applications in Industry

Image Recognition and Computer Vision

Natural Language Processing (NLP)

Recommender Systems

Fraud Detection

Demand Forecasting

Financial Analysis and Trading

Autonomous Vehicles

Customer Segmentation and Personalization

Cybersecurity

Neural Networks

in

Economics and Finance

Neural Networks in Economics and Finance

- Artificial neural networks (ANNs) have been widely applied to economic and finance forecasting as a powerful modeling technique for prediction of foreign exchange rates, stock market index, economic growth, trade flows, investments, and more.
- Predictive modelling of economic and financial times series has always been of a strategic importance for a country or a geographical region, especially when related to a crucial commodity on which the whole industry and society depends.
- Neural network inputs are univariate or multivariate. Nonlinear combining forecasting by neural networks provides encouraging results.
- Prediction performance of neural networks can be improved using advanced generations.

Neural Networks in Economics and Finance

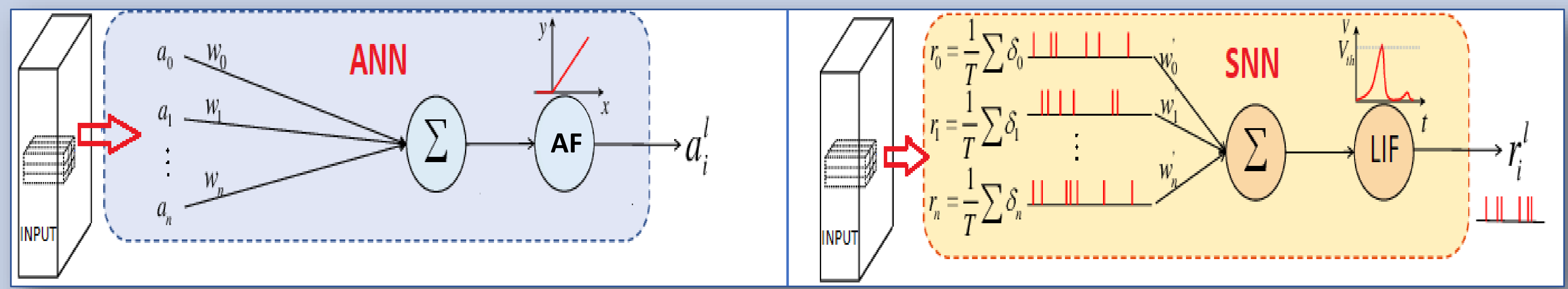
	Traditional Statistical Models	Neural Network Models
Fundamentals	Based on mathematical and statistical principles.	Mimic the human brain in its structure and work.
Model Flexibility	Examine linear relationships based on predefined assumptions.	Examine non-linear relationships and capture complex patterns.
Model prerequisites	Undergo many testing procedures: trends, seasonality, serial correlation, auto correlation and heteroskedasticity, etc.	Undergo learning procedures, such as supervised learning, unsupervised learning, semi-supervised learning, etc.
Feature Engineering	Require explicit feature selection.	Can learn relevant features directly from raw data.
Model Interpretability	More interpretable, providing clear insights into the relationship between variables.	Considered black-box models, making it challenging to interpret their inner workings.
Model Scalability	Deal with small to moderate-sized datasets.	Handle large-scale, high-dimensional datasets.
Data Requirements	Work better with smaller datasets.	Require large amounts of labeled training data to achieve good performance.

Neural Networks in Economics and Finance

	Traditional Neural Network Models	Spiking Neural Network Models
Fundamentals	Used in many machine learning applications such as feedforward and recurrent NN.	A specific type of neural network model inspired by the biological behavior of neurons.
Computational Mechanisms	Composed of artificial neurons with continuous activation values.	Leverage spike-based coding and integrate-and-fire mechanisms
Learning and Training	Based on the principles of forward propagation and backpropagation.	Training algorithms for spiking neural networks, such as Spike-Time-Dependent Plasticity (STDP)
Representation of Information	Focus on weights and continuous real activation values.	Spiking neural networks represent information through discrete spikes
Model Efficiency	Efficient at working with vector data and solving pattern recognition tasks.	Computationally efficient when modeling spatiotemporal data continuously changing in time
Temporal Dynamics	Mostly controlled by gradient-based optimization techniques.	Model the spatio-temporal dynamics of neuron firing and spike timing,

Neural Networks in Economics and Finance

	Traditional Neural Network Models	Spiking Neural Network Models



Neural Network Models for Predictive Analysis in Economics and Finance[2]

EFuNN → **DENFIS** → **NeuCube**

Based on Evolving COnnectionist Systems (ECOS) principles[3]

- ECOS are artificial neural network algorithms first proposed and developed by Kasabov in 1998.
- ECOS are fast and efficient learning algorithms capable of adapting to new data without forgetting the old.
- ECOS can learn incrementally from incoming data in both supervised and unsupervised modes, allowing their structure and functionality to evolve (change over time) with little to no prior knowledge.
- ECOS facilitate extracting of fuzzy rules from a trained model.

2- N. Kasabov, "Time-space, spiking neural networks and brain-inspired artificial intelligence," vol. 7, Springer, 2019.

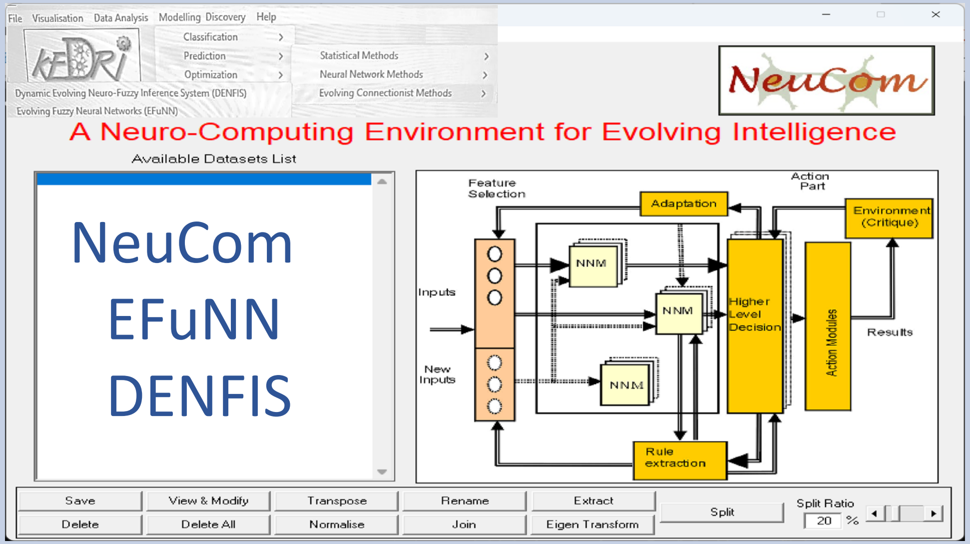
3- N. Kasabov, "Evolving connectionist systems: methods and applications in bioinformatics, brain study and intelligent machines," Springer Verlag, London, New York, Heidelberg, 2002.

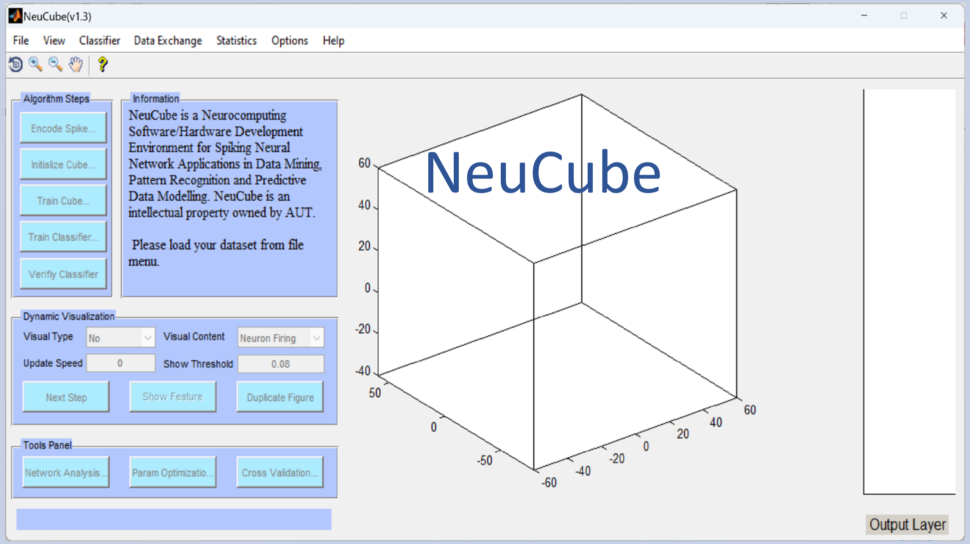
Neural Network Models for Predictive Analysis in Economics and Finance

EFuNN → DENFIS → NeuCube

The best manifestations based on ECOS principles are:

- Neuro-fuzzy models **EFuNN** and **DENFIS** available from the NeuCom environment [*https://theneucom.com*]
- BI-SNN based model **NeuCube**, latest generation in AI, available from [https://kedri.aut.ac.nz/neucube].

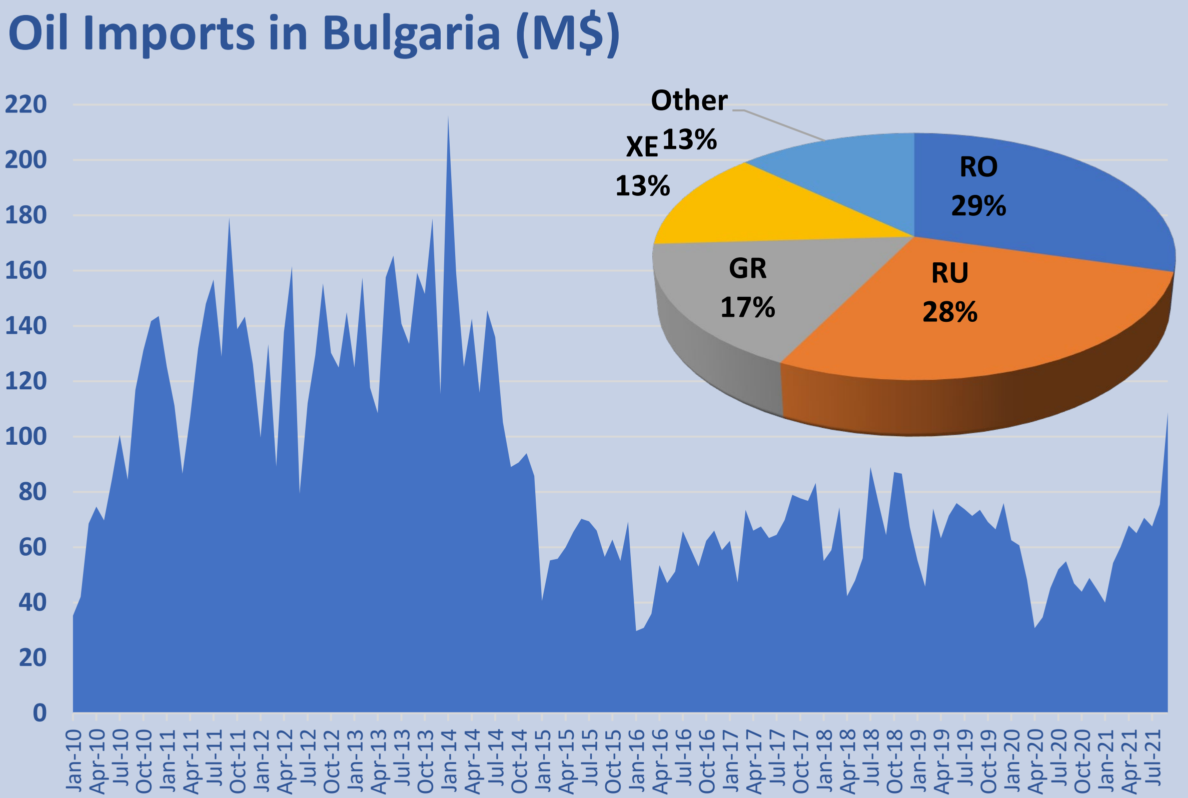




Neural Network Models for Predictive Analysis in Economics and Finance

Case Study I: Bulgarian Imports of Petroleum Oil[4]

- Oil remains the primary energy, despite all efforts to alternative environmentally friendly sources.
- Oil accounts for 1/3rd of EU's internal energy demand.
- Bulgaria rely on Russia & Romania for oil imports.
- The analyzed dataset includes monthly time series imports in millions of US Dollars from Jan 2010 to Sep 2021, resulting in 141 temporal data.
- Including 18 features for major oil trading partners, and dependent variable is imports from Russia in next timestamp.



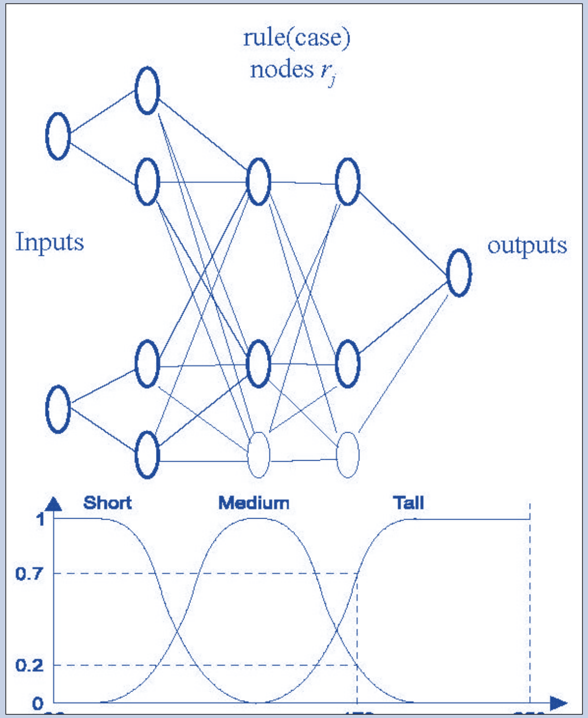
4- I. Abouhassan, N. Kasabov, G. Popov and R. Trifonov (2022), "Why Use Evolving Neuro-Fuzzy and Spiking Neural Networks for incremental and explainable learning of time series? A case study on predictive modelling of trade imports and outlier detection," IEEE 11th International Conference on Intelligent Systems (IS), Warsaw, Poland, 2022, pp. 1-7, doi: 10.1109/IS57118.2022.10019673

Neural Network Models for Predictive Analysis in Economics and Finance

Model I: EFuNN[5]

Introduction:

- Evolving Fuzzy Neural Network (EFuNN) is a hybrid of two major AI paradigms: NN adaptability and fuzzy logic interpretability.
- EFuNN learns incrementally from data, and evolves/forms clusters in **supervised** way, continuously adapting and refining their knowledge based on new information.
- Cluster centers are hidden (rule) nodes defined by weights of the connections between input variables
- Clusters grow and shrink in radius through a learning algorithm.
- EFuNN outperform traditional static models, and well-suited for pattern recognition, prediction, and decision-making.



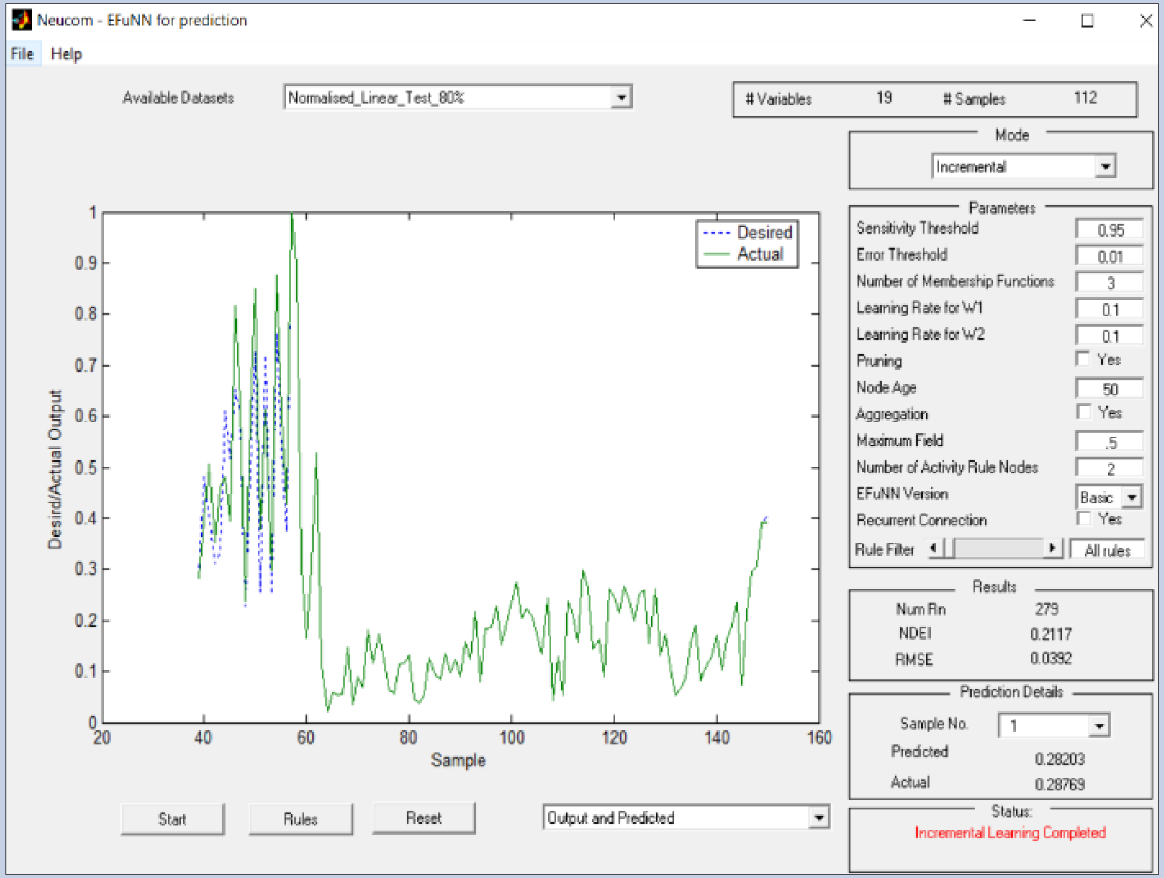
5- N. Kasabov, "Evolving fuzzy neural networks for supervised/ unsupervised online knowledge-based learning," IEEE Trans Syst Man Cybern B Cybern; 31(6):902-18. doi: 10.1109/3477.969494. PMID: 18244856, 2001.

Neural Network Models for Predictive Analysis in Economics and Finance

Model I: EFuNN

Data modelling:

- Dataset is split into 20% for training and 80% for incremental learning & testing.
- Setting hyperparameters, such as max cluster radius (sensitivity threshold) set to 0.95, and level of error tolerance for the output (error threshold) set to 0.01.
- In fuzzy inference system, three membership functions are used (MF1–small; MF2–medium; MF3–large value).
- Two hidden layers are constructed, each with a learning rate of 0.1 for weights of 1st & 2nd layers.
- Pruning of nodes, recurrent connections, and merging similar rule nodes are omitted.
- Model's accuracy measured by root mean squared error, RMSE = 3.92%.



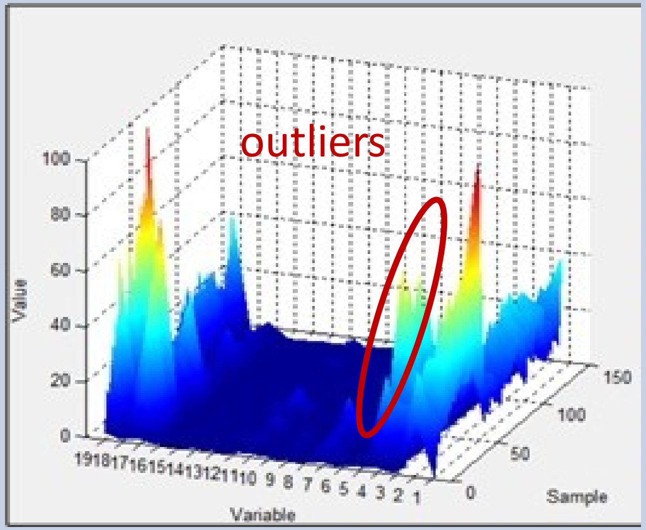
EFuNN model for incremental learning and prediction (regression) of the output time series one time step ahead.

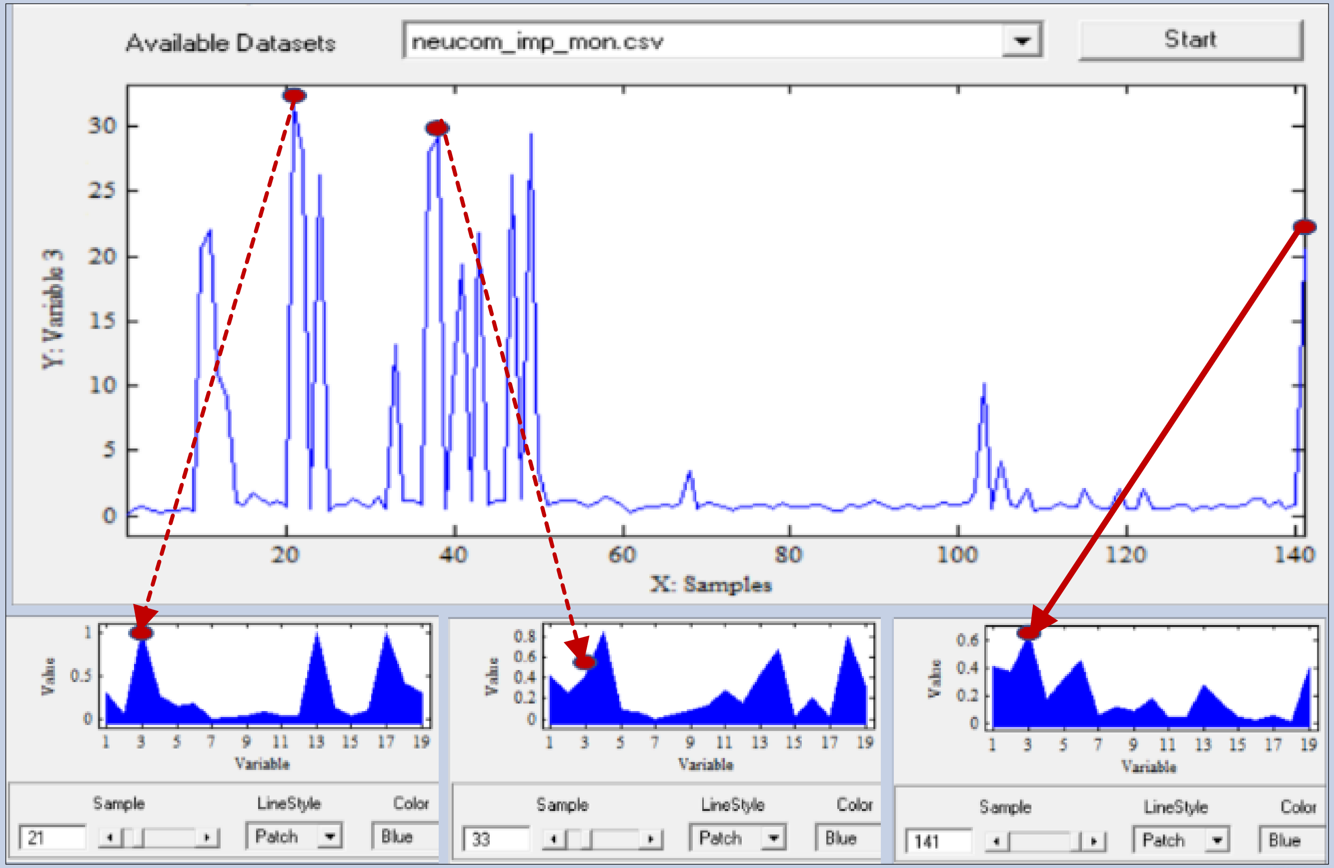
Neural Network Models for Predictive Analysis in Economics and Finance

Model I: EFuNN

Analysis and visualization of outliers:

- Imports from Italy shows peaks in three different samples (time periods).
- When compared to imports from other countries, samples 21 and 33 may not be outliers, as shown in the bar chart, but sample 141 may be.





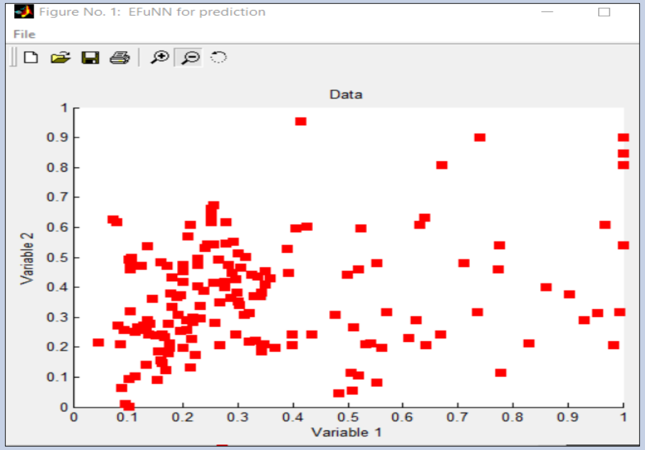
Graphical representation of input variable

Neural Network Models for Predictive Analysis in Economics and Finance

Model I: EFuNN

Knowledge extraction:

- Each node (red squares) represents a fuzzy rule denoting the cluster center and the number of samples (vectors) allocated to this cluster by the learning algorithm.
- If a cluster consists of only one member, this indicates an outlier.
- EFuNN method enables knowledge extraction of fuzzy rules.



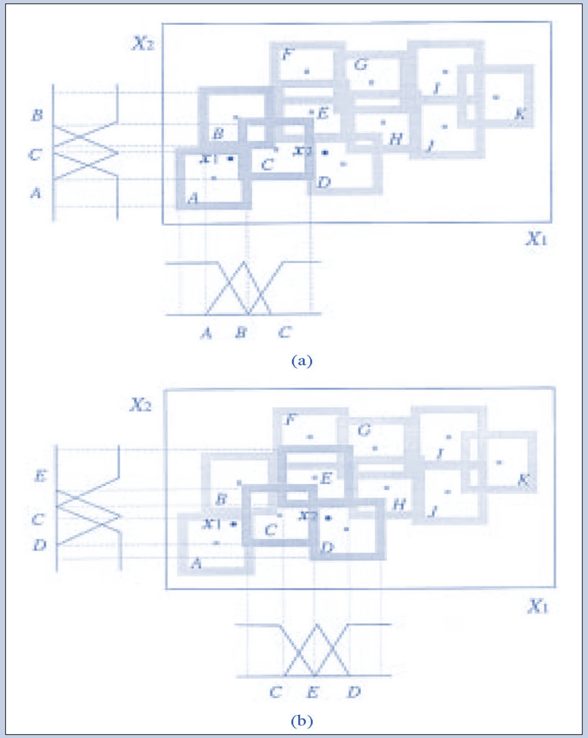
Rule 1: If (an input vector is in the cluster defined by the center (rule node) as connection weights between the fuzzified input variables Var1 to Var18
[Var 01] -->[(MF1) = 0.909 & (MF2) = 0.091 & (MF3) = 0.000] &
[Var 02] --> [(MF1) = 0.566 & (MF2) = 0.434 & (MF3) = 0.000] &
[Var 03] --> [(MF1) = 0.909 & (MF2) = 0.091 & (MF3) = 0.000] &
[Var 04] --> (MF1) = 0.909 & (MF2) = 0.091 & (MF3) = 0.000 &
[Var 05] --> (MF1) = 0.738 & (MF2) = 0.262 & (MF3) = 0.000 &
[Var 06] --> (MF1) = 0.908 & (MF2) = 0.092 & (MF3) = 0.000 &
[Var 07] --> (MF1) = 0.000 & (MF2) = 0.501 & (MF3) = 0.499 &
[Var 08] --> (MF1) = 0.851 & (MF2) = 0.149 & (MF3) = 0.000 &
[Var 09] --> (MF1) = 0.909 & (MF2) = 0.091 & (MF3) = 0.000 &
[Var 10] --> (MF1) = 0.000 & (MF2) = 0.981 & (MF3) = 0.019 &
[Var 11] --> (MF1) = 0.000 & (MF2) = 0.751 & (MF3) = 0.249 &
[Var 12] --> (MF1) = 0.893 & (MF2) = 0.107 & (MF3) = 0.000 &
[Var 13] --> (MF1) = 0.901 & (MF2) = 0.099 & (MF3) = 0.000 &
[Var 14] --> (MF1) = 0.190 & (MF2) = 0.810 & (MF3) = 0.000 &
[Var 15] --> (MF1) = 0.906 & (MF2) = 0.094 & (MF3) = 0.000 &
[Var 16] --> (MF1) = 0.293 & (MF2) = 0.707 & (MF3) = 0.000 &
[Var 17] --> (MF1) = 0.909 & (MF2) = 0.091 & (MF3) = 0.000 &
[Var 18] --> (MF1) = 0.813 & (MF2) = 0.187 & (MF3) = 0.000 &
then (Output value is calculated as):
Output for (MF1) = 0.907 Output for (MF2) = 0.093
Output for (MF3) = 0.000 receptive field = 0.050
max radius = 0.309 accommodated training examples =1 (outlier!)

Neural Network Models for Predictive Analysis in Economics and Finance

Model II: DENFIS[6]

Introduction:

- Dynamic Evolving Neuro-Fuzzy Inference System (DENFIS) is a combination of dynamic learning and nonlinear approximation of NN and the inherent reasoning and uncertainty management of fuzzy logic.
- DENFIS develops and optimizes fuzzy rules and membership functions based on incoming data to capture patterns and relationships within the data, making it well-suited for modeling, prediction, classification, and decision-making applications.
- DENFIS could handle evolving data distributions, sudden changes, and trends, making it a robust tool in finance and healthcare where accuracy and flexibility are demanded.



Two fuzzy rules perform inference on input vectors (a) and (b) that is entered later.

6- N. Kasabov, and Q. Song, "DENFIS: dynamic evolving neuro-fuzzy inference system and its application for time-series prediction," IEEE Trans. on Fuzzy Systems, vol.10, No.2, 144-154, April 2002.

Neural Network Models for Predictive Analysis in Economics and Finance

Model II: DENFIS

Data structure:

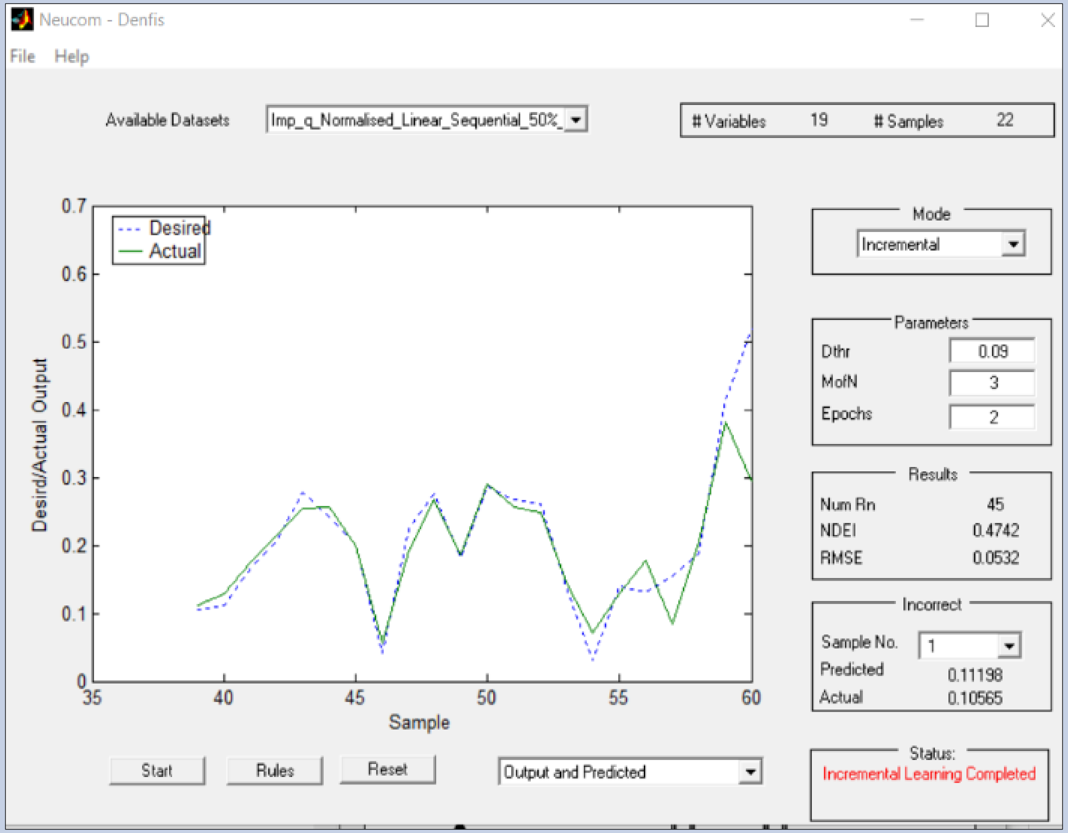
- The time series is divided into equal subsets: 50% for training and 50% for incremental learning and testing. The dependent (output) variable will be imports from Russia in the next quarter.
- DENFIS is a Fuzzy Inference System that evolves clusters incrementally from data in an **unsupervised** way (as a difference from EFuNN) and calculates a function for each cluster that approximates all data in this cluster.
- DENFIS employs an Evolving Clustering Method (ECM), a fast distance-based, one-pass algorithm for estimating the number of clusters in a dataset.

Neural Network Models for Predictive Analysis in Economics and Finance

Model II: DENFIS

Data modelling:

- The maximum radius of the rule nodes in the network, denoted as distance threshold, is set to 0.09.
- Three nodes are chosen to estimate the output of the current sample, and two learning iterations (epochs) are selected to train the network.
- The model's output, as measured by root mean squared error, RMSE=5.32%



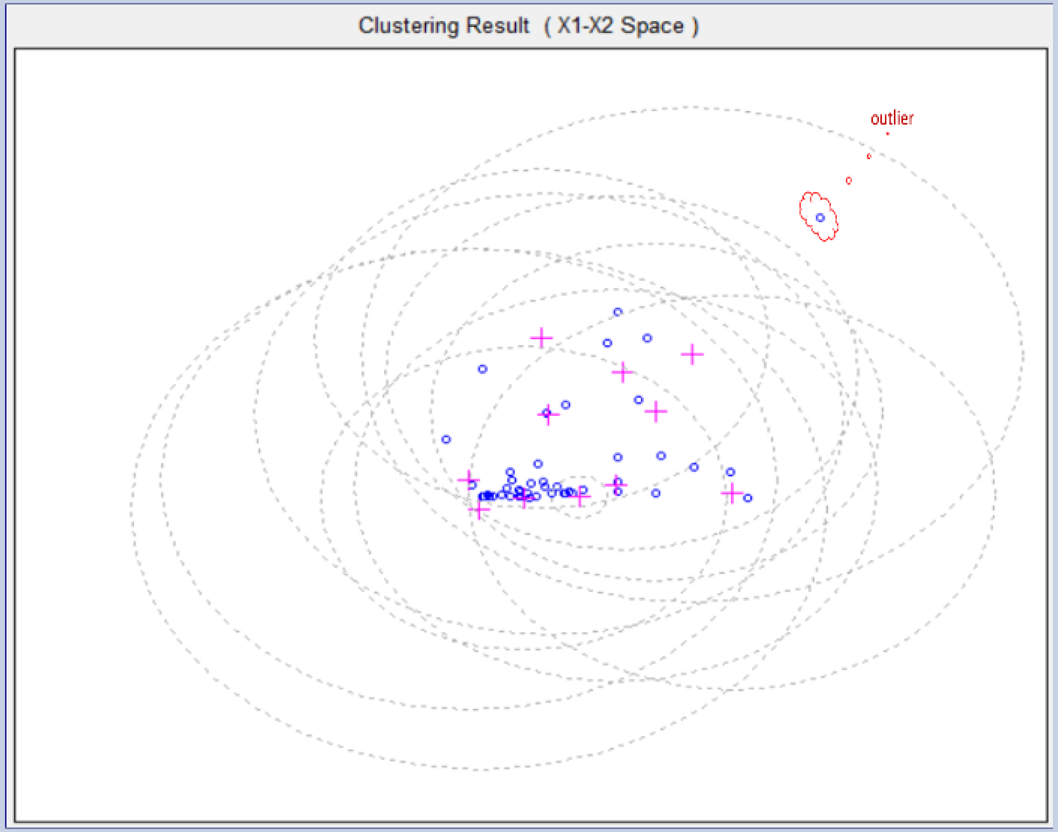
DENFIS method for incremental learning and regression

Neural Network Models for Predictive Analysis in Economics and Finance

Model II: DENFIS

Analysis and visualization of clusters:

- The maximum distance between a data point and the cluster center, as well as the number of clusters to be created, are controlled by a predefined cluster radius of 0.2 as a threshold.
- The clustered data are represented by blue circles, and the cluster centers are represented by pink crosses. Dotted circles denote the clusters.



Evolving clustering data in DENFIS

Neural Network Models for Predictive Analysis in Economics and Finance

Model II: DENFIS

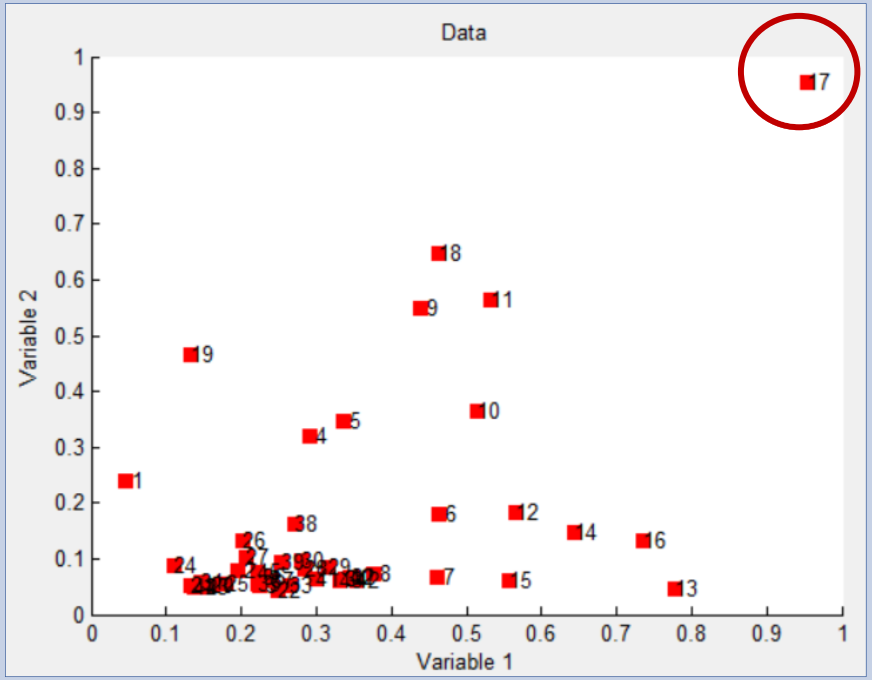
Knowledge extraction:

- DENFIS automatically detect outliers from a streaming data (rule 17).
- DENFIS model generates rule nodes after its training, and allows fuzzy rules to be extracted.

Rule 1:
if X1 is GaussianMF (Small_0.50 Large_0.05)
X2 is GaussianMF (0.50 0.24) X10 is GaussianMF (0.50 0.21)
X3 is GaussianMF (0.50 0.21) X11 is GaussianMF (0.50 0.06)
X4 is GaussianMF (0.50 0.27) X12 is GaussianMF (0.50 0.22)
X5 is GaussianMF (0.50 0.05) X13 is GaussianMF (0.50 0.05)
X6 is GaussianMF (0.50 0.05) X14 is GaussianMF (0.50 0.49)
X7 is GaussianMF (0.50 0.26) X15 is GaussianMF (0.50 0.05)
X8 is GaussianMF (0.50 0.05) X16 is GaussianMF (0.50 0.95)
X9 is GaussianMF (0.50 0.05) X17 is GaussianMF (0.50 0.49)
then X18 is GaussianMF (0.50 0.46)

$$Y = 0.95 + 0.50 * X1 - 0.37 * X2 + 0.12 * X3 - 0.02 * X4 + 0.05 * X5 + 0.38 * X6 + 0.16 * X7 - 0.05 * X8 + 0.18 * X9 - 0.04 * X10 + 0.12 * X11 - 0.02 * X12 - 0.34 * X13 + 0.24 * X14 - 0.34 * X15 + 0.14 * X16 - 0.04 * X17 - 0.14 * X18$$

Where: the fuzzy values of the input variables Var1 to Var18 define the cluster center and the regression function is defined as an approximator of the data in this cluster.



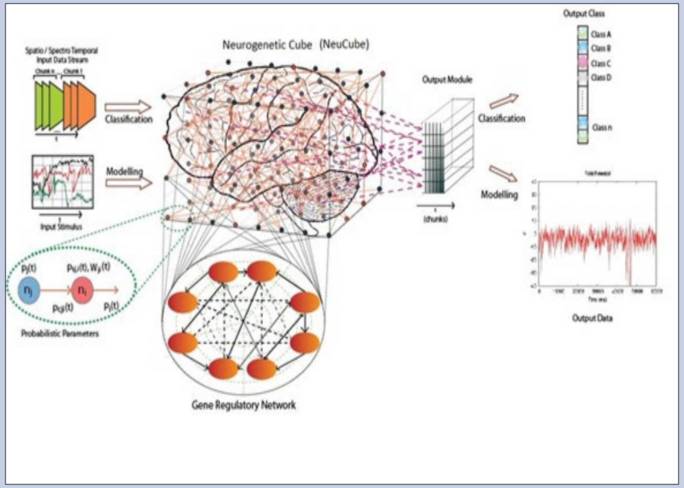
Rule nodes representation in DENFIS. Each point is a cluster center.

Neural Network Models for Predictive Analysis in Economics and Finance

Model III: NeuCube[7]

Introduction:

- NeuCube is initially proposed by Kasabov to model spatio-temporal brain data. NeuCube is a computer model that uses the structure and function of the human brain to handle multi-modal input, multi-dimensional information, and temporal sequences.
- NeuCube is based on brain-inspired spiking neural networks, mimic brain neurons to capture data dynamics and temporal relationships.
- NeuCube's breakthrough in unsupervised learning allows it to identify meaningful data representations and associations without labels.
- NeuCube combines visuals, text, sensor signals, and other makes it ideal for time-series analysis, sensor data fusion, and cognitive modeling.

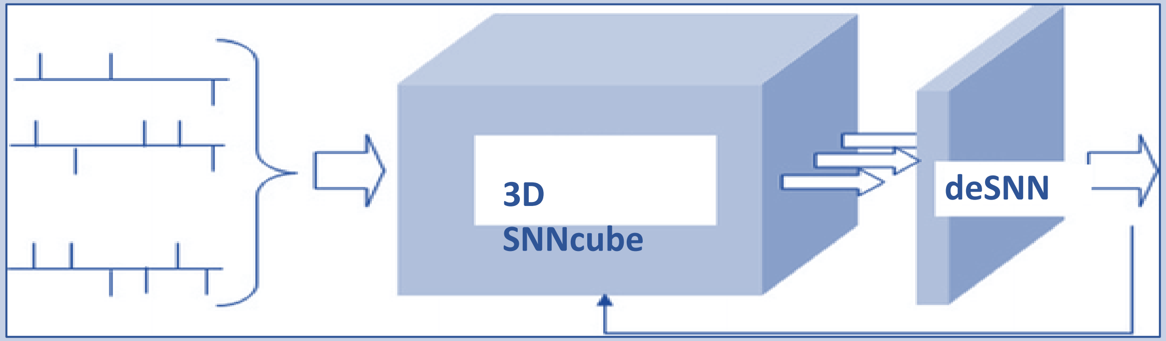


A NeuCube architecture for spatio-temporal data

7- N. Kasabov, "Neucube: a spiking neural network architecture for mapping, learning and understanding of spatio-temporal brain data," Neural Networks; 52:62-76. doi: 10.1016/j.neunet.2014.01. 006. PMID: 24508754, Apr 2014.

Neural Network Models for Predictive Analysis in Economics and Finance

Model III: NeuCube



Data structure:

NeuCube consists of:

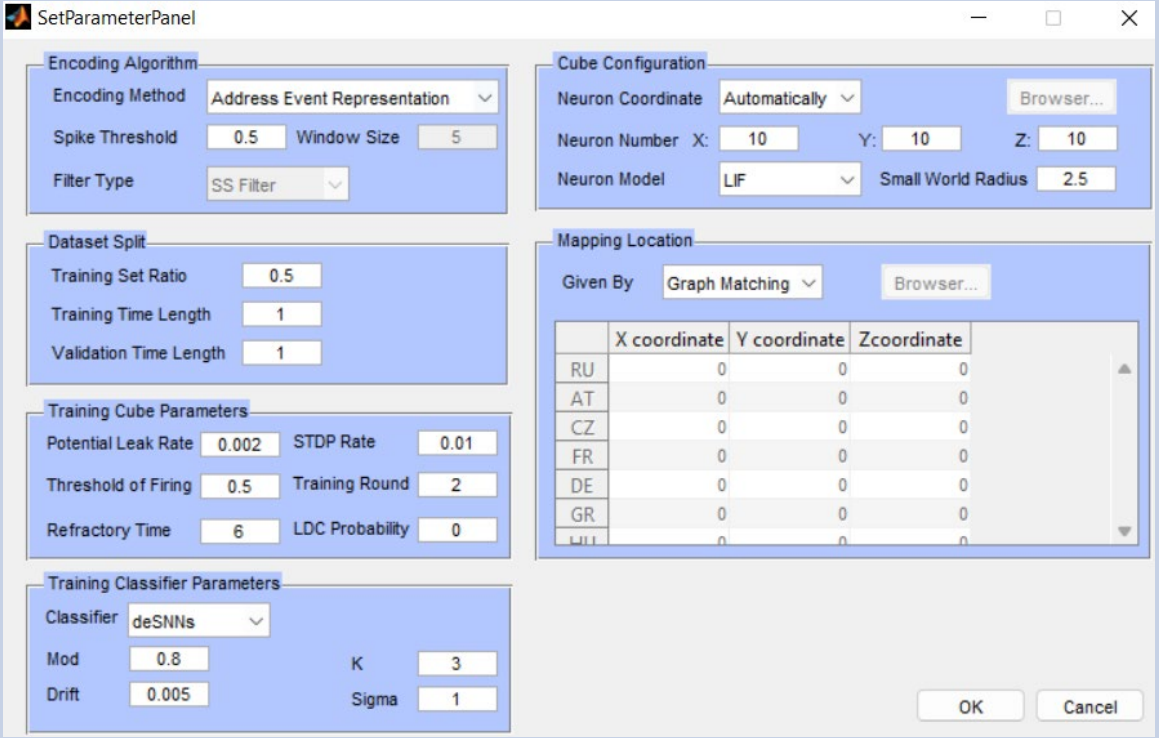
- The input data encoding module, which transforms continuous input data into trains of spikes, uses encoding algorithms, such as Threshold based.
- 3D SNNcube module, where spatio-temporal data are mapped into predefined areas and unsupervised training of STDP is applied that allows learning spatio-temporal relations from input data.
- Output classification module for supervised learning using dynamic evolving Spiking Neural Networks (deSNN) classifier/regressor, where an output neuron is dynamically allocated and connected to the neurons in the SNNcube using Rank Order rule and a drift parameter. Neurons with similar weight vectors are merged using Euclidean distance.

Neural Network Models for Predictive Analysis in Economics and Finance

Model III: NeuCube

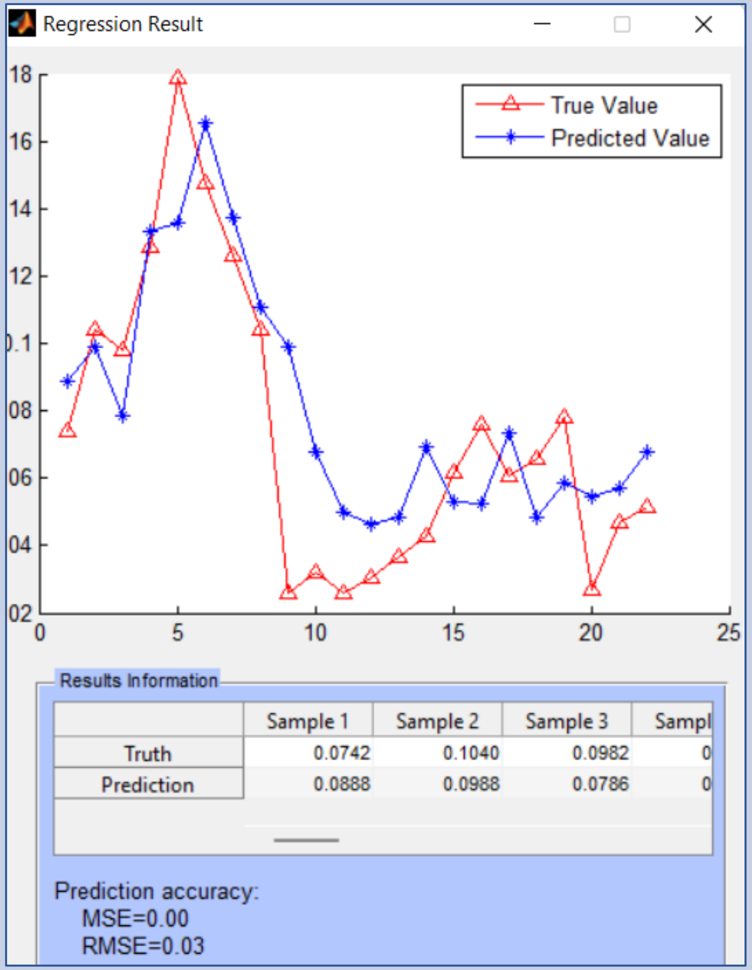
Data modelling:

- The original dataset is segmented into 44 samples with one sliding step to predict next timestamp.
- The sampled dataset is split into 50% for training and 50% for incremental learning and testing.
- Threshold-based encoding method is used to discretize continuous data streams into spikes with a spiking threshold of 0.5.
- A graph matching algorithm is used, to generate a 3D SNN cube with 1000 neurons.



Neural Network Models for Predictive Analysis in Economics and Finance

Model III: NeuCube



Data modelling:

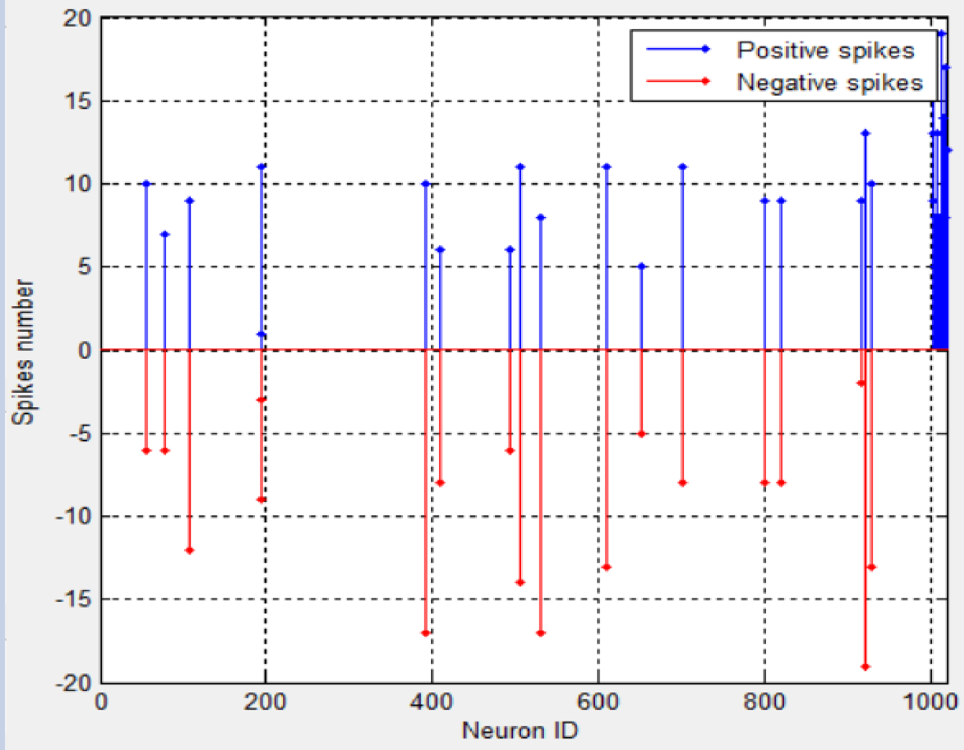
- The NeuCube is modeled using the Leaky-Integrate-and-Fire spiking neuron model with a Small World Connectivity radius of 2.5.
- Training parameters: Firing threshold=0.5; Leaking rate=0.002; Refractory time=6; and STDP learning rate=0.01.
- Based on the Rank-Order learning rule, the mod and drift parameters of the deSNN are set to 0.8 and 0.005, respectively.
- The overall prediction accuracy attained by this model, as measured by the root-mean square error, RMSE=3% which is better than that of the EFuNN and DENFIS methods.

Neural Network Models for Predictive Analysis in Economics and Finance

Model III: NeuCube

Analysis and visualization:

- Theoretically explained, each feature in the SNNcube map is represented by specific initial (x, y, z) coordinates generated by the model.
- In supervised learning, the deSNN regression algorithm allows each output neuron to be associated with a specific country and connected to each other country with a specific weight.



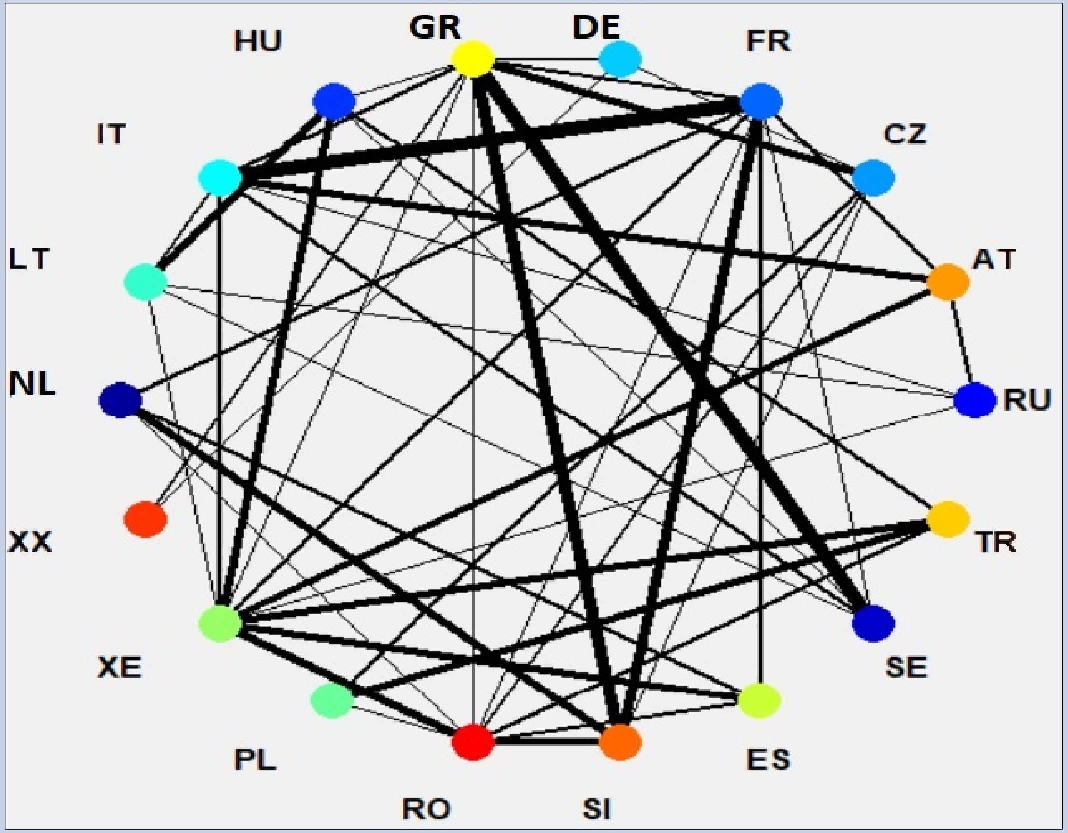
positive and negative spike emission histogram generated by all neurons during the training process in a NeuCube

Neural Network Models for Predictive Analysis in Economics and Finance

Model III: NeuCube

Knowledge extraction :

- Based on the clustering method of connection weights, the interactions between neuron clusters is computed based on the modulation factor and drift parameters. As a result, depending on the timing of incoming spikes, the interaction between countries is learned in the model.
- Thicker lines indicate active interaction between neurons. Interaction means, that if one variable changes its value, the other one changes its value in the next time moment.
- The NeuCube model's graphical visualization of the analyzed data is not possible in traditional machine learning systems and data mining algorithms.



Spike interaction in NeuCube shows the exchange of information between input variables over consecutive time units during learning in the SNNcube.

Neural Network Models for Predictive Analysis in Economics and Finance

EFuNN → DENFIS → NeuCube

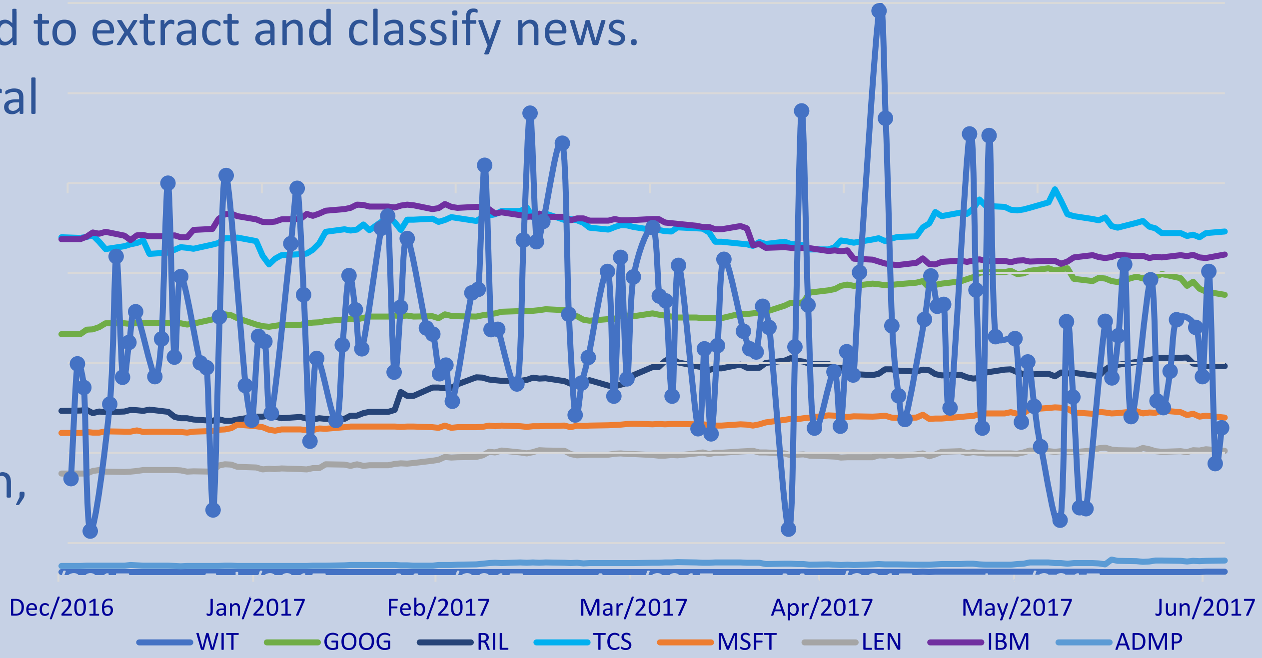
Discussion and Conclusion

- Three widely used ECOS-based NN are excellent for modelling of economic and financial time series data, revealing abnormality, and understanding their complex behavior.
- EFuNN and DENFIS are vector-based methods, where the size of the input is fixed and loaded to the model all at once in time.
- EFuNN and DENFIS require data normalization prior to modeling using linear or logarithmic methods, which is not a requirement in the eSNN.
- EFuNN and DENFIS learn incrementally by evolving clusters and allocating rules for each cluster. They can capture outliers automatically;
- NeuCube deals with temporal and spatio-temporal data, where the input size is increased by number of samples that feed the model continuously over time
- Number of observations is then reduced considering the encoded spikes that reflect the changes in input between consecutive data over time.
- NeuCube represent dynamic interactions between variables in time, and how variables correlate to each other in terms of changing their values.

Neural Network Models for Predictive Analysis in Economics and Finance

Case Study II: Integrated Modelling of Financial Time series and online News data[8]

- News has significant impact on market sentiment and prices.
- Machine learning techniques have already been used to extract and classify news.
- NeuCube is efficient for temporal and spatio-temporal data modelling and online learning.
- NeuCube allows for extraction of meaningful information and knowledge from model.
- BI-SNN NeuCube is efficient to develop models that integrate multiple time series and online information, for a better predictive modelling and explainable learning.

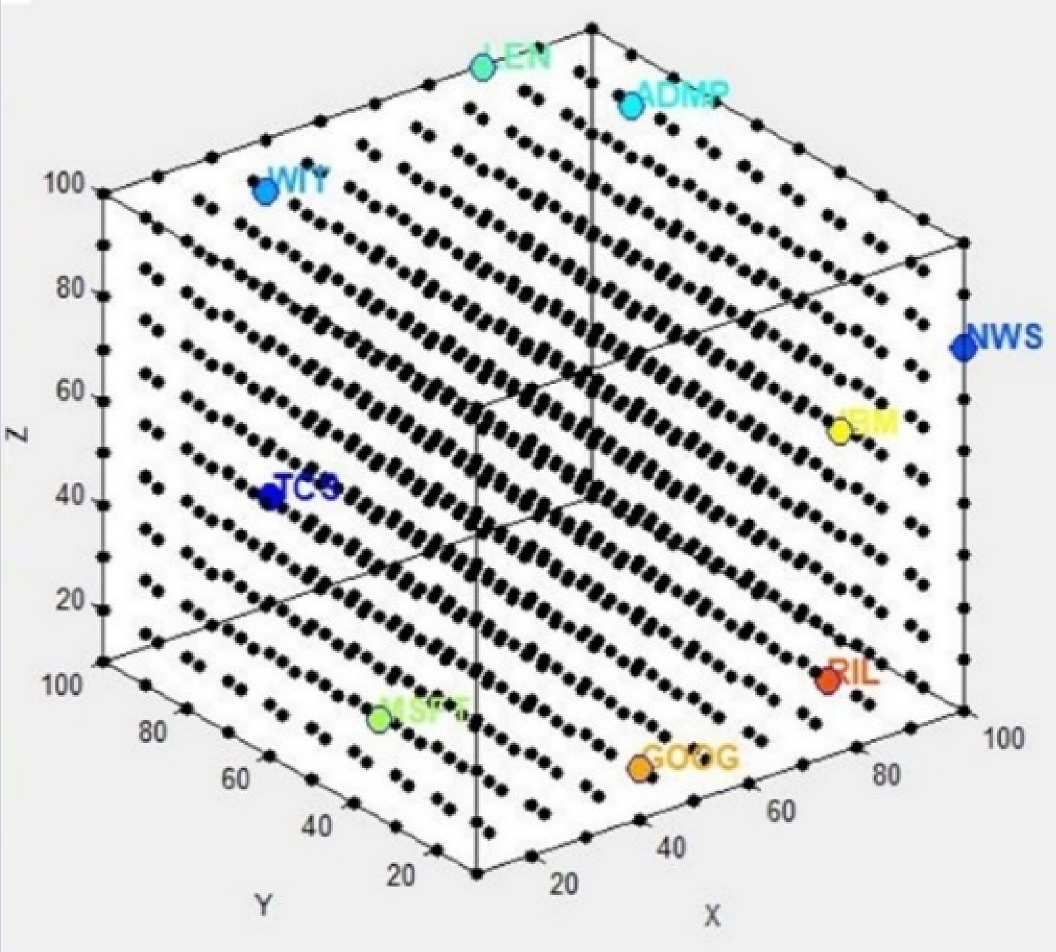


8- N. Kasabov, I. AbouHassan, V. Jagtap, P. Kulkarni (2022). *Spiking Neural Networks for Predictive and Explainable Modelling of Multimodal Streaming Data with a Case Study on Financial Time-series and Online News. Preprint, Research Square, doi:10.21203/rs.3.rs-2262084/v1.*

Neural Network Models for Predictive Analysis in Economics and Finance

Case Study: integrated modelling of financial time series and online newsdata

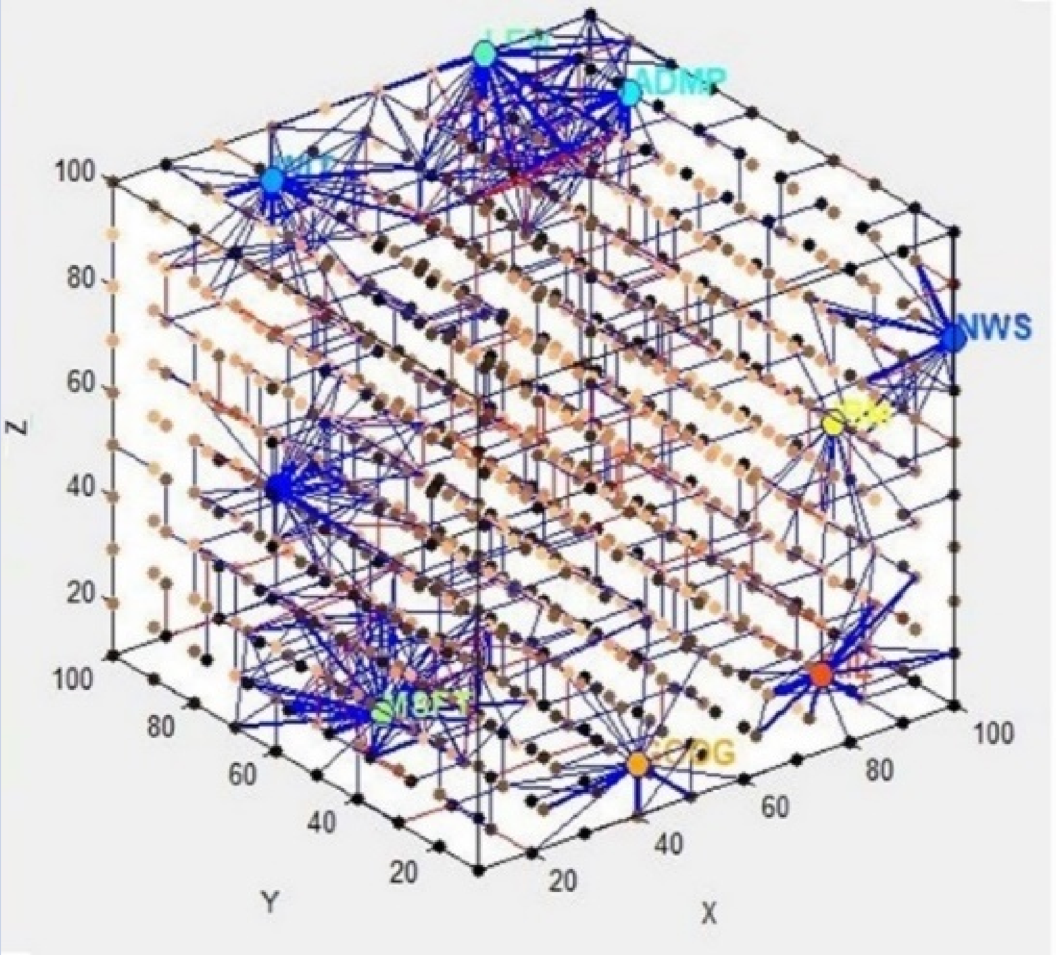
- Mapping of 8 stock indices and news variable into a 3D-SNNcube.
- The size of the SNNcube is scalable



Neural Network Models for Predictive Analysis in Economics and Finance

Case Study: integrated modelling of financial time series and online newsdata

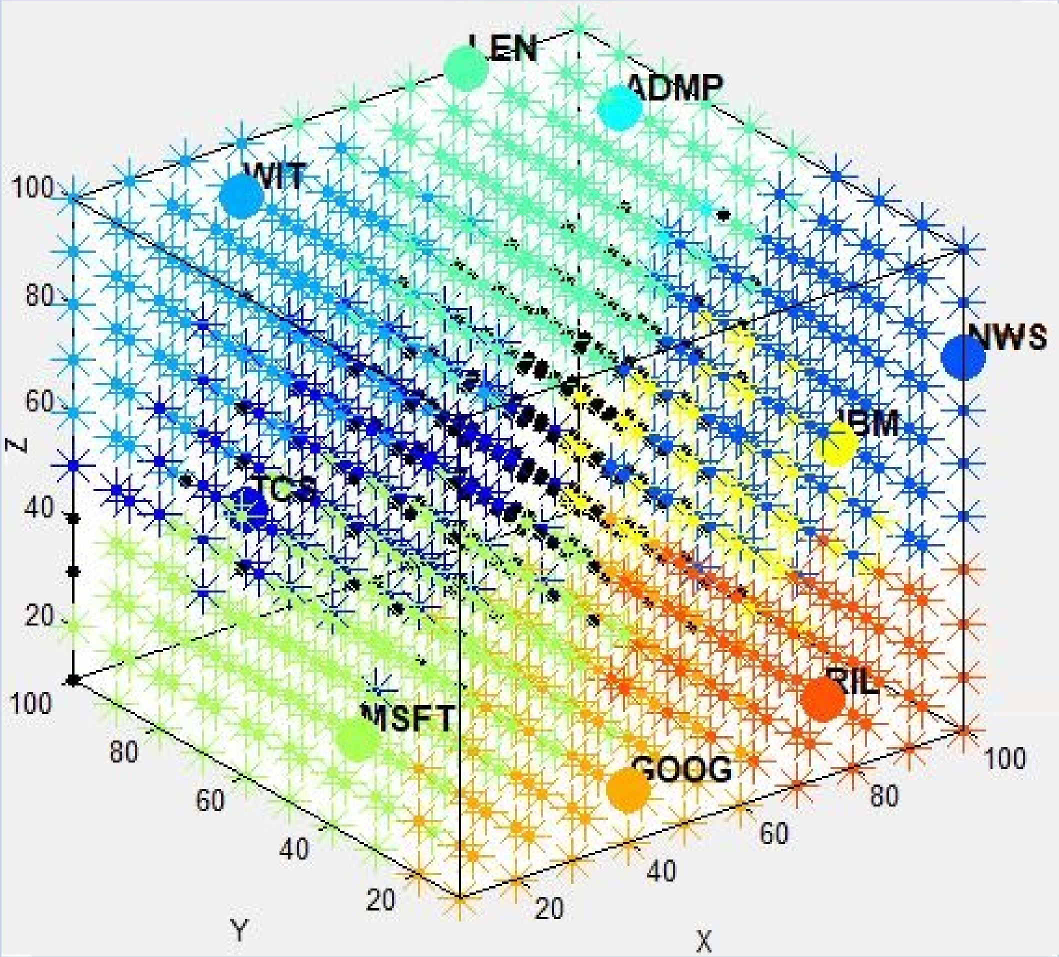
- Connectivity of a trained NeuCube with several training samples.



Neural Network Models for Predictive Analysis in Economics and Finance

Case Study: integrated modelling of financial time series and online newsdata

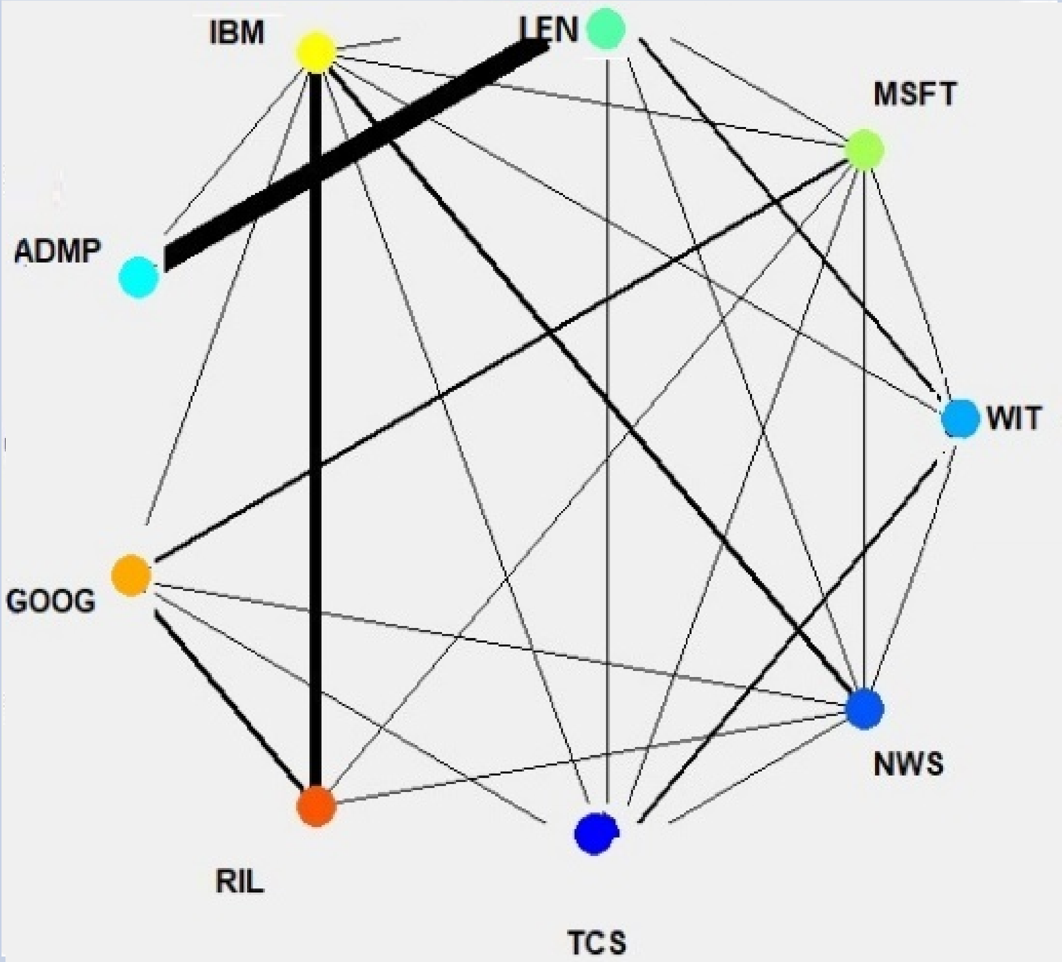
- Dynamic variable interaction graph represents how much changes in one variable (causing a spike) correlate with changes in another variable at the next time, including both time series and online news variable.



Neural Network Models for Predictive Analysis in Economics and Finance

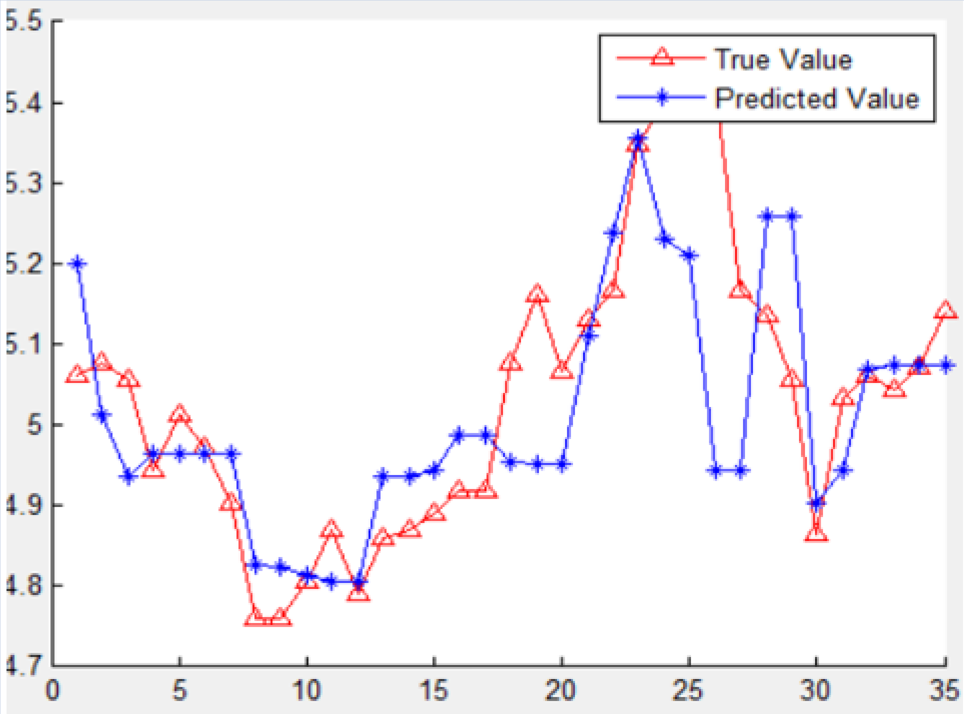
Case Study: integrated modelling of financial time series and online newsdata

- Dynamic relationships between stock indices and news.
- The thicker the connections, more activity between nodes, thus more influence to each other.

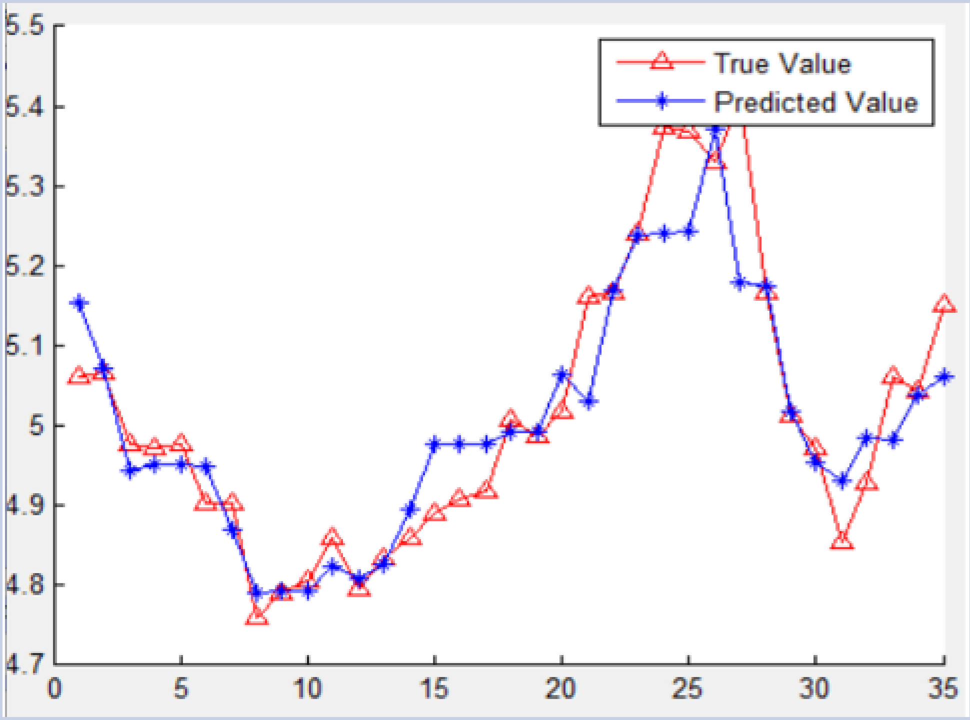


Neural Network Models for Predictive Analysis in Economics and Finance

Case Study: integrated modelling of financial time series and online newsdata



Regression results of closing stock without news



with news.

Neural Network Models for Predictive Analysis in Economics and Finance

Case Study III: NeuCube-based Predictive Associative Memory for Time Series – A Case Study on Trade Data[9]

- Spatio-Temporal Associative Memory (STAM) - a promising approach to machine intelligence:
- A machine learning model, inspired by learning principles in the human brain, and implemented on NeuCube.
- STAM model is trained on a full set of spatio-temporal variables (global learning) and effectively recalled and updated (locally) on a subset of the variables measured at different time intervals.
- STAM model learns the dynamics of input features (trade by country), and with just a few variables, it accurately predicted future trade indexes.
- STAM model is potential to revolutionize predictive analytics, particularly in challenging scenarios where data collection is severely impacted by factors like pandemics, crises, or natural disasters.
- STAM model reduces computational overhead while maintaining high accuracy, a unique feature that sets it apart from traditional deep neural networks.

9- N.Kasabov, Spatio-Temporal Associative Memories in Brain-inspired Spiking Neural Networks: Concepts and Perspectives. TechRxiv. Preprint. https://doi.org/10.36227/techrxiv.23723208.v1, 2023.

Thank you