# Advanced Artificial Intelligence Technologies and Applications

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Full course DLU, 2023, Lecture Content

# 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)
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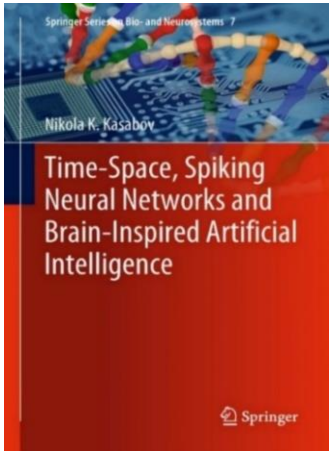
17. AI applications for multisensory environmental data (Ch19). Revision of the course.




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

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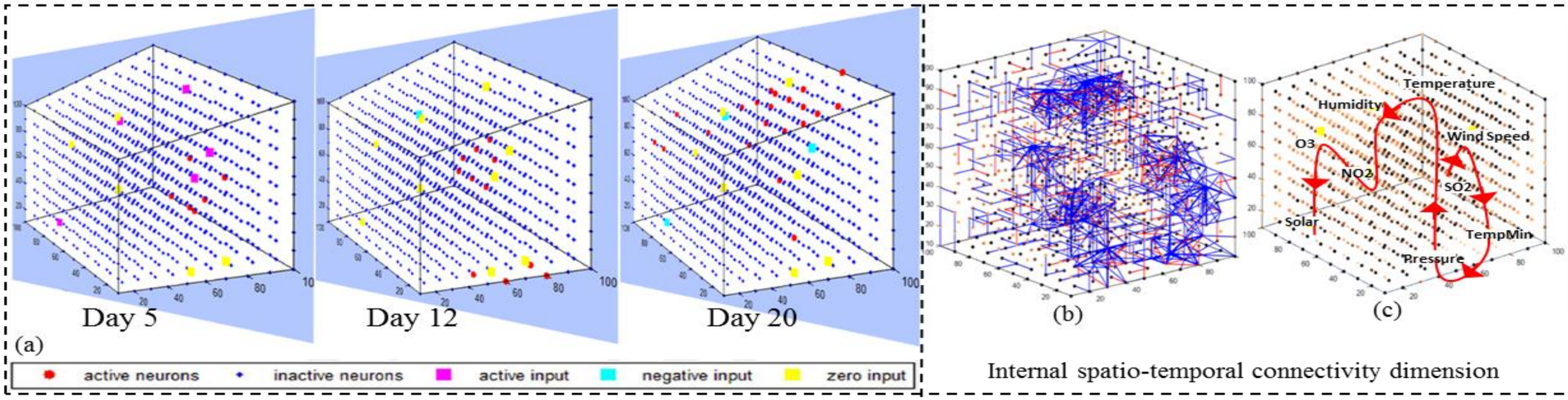
# Chapter 19. Deep learning of multisensory streaming data

Kasabov, N., Feigin, V., Hou, Z. -G., Chen, Y., Liang, L., Krishnamurthi, R., Parmar, P. (2014). Evolving spiking neural networks for personalised modelling, classification and prediction of spatio-temporal patterns with a case study on stroke. Neurocomputing, 134, 269-279. doi:10.1016/j.neucom.2013.09.049

Three snapshots of a NeuCube model during training on temporal climate and air pollution data of 9 variables, measured on each of 20 days before a stroke event happened to patients from a selected group (the left 3 figures). The evolved connectivity in the 3D SNN model after training – spatio-temporal structural patterns of connections are learned in the 3D dimensionality of the model. A dynamic functional pattern learned in the functional space of climate variable changes (the right most figure).



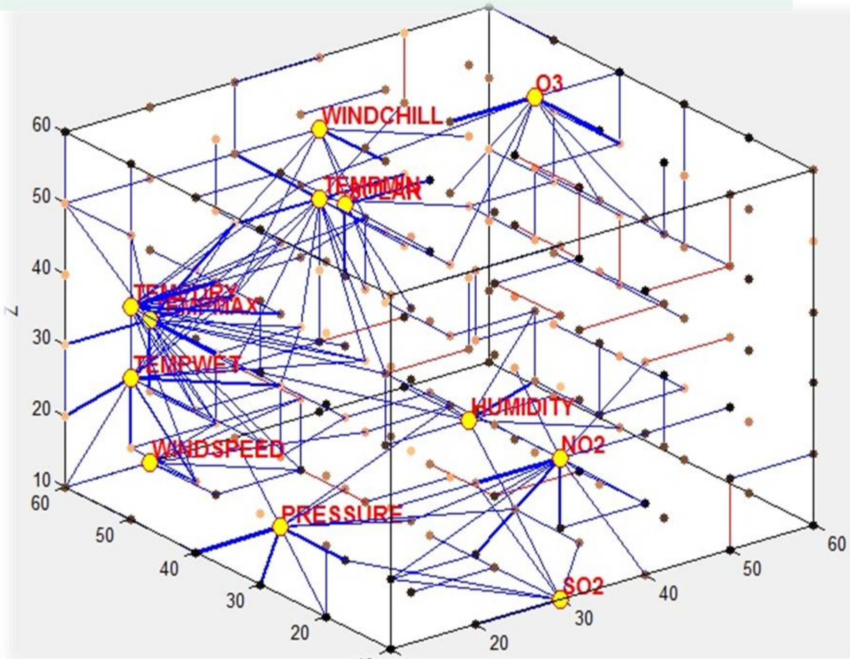

**A spatio-temporal rule extracted from a trained SNNcube on climate data relate to a high risk of stroke for a group of individuals**

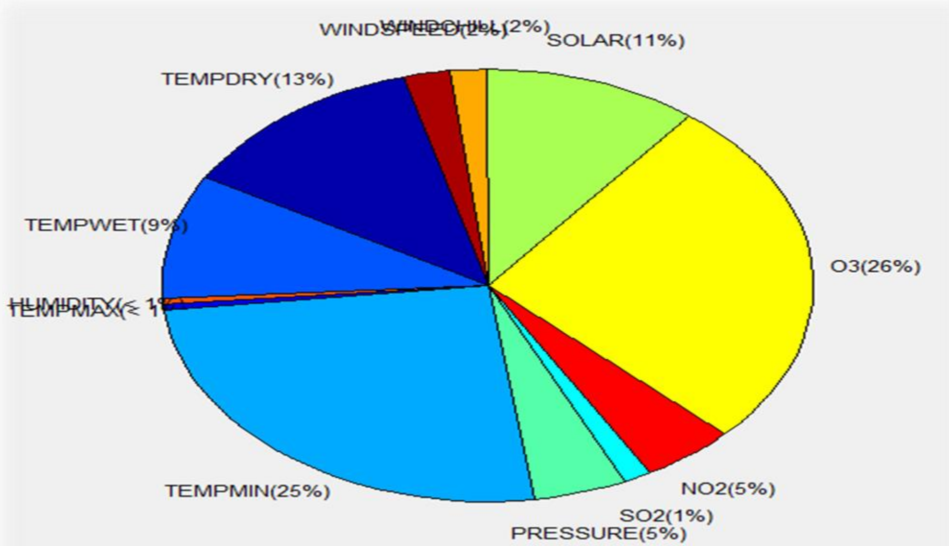
IF SO2 changes around time T1) AND (Wind Speed changes around time T2)
AND (TempMin changes around time T3) AND (Pressure changes around time T4)
AND (AvTemp changes around time T5) AND (Humidity changes around time T6)
AND (NO2 changes around time T7) AND (O3 changes around time T8) AND (Solar eruption around T9)
THEN (High risk of stroke for the individual X and the group she/he belongs to)

# Personalised prediction of risk for stroke days ahead

(N.Kasabov, M. Othman, V.Feigin, R.Krishnamurti, Z Hou et al - Neurocomputing 2014)

| METHODS | SVM | MLP | KNN | WKNN | NEUCUBE[ST] |
|---|---|---|---|---|---|
| 1 day earlier (%) | 55 *(70,40)* | 30 *(50,10)* | 40 *(50,30)* | 50 *(70,30)* | **95** ***(90,100)*** |
| 6 days earlier (%) | 50 *(70,30)* | 25 *(20,30)* | 40 *(60,20)* | 40 *(60,20)* | **70** ***(70,70)*** |
| 11 days earlier (%) | 50 *(50,50)* | 25 *(30, 20)* | 45 *(60,30)* | 45 *(60,30)* | **70** ***(70,70)*** |



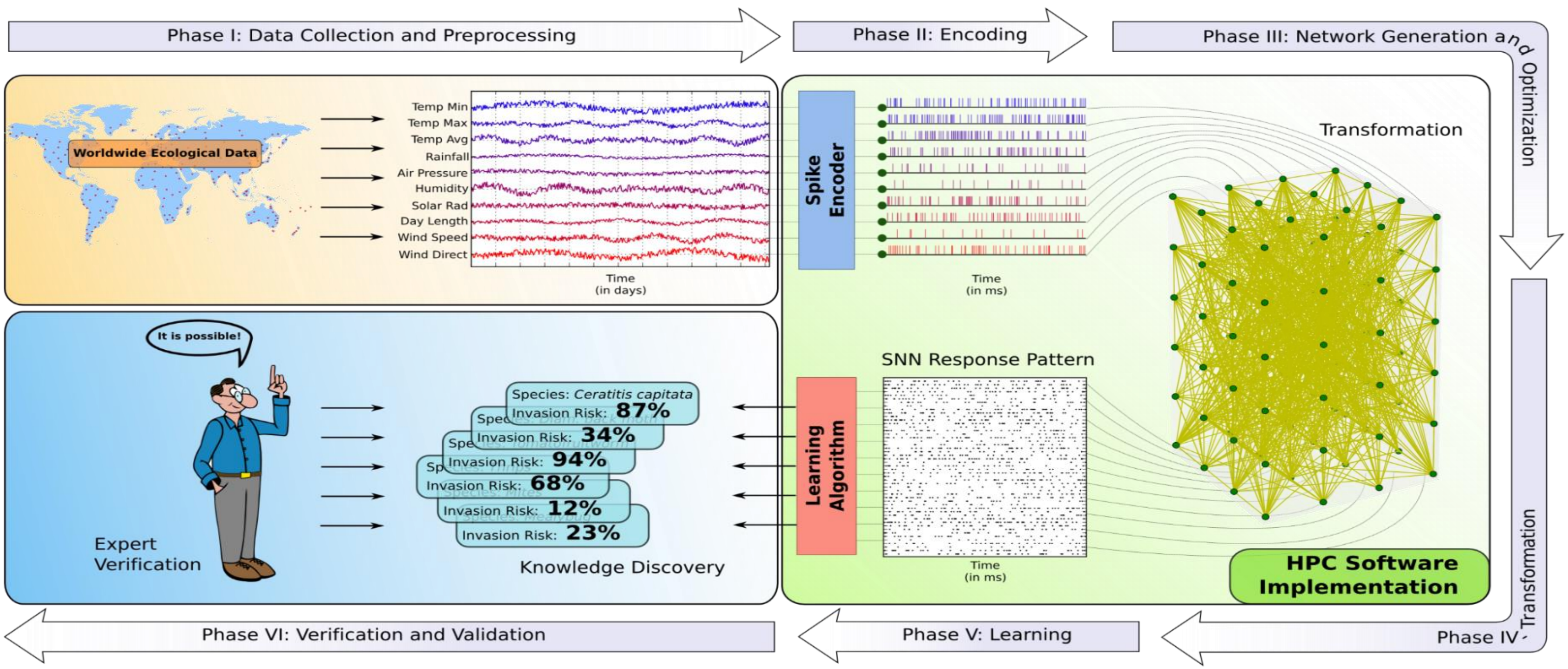




*(d) Neuron proportion based on spike transmission*

- SNN achieve better accuracy
- SNN predict stroke much earlier than other methods
- New information found about the predictive relationship of variables

# Multisensory Predictive Modelling of Time Series Data

Example: Predicting establishment of harmful species based on temporal climate data streams



# Predicting extreme weather conditions using satellite image data

(AUT/KEDRI + Met Services NZ)

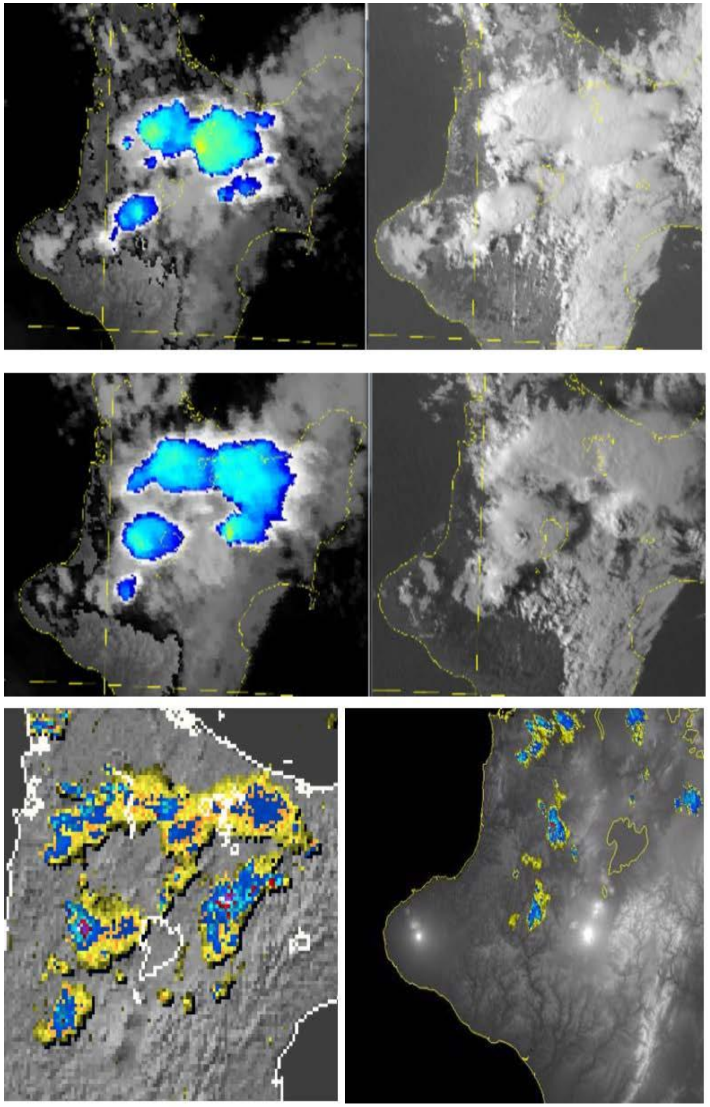


Figure 2. Example of infrared (top left) and visible band (top right) Himawari 8 imagery of a developing convective system. The middle row shows thesame view an hour later as the cloud clusters continue to evolve. The bottom images are rain radar images of the later time showing areas of intenserainfall associated with the convective activity.

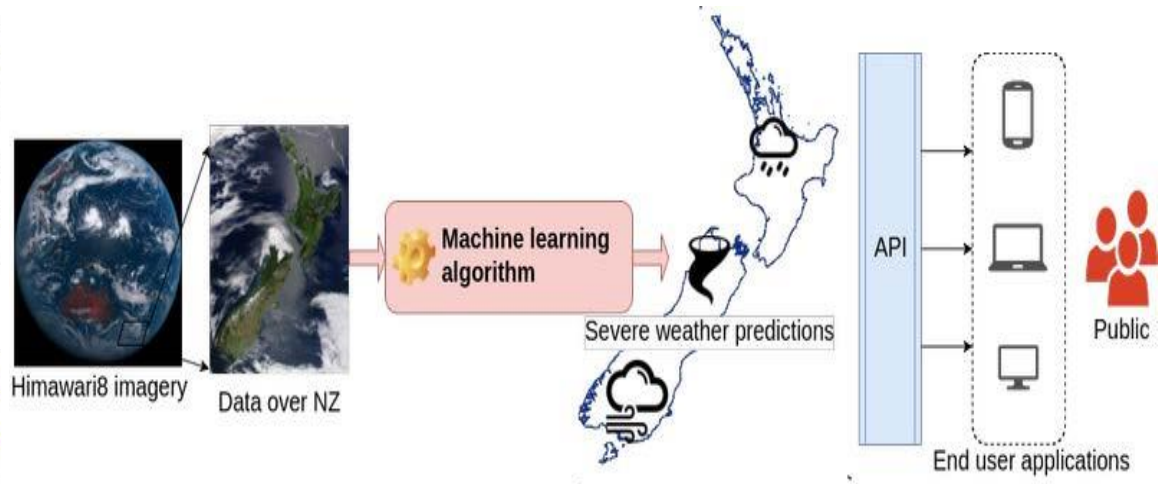



Figure 3. Overview of the implementation pathway to transform satellite imagery into end-user tools.

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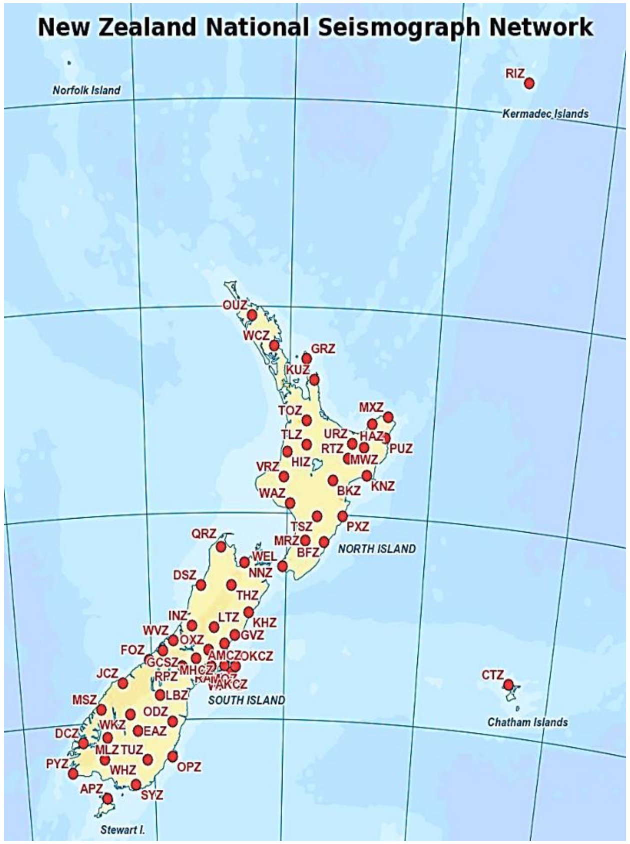
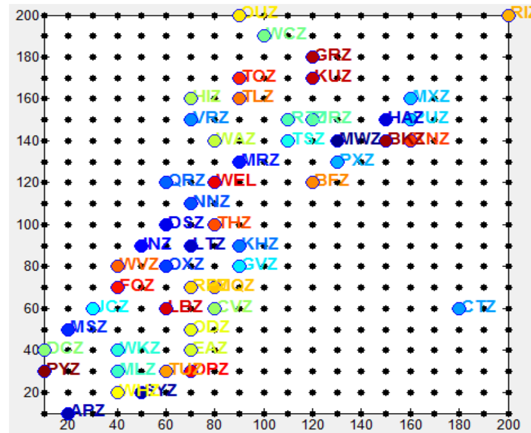
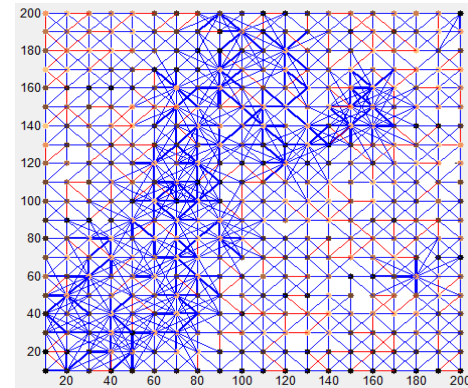
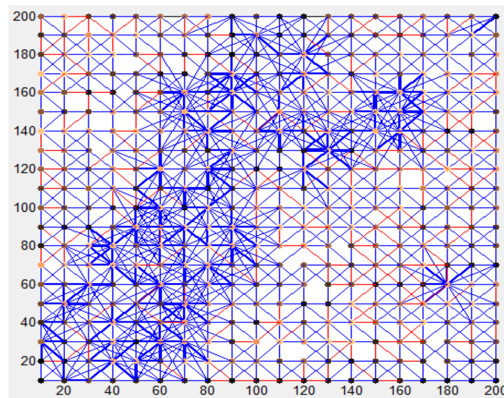
# Seismic TSD modelling for earthquake prediction

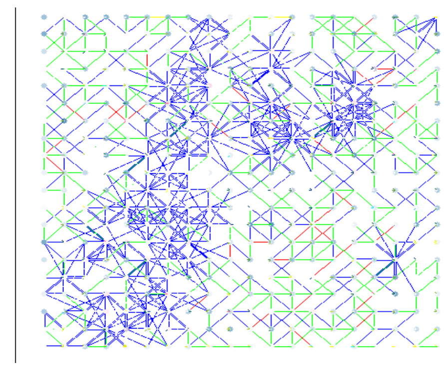
N. Kasabov, N. Scott, E.Tu, S. Marks, N.Sengupta, E.Capecci, M.Othman,M. Doborjeh, N.Murli,R.Hartono, J.Espinosa-Ramos, L.Zhou, F.Alvi, G.Wang, D.Taylor, V. Feigin,S. Gulyaev, M.Mahmoudh, Z-G.Hou, J.Yang, Design methodology and selected applications of evolving spatio- temporal data machines in the NeuCube neuromorphic framework, Neural Networks, v.78, 1-14, 2016. http://dx.doi.org/10.1016/j.neunet.2015.09.011.









| Measure | NeuCube | SVM | MLP |
|---|---|---|---|
| 1h ahead | **91.36%** | 65% | 60% |
| 6h ahead | **83%** | 53% | 47% |
| 12h ahead | **75%** | 43% | 46% |

**P**redicting risk for earthquakes, tsunami, land slides, floods – how early and how accurate?

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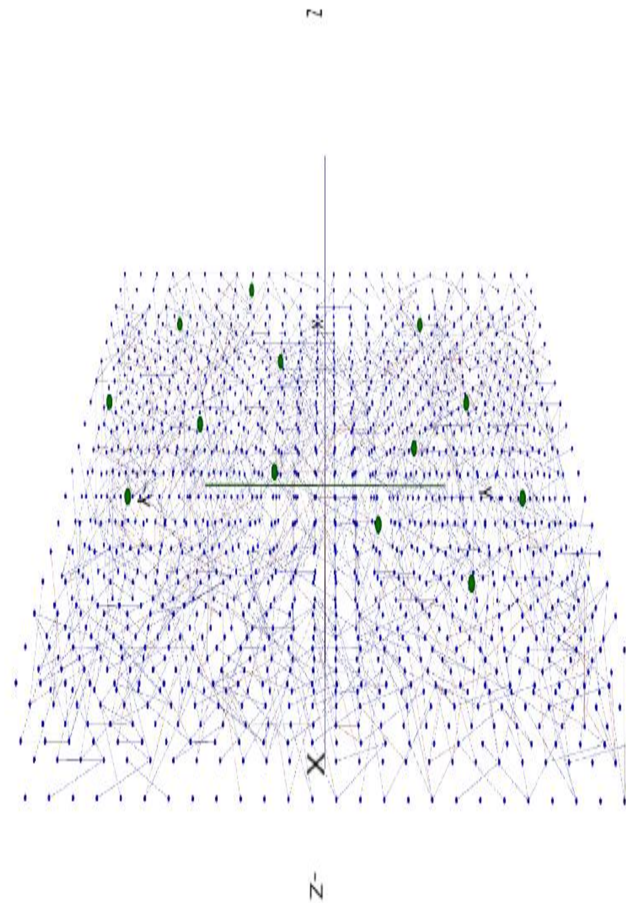
# Wind TSD modelling for energy prediction from wind turbines

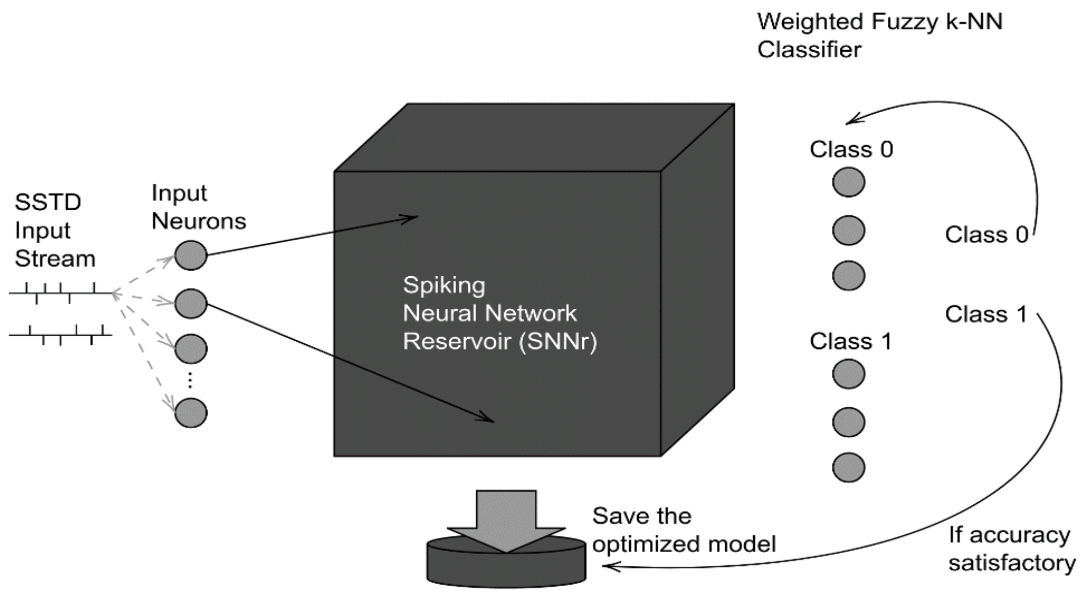
New Zealand

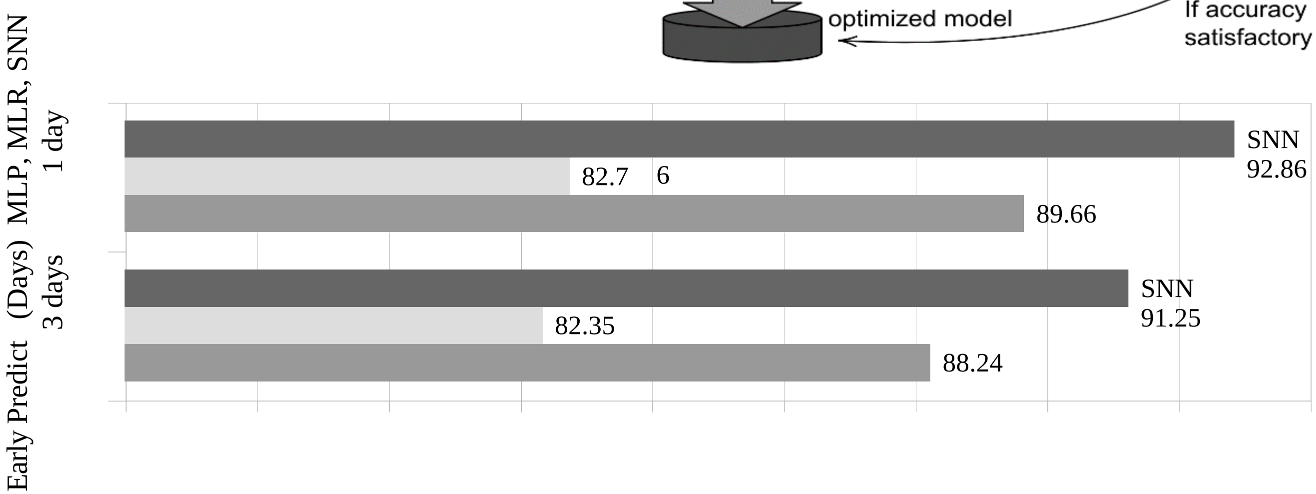


Xinjiang, China (中国新疆）

# Flood events risk assessment using environmental TSD

Mohd Hafizul Afifi Abdullah, **Muhaini Othman**, Shahreen Kasim, Siti Aisyah Mohamed, Evolving spiking neural networks methods for classification problem: a case study in flood events risk assessment, Indonesian Journal of Electrical Engineering and Computer Science Vol. 16, No. 1, October 2019, pp. 222~229 ISSN: 2502-4752, DOI: 10.11591/ijeecs.v16.i1.pp222-229, *http://iaescore.com/journals/index.php/ijeecs*

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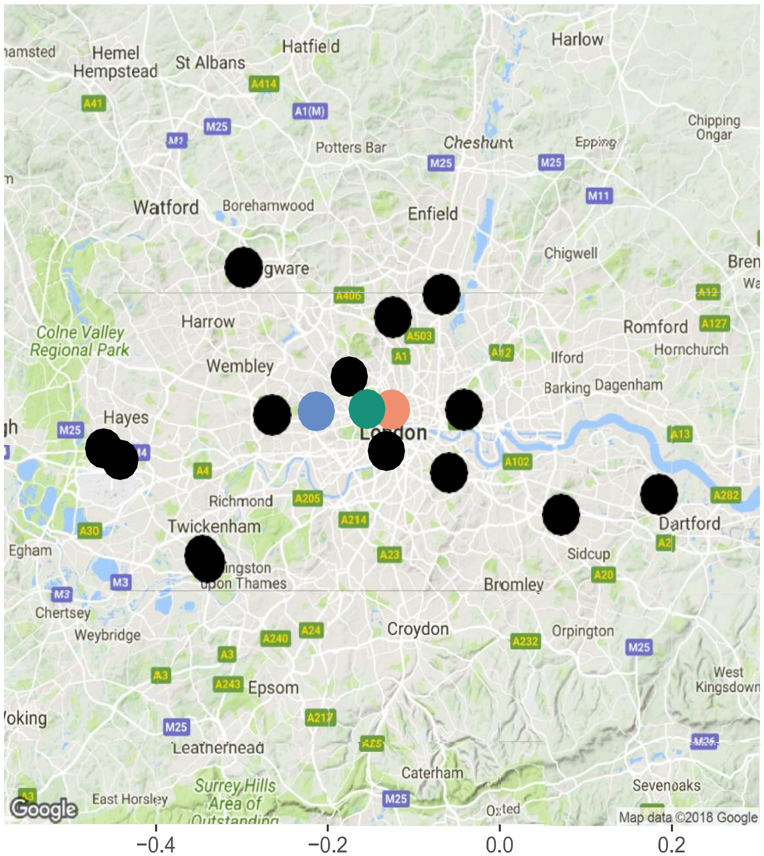
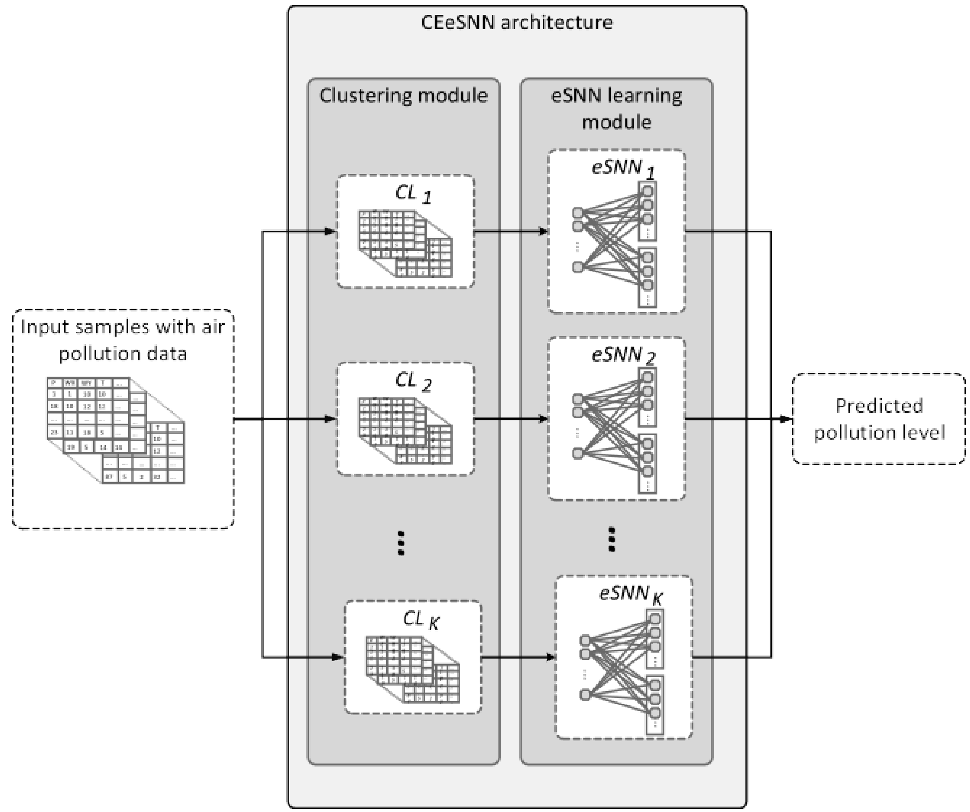
# Using an ensemble of eSNN for Predicting Hourly Air Pollution in London Area from sensory TSD






P. S. P Maciaga, N. K. Kasabov, M. Kryszkiewicza, R. Benbenik, Prediction of Hourly Air Pollution in London Area Using Evolving Spiking Neural Networks, Environmental Modelling and Software, Elsevier, vol.118, 262-280, 2019, https://www.sciencedirect.com/science/article/pii/S1364815218307448?dgcid=author

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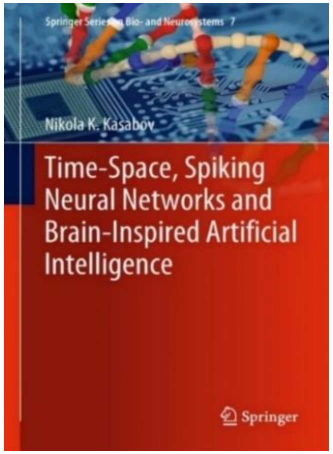


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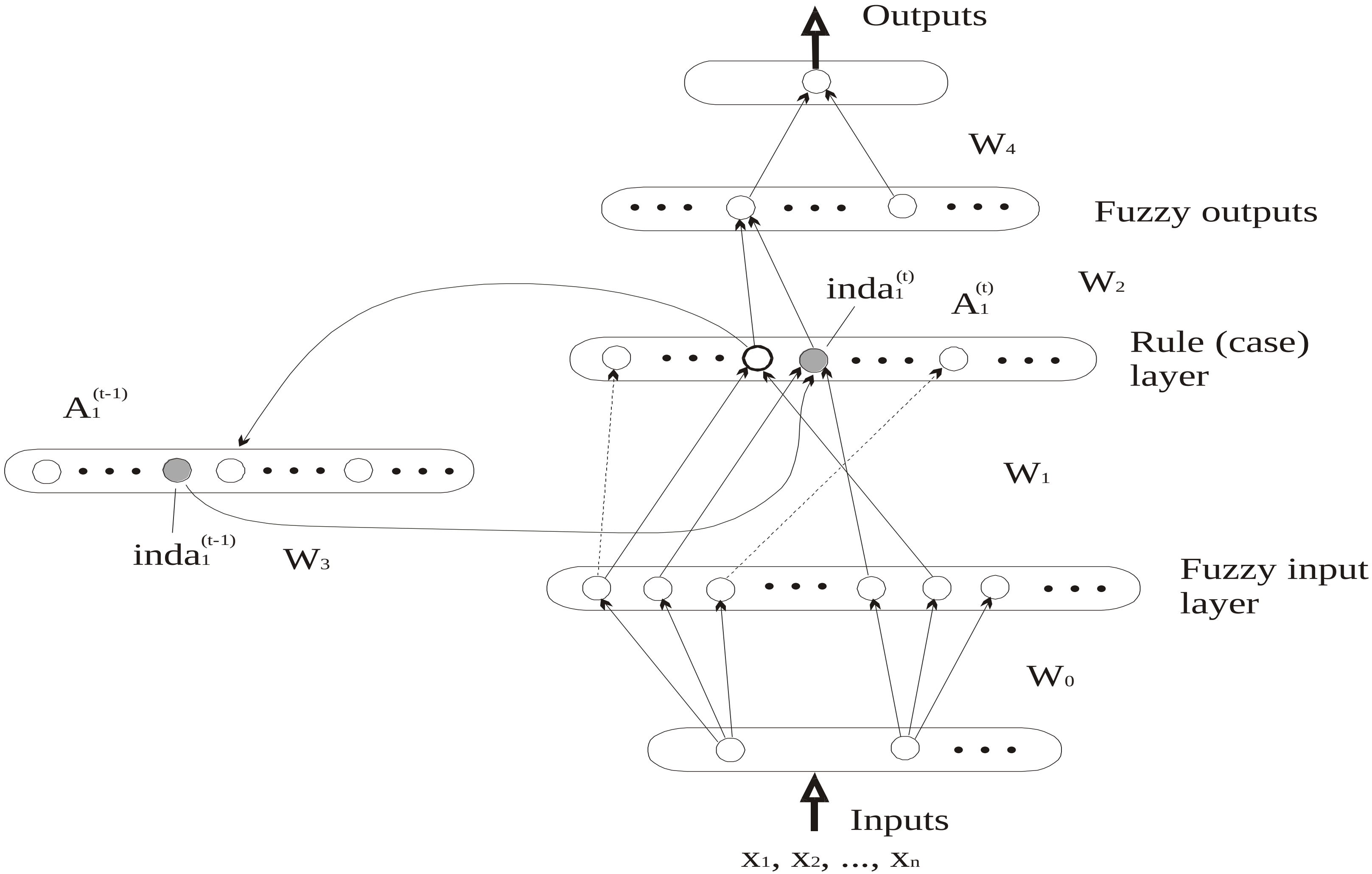
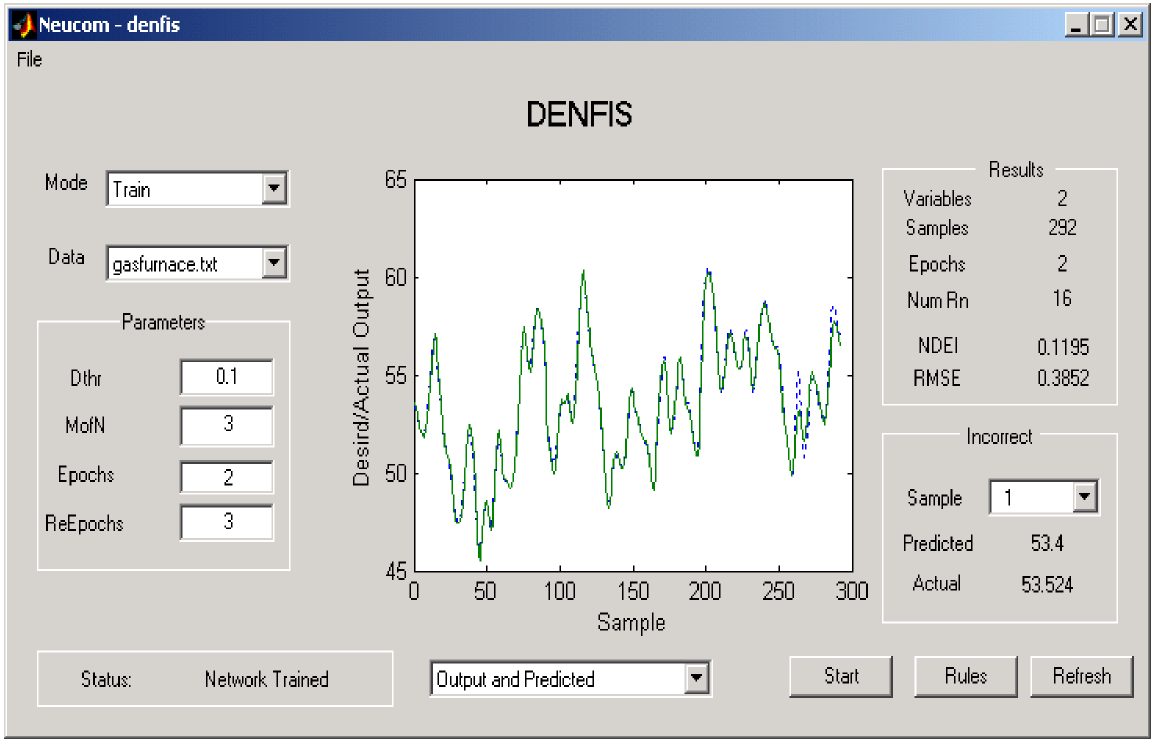
# An EFuNN architecture with a feedback connection



# Dynamic Evolving Neuro-Fuzzy Systems (DENFIS)

*Kasabov, N., and Song, Q., DENFIS: Dynamic Evolving Neural-Fuzzy Inference System and its Application for Time Series Prediction, IEEE Trans.on Fuzzy Systems, 2002, April*

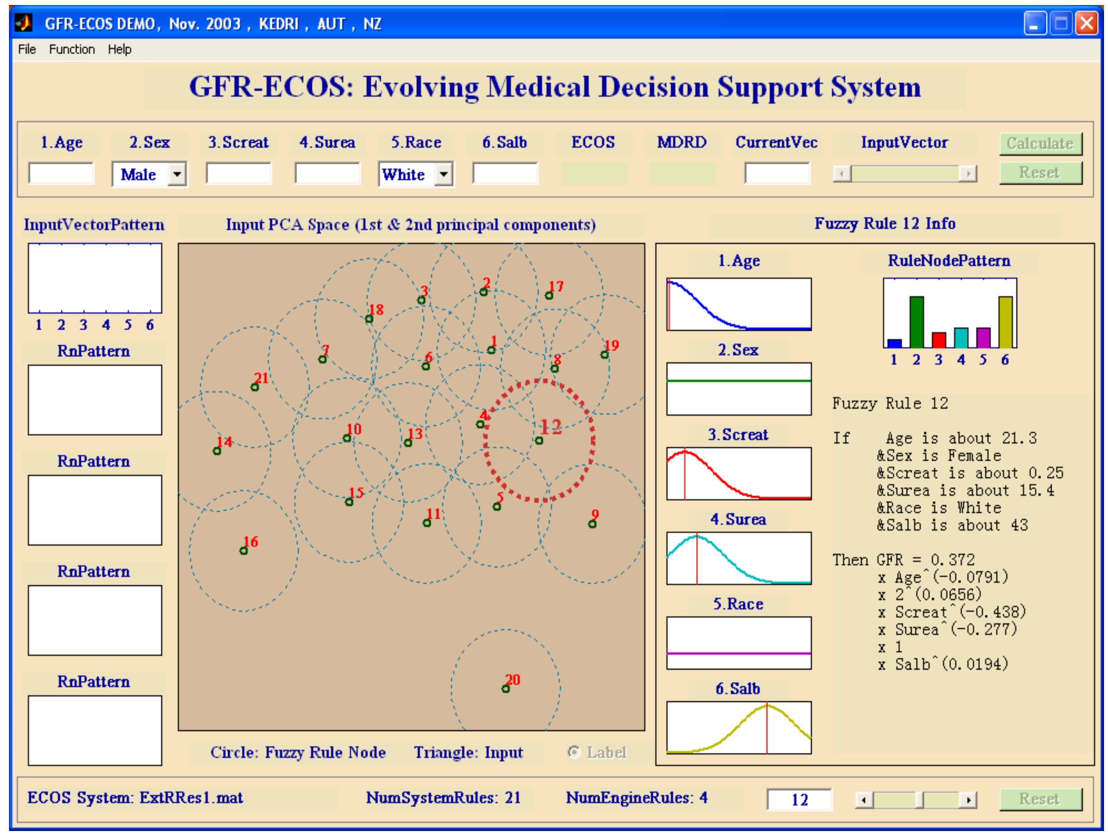
- Modeling, prediction and knowledge discovery from dynamic time series
- Cluster –based local modelling where each cluster evolves a model (a function) of the same type



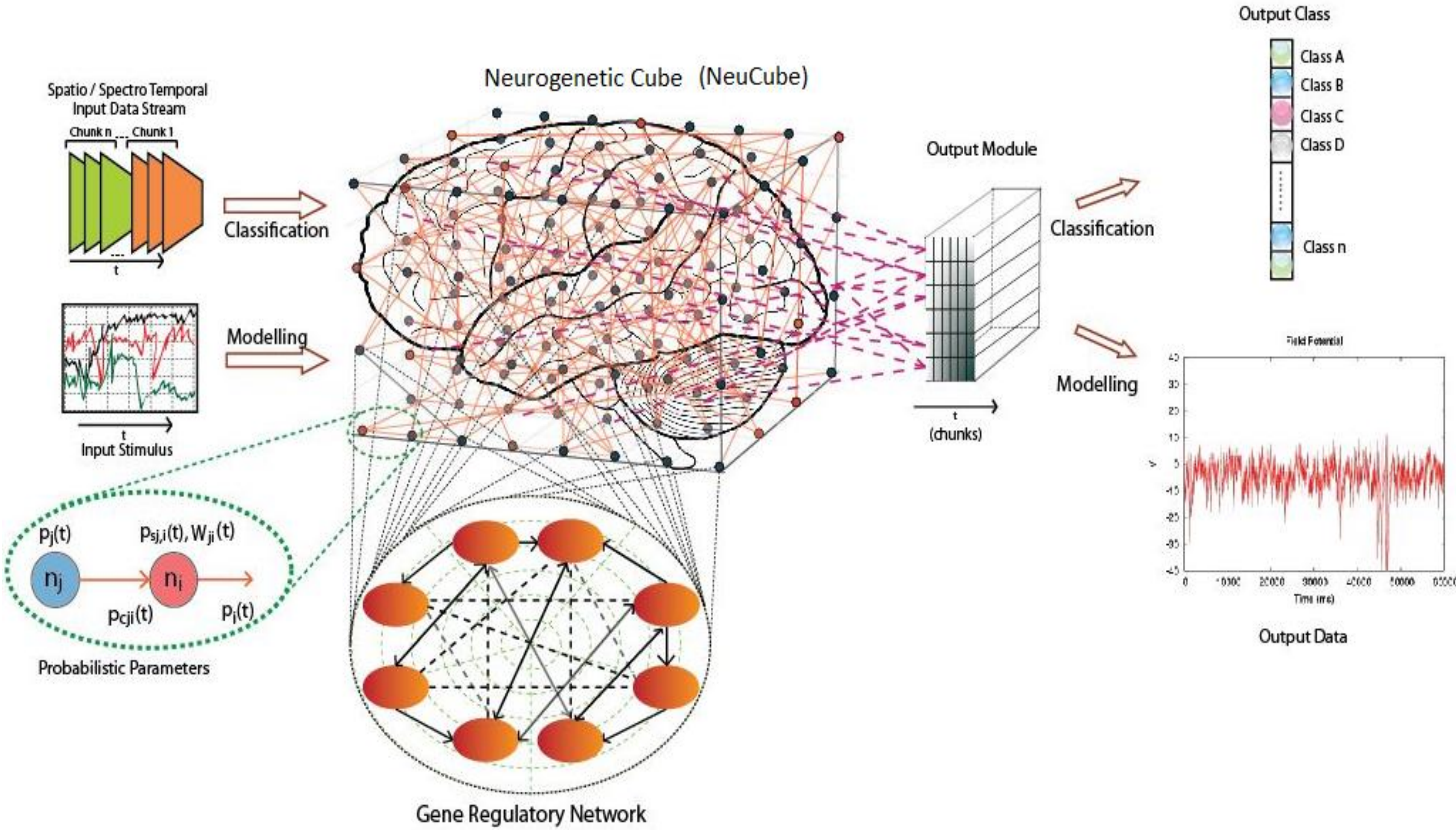
# Example: Local, adaptive GFR Renal Function Evaluation System based on DENFIS

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).



# The NeuCube Architecture



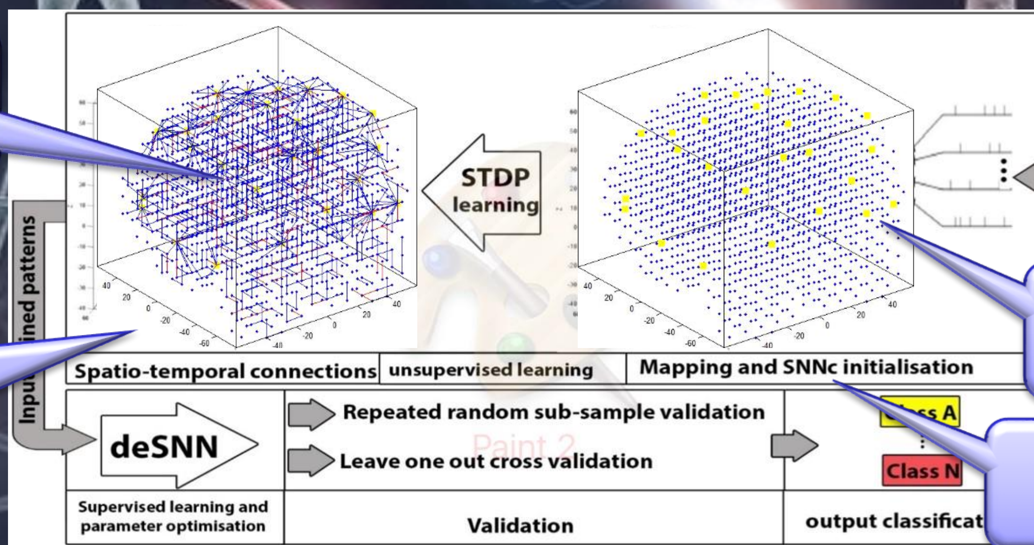

Kasabov, N., NeuCube: A Spiking Neural Network Architecture for Mapping, Learning and Understanding of Spatio-Temporal Brain Data, Neural Networks, vol.52, 2014.

E. Tu, N. Kasabov, J. Yang, Mapping Temporal Variables into the NeuCube Spiking Neural Network Architecture for Improved Pattern Recognition and Predictive Modelling, IEEE Trans. on Neural Networks and Learning Systems, 28 (6), 1305-1317,, 2017 DOI: 10.1109/TNNLS.2016.2536742, 2017.

# Deep learning in NeuCube

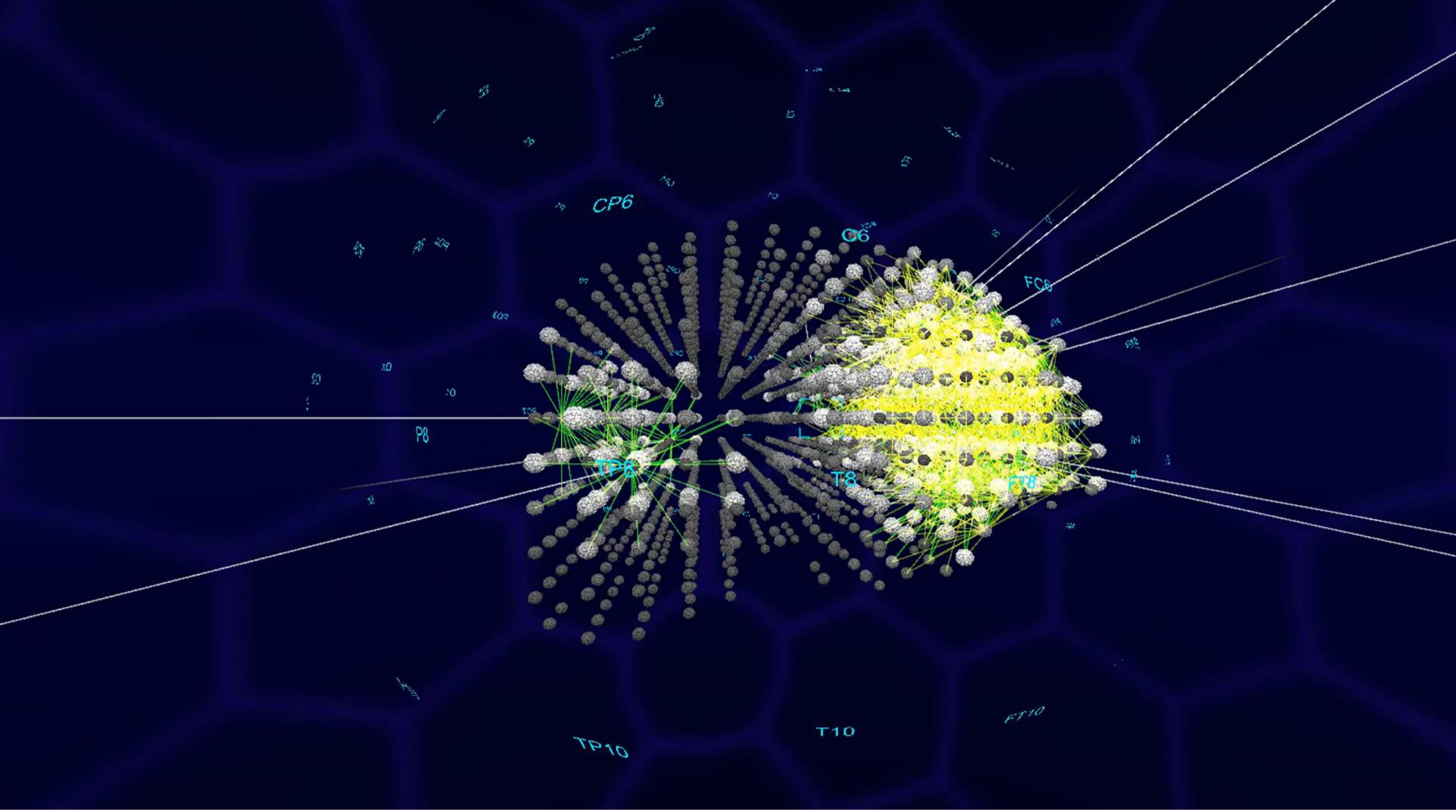
Creation of Neuron Connections During The Learning

The More Spike Transmission, The More Connections Created




Spike Trains Entered to the SNNc

Neuron Spiking Activity During the STDP Learning



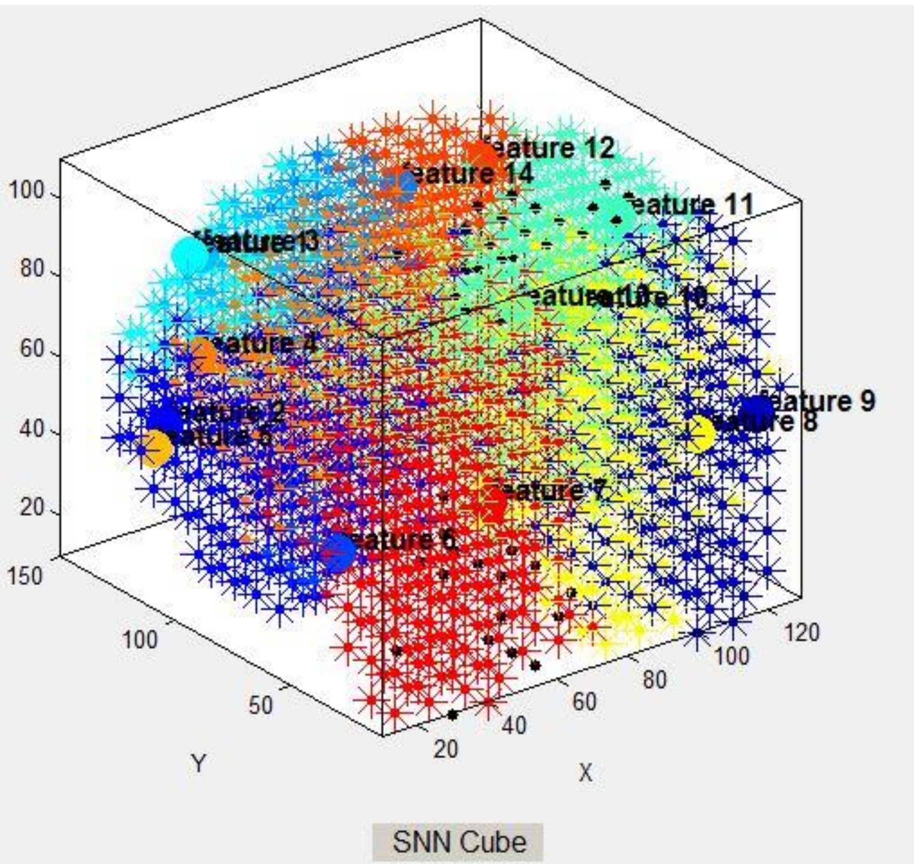

N. Kasabov, N. Scott, E.Tu, S. Marks, N.Sengupta, E.Capecci, M.Othman,M. Doborjeh, N.Murli,R.Hartono, J.Espinosa-Ramos, L.Zhou, F.Alvi, G.Wang, D.Taylor, V. Feigin,S. Gulyaev, M.Mahmoudh, Z-G.Hou, J.Yang, Design methodology and selected applications of evolving spatio- temporal data machines in the NeuCube neuromorphic framework, Neural Networks, v.78, 1-14, 2016. http://dx.doi.org/10.1016/j.neunet.2015.09.011.

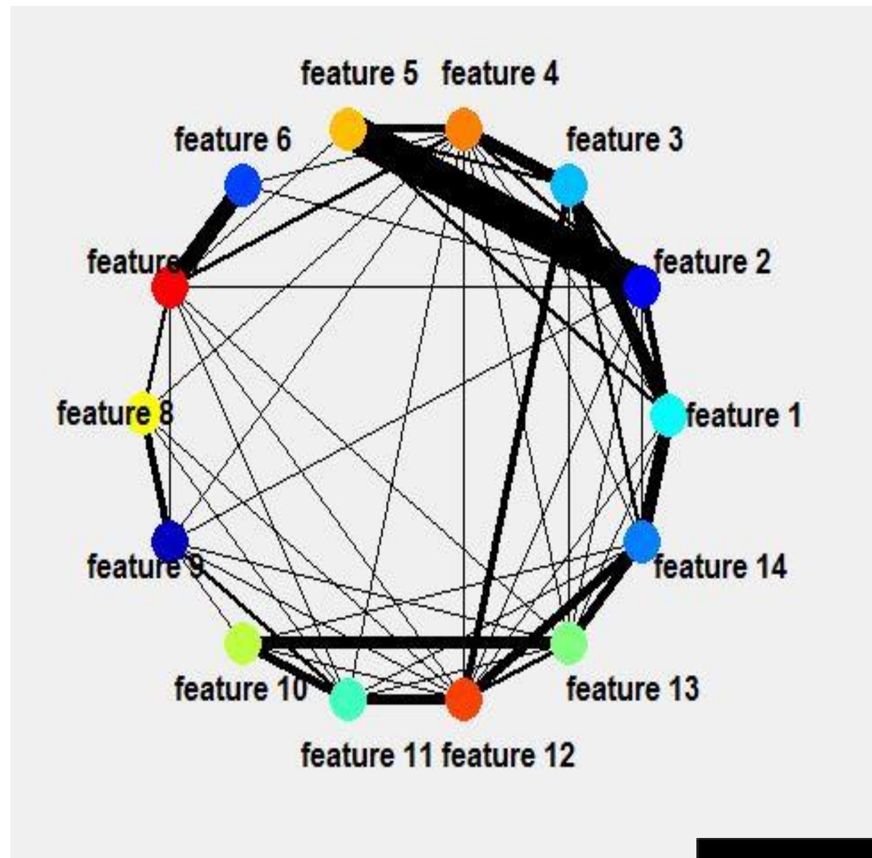
# Capturing time-space knowledge as information exchange between clusters

- Clusters of highly connected neurons to input neurons;

- Clusters of spiking activity spread from input neurons ;

- A graph of information exchange between spatially distributed clusters around the inputs

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# Design methodology for application oriented SNN

- Analysis of the type of data and possible solutions to the problem
- SNN reservoir design according to a template (brain template or other)
- Input data transformation into spike sequences;
- Mapping input variables into spiking neurons
- Deep unsupervised learning spatio-temporal spike sequences in a scalable 3D SNN reservoir;
- Supervised learning and classification of data over time;
- Dynamic parameter optimisation;
- Model visualisation
- Extracting deep knowledge from a trained SNN
- Adaptation on new data in an on-line/ real time mode;
- Extracting of modified knowledge
- Implementation of a SNN model: von Neumann vs neuromorphic hardware systems

# Thank you and Questions?

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