

Cognitive Systems Engineering

Course organiser: Prof. Shihua Zhou



Course presenter

Prof Nikola Kasabov

Visiting Professor at Dalian University

Life FIEEE, FRSNZ, FINNS, DVF RAE UK

Founding Director KEDRI

Professor, Auckland University of Technology, NZ

George Moore Chair/Professor, Ulster University, UK

Honorary Professor, University of Auckland NZ, Peking University China

Visiting Professor IICT/Bulgarian Academy of Sciences and Teesside University UK

Doctor Honoris Causa Obuda University Budapest

Director, Knowledge Engineering Consulting Ltd (<https://www.knowledgeengineering.ai>)



Assistant

Doct Ms Iman AbouHassan

iabouhassan@tu-sofia.bg

abouhassan.iman@gmail.com



Cognitive System Engineering

Cognitive systems (CogSys) are software-hardware systems that have their structure and functionality based on principles of information processing in the human brain. They are part of AI, but AI includes also other systems that manifest cognitive behaviour, such as speech and image recognition, learning and reasoning, but using other methods, such as statistical, empirical, abstract logic, etc.

The course is by research papers.

Every topic will include:

1. Topic/task/problem specification
2. Previously published methods for solving the problem
3. Description of the method and in the paper under discussion
4. **Software implementation**, experimental results and discoveries
5. **Applications**
6. Future work to be done for this problem and questions for individual work

Expected results:

1. Students obtain new knowledge and skills in the area of CogSys for AI applications.
2. Students can learn to take a critical approach to the existing methods and systems.
3. Students can get confidence that they can suggest new methods and to publish them in good journals.

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

ZOOM link for all lectures:

<https://us05web.zoom.us/j/4658730662?pwd=eFN0eHRcN3o4K0FaZ0lqQmN1UUgydz09>



CogSysEn: Lecture Topics

1. Introduction to the course

Part I : Learning systems

2. Deep learning and deep knowledge representation in the human brain

-Chapter 3 from: N.Kasabov, *Time-space, spiking neural networks and brain-inspired artificial intelligence*, Springer-Nature, 2029

3. Modelling brain dynamics

- Benuskova, L., Kasabov, N. Modeling brain dynamics using computational neurogenetic approach. *Cogn Neurodyn* 2, 319–334 (2008). <https://doi.org/10.1007/s11571-008-9061-1>

4. Evolving learning systems

- N. Kasabov, "Evolving fuzzy neural networks for supervised/unsupervised online knowledge-based learning," in *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, vol. 31, no. 6, pp. 902-918, Dec. 2001, doi: 10.1109/3477.969494.

- NeuCom software (<https://theneucom.com>): EFuNN

5. Neuro—fuzzy learning and inference systems: DENFIS

- Kasabov, N. K., & Song, Q. (2002). DENFIS: dynamic evolving neural-fuzzy inference system and its application for time-series prediction. *IEEE transactions on Fuzzy Systems*, 10(2), 144-154.

- DENFIS software in Python.

6. Spatio-temporal learning systems: SNN

- N. Kasabov, K. Dhoble, N. Nuntalid, G. Indiveri, Dynamic evolving spiking neural networks for on-line spatio- and spectro-temporal pattern recognition. *Neural Networks*, 41(1995), 188–201 (2013). <https://doi.org/10.1016/j.neunet.2012.11.014>.

7. Reservoir computing and Brain-inspired SNN

- S. Schliebs, A. Mohemmed, N. Kasabov, Are probabilistic spiking neural networks suitable for reservoir computing? in *International Joint Conference on Neural Networks (San Jose, USA, 2011)*, pp. 3156–3163.

- N. Kasabov, NeuCube: a spiking neural network architecture for mapping, learning and understanding of spatio-temporal brain data. *Neural Netw.* 52(2014), 62–76 (2014).

8. Integrated learning systems:

- P. Koprinkova-Hristova, D. Penkov, S. Nedelcheva, S. Yordanov and N. Kasabov, "On-line Learning, Classification and Interpretation of Brain Signals using 3D SNN and ESN," 2023 *International Joint Conference on Neural Networks (IJCNN)*, Gold Coast, Australia, 2023, pp. 1-6, doi: <https://doi.org/10.1109/IJCNN54540.2023.10191974>,

- AbouHassan et al, NeuDen: Integrating evolving Neuromorphic spiking neural networks and Dynamic evolving neuro-fuzzy systems for predictive and explainable learning of multiple time series



Lecture 5: Neuro—fuzzy learning and inference systems: DENFIS

1. Main cognitive principles of evolving systems:

- The system evolves its structure and functionality incrementally from incoming data (it is not a fixed structure for ever!!);
- *Evolving means developing. Nothing in the universe, including the human brain, is fixed, everything is evolving.*
- The evolving structure is based on *evolving clustering* of incoming data, i.e. **continuous association of data based on their similarity**.
- Centers of clusters are captured (learned) as neurons in a neuronal structure, named here: Evolving Connectionist System (**ECOS**).
- Clustering can be supervised, e.g. clusters are formed based on both similar input vectors and similar (same) outputs. Example: EFuNN.
- **Clustering can be unsupervised , e.g. clusters are created based only on similarity of input vectors and then within the cluster, there is a function derived to approximate the data in each cluster. Example: DENFIS (lecture 5).**
- The clusters represent **knowledge**, which is evolving knowledge.
- ECOS are **“life-long” learning systems**.
- ECOS are **robust** to noise and perturbations in data based on the fuzzification of the data.
- ECOS are **multi-model systems**, e.g. local models are represented by the clusters and their integration is done at the output. This is contrast to most of the AI systems that are based on a single model (e.g. a regression function) .

Kasabov, N. ECOS - A framework for evolving connectionist systems and the 'eco' training method, in: S.Usui and T.Omori (eds) Proceedings of ICONIP'98 - The Fifth International Conference on Neural Information Processing, Kitakyushu, Japan, 21-23 October 1998, IOS Press, vol.3, 1232-1235

Kasabov, N. *Evolving Connectionist Systems*, Springer Verlag, London, (2007) 458p (first edition 2003)

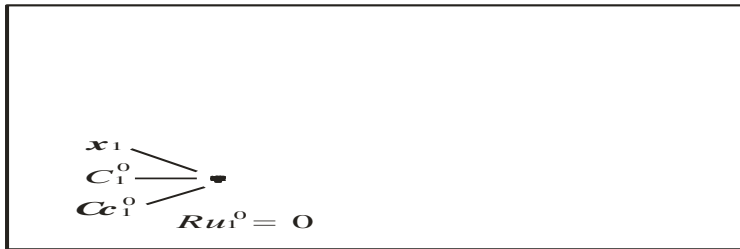


DENFIS:

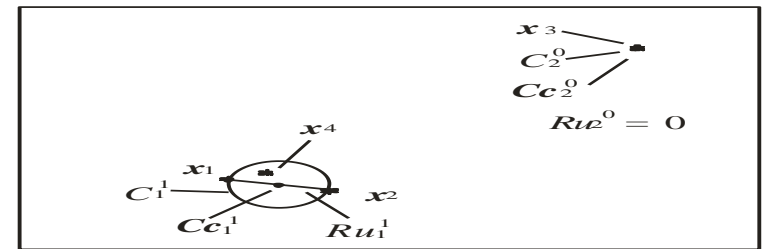
Local learning based on clustering of input vectors and learning local models

The original paper: Kasabov, N. K., & Song, Q. (2002). DENFIS: dynamic evolving neural-fuzzy inference system and its application for time-series prediction. *IEEE Transactions on Fuzzy Systems*, 10(2), 144-154.

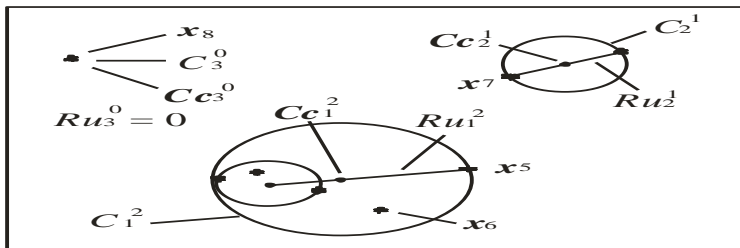
(a)



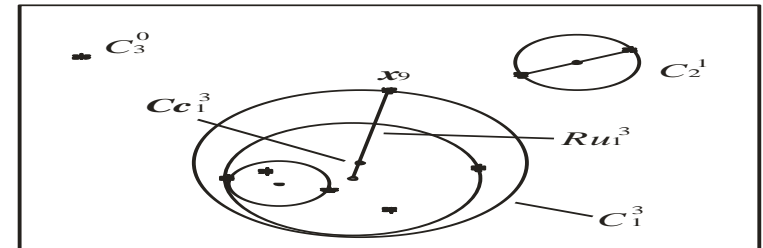
(b)



(c)



(d)



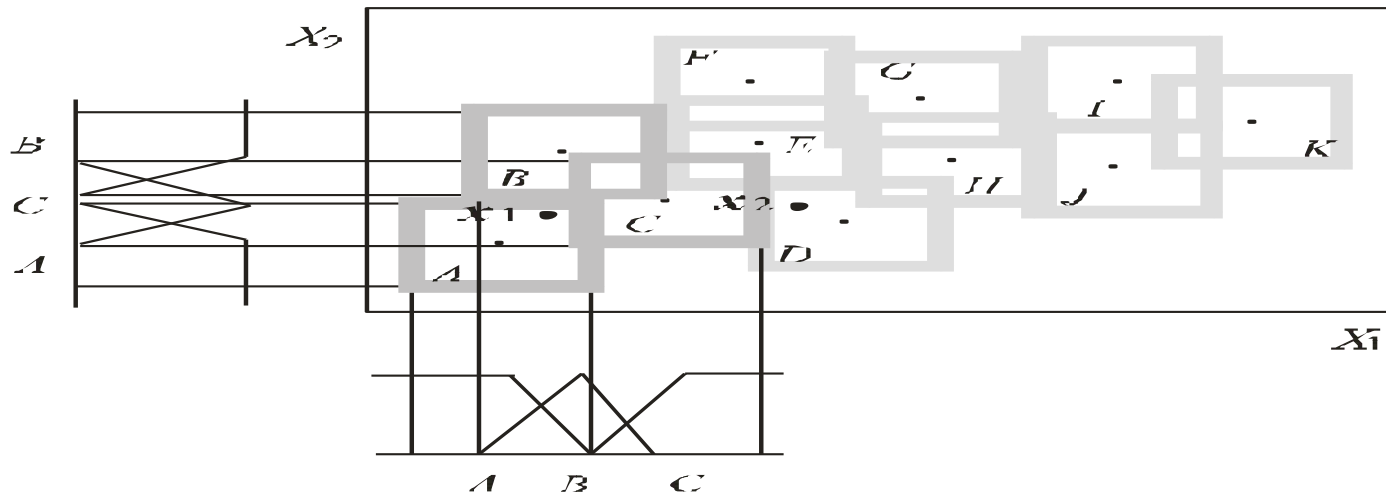
- x_i : sample
- Cc_j^k : cluster centre
- C_j^k : cluster
- Ru_{ij}^k : cluster radius

An evolving clustering process using ECM with consecutive examples x_1 to x_9 in a 2D space (Kasabov and Song, DENFIS, IEEE Tr FS, 2002)

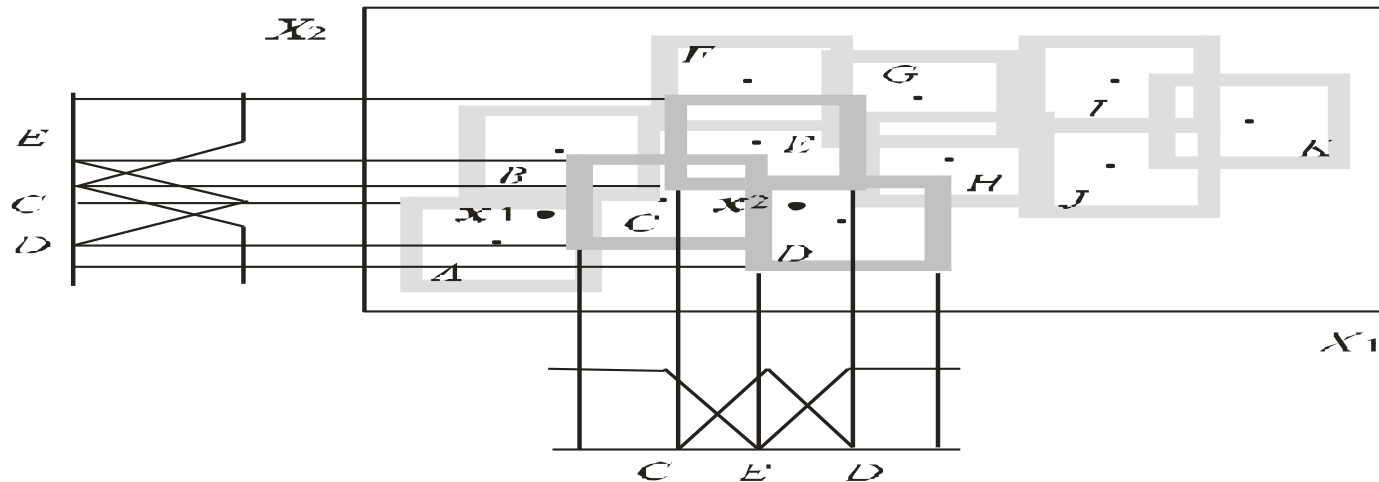
DENFIS

Learning and Inference in DENFIS

(a) Fuzzy rule group 1 for a DENFIS



(b) Fuzzy rule group 2 for a DENFIS



Kasabov, N., and Song, Q., DENFIS: Dynamic Evolving Neural-Fuzzy Inference System and its Application for Time Series Prediction, IEEE Transactions on Fuzzy Systems, Vol. 10, 2, April, (2002) 144-154

Rules can be extracted at each phase of learning and they may overlap

Neucom - Denfis

Help

Available: Gasfurnace_Normalised_3.txt # 3 # 292

Data

Mode: Train

Parameter:

Dthr: 0.1
MofN: 3
Epochs: 2

Results:

Num: 16
NDEI: 0.1134
RMSE: 0.0245

Uncorrect:

Sample: 1
Predictor:
Actual:

Status: Network Trained

Start Rules Reset

Label Ce
 Label Sarr

View Data

Help

Environment for Evolving Intelligence

Rename Extract Split Split Ratio 80%
Join Eigen Transform

disrules

```

Rule 1:
if X1 is GaussianMF( 0.50 0.47)
   X2 is GaussianMF( 0.50 0.53)
then Y = 1.46
    - 0.52 * X1
    + 0.59 * X2

Rule 2:
if X1 is GaussianMF( 0.50 0.32)
   X2 is GaussianMF( 0.50 0.61)
then Y = 1.44
    - 0.47 * X1
    + 0.59 * X2

Rule 3:
if X1 is GaussianMF( 0.50 0.62)
   X2 is GaussianMF( 0.50 0.45)
then Y = 1.46
    - 0.52 * X1
    + 0.61 * X2

Rule 4:
if X1 is GaussianMF( 0.50 0.70)
   X2 is GaussianMF( 0.50 0.31)
then Y = 1.47
    - 0.52 * X1
    + 0.60 * X2

Rule 5:
if X1 is GaussianMF( 0.50 0.81)

```

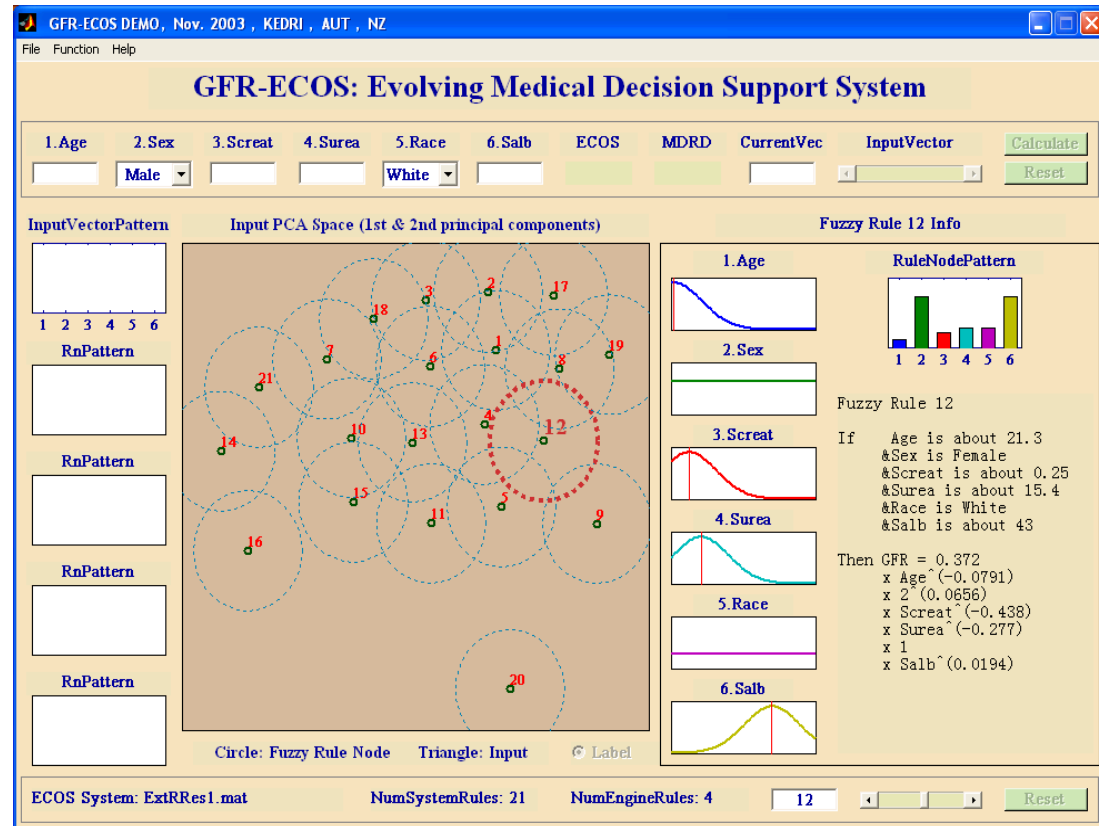
Save to Text File



Example: Local, adaptive 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).

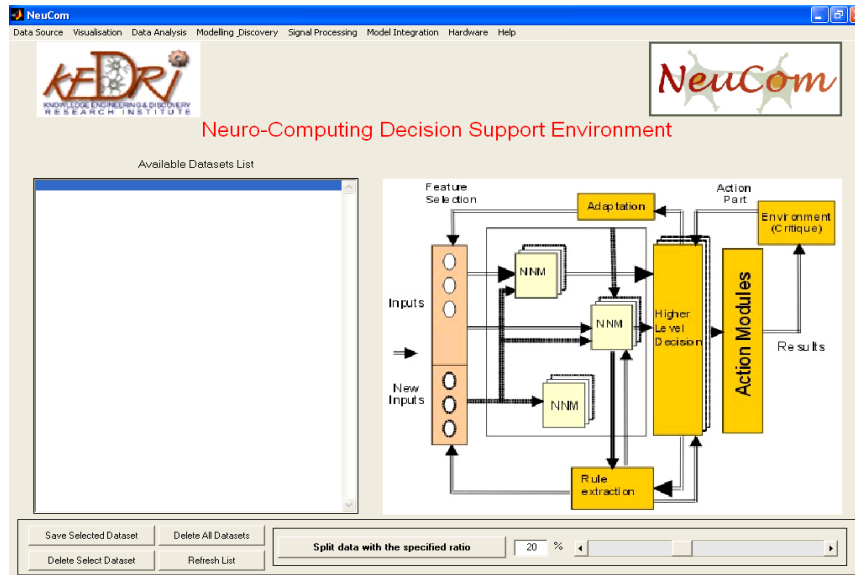


3. Software implementations:

DENFIS for time series prediction

MATLAB version (DENFIS as part of NeuCom):

<https://www.kedri.aut.ac.nz/neucom>, or <http://theneucom.com>



Python versions:

<https://github.com/sangbijaksana/denfis>

<https://github.com/cran/frbs/blob/master/man/DENFIS.Rd>



4. Applications of DENFIS

General application area:

Modeling, prediction and knowledge discovery from dynamic time series.

Specific applications:

Specific applications

- (cited in 1500+) (Google Scholar):

http://scholar.google.com/citations?hl=en&user=YTa9Dz4AAAAJ&view_op=list_works

- Google search on DENFIS: 92,000 returns
- Predictions in health;
- Environmental prediction
- Financial and economic data prediction, e.g.:
- I. Abouhassan, N. Kasabov, G. Popov and R. Trifonov, "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," 2022 IEEE 11th International Conference on Intelligent Systems (IS), Warsaw, Poland, 2022, pp. 1-7, doi: <https://doi.org/10.1109/IS57118.2022.10019673>.

5. Future work and what have we learned from lectures 4 and 5

Future work:

Integrating DENFIS with other learning methods for a better modelling of a streaming multiple time series in their temporal relationship

What have we learned from lectures 4 and 5?

The software/hardware engineering systems that we develop should be:

- evolving in structures and functionality in on-line;
- adaptive, to accommodate changes in data over time;
- knowledge-based, to reveal new knowledge;
- multi-model (multiple local models).

