"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. Al 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. NeuCom.
- 4. Deep neural networks (Ch.2, 48-50 + extra reading).
- 5. Evolving connectionist systems (ECOS) (Ch2, 50-78). Experiments with 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). NeuCube software (IA)
- 9. Evolutionary and quantum inspired computation (Ch.7)
- 10. AI applications in health (Ch.8-11)
- 11. Al applications for computer vision (Ch.12,13)
- 12. Al for brain-computer interfaces (BCI) (Ch.14)
- 13. AI for language modelling. ChatBots (extra reading)
- 14. Al in bioinformatics and neuroinformatics (Ch15,16, 17,18)
- 15. Al applications for multisensory environmental data (Ch.19)
- 16. Al in finance and economics (Ch19)
- 17. Neuromorphic hardware and neurocomputers (Ch20).



Time-Space, Spiking Neural Networks and Brain-Inspired Artificial Intelligence

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/chinac

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



Lecture 3. Neural networks- Fundamentals.

(Ch2 from the text book, 39-48)

(Ch.4 from "Foundations of NN, FS and KE)

- 1. What are neural networks (NN)?
- 2. NN for unsupervised learning. SOM.
- 3. NN for supervised learning: MLP.
- 4. Computational modelling with NN. The NeuCom software.
- 5. Questions for individual work



1. What are artificial neural networks (Chapter 2)

- ANN are computational models that mimic the nervous system in its main function of adaptive learning Fig.2.1.
- ANN can *learn* from data and make *generalisations*
- ANN are *universal computational models*
- Software and hardware realisation of ANN
- The area of neurocomputing

History of ANN:

- 1943, McCulloch and Pitts neuron
- 1962, Rosenblatt Perceptron
- 1971- 1986, Amari, Rumelhart, Werbos: Multilayer perceptron
- Self-organising maps (SOM), Kohonen
- Adaptive resonance theory (Grossberg)
- Evolving connectionist systems, 2001(Kasabov)
- Spiking neural networks

N. Kasabov (1996), Foundations of Neural Networks, Fuzzy Systems and Knowledge

Engineering, MIT Press, Cambridge, Massachusetts, USA, 1996.









2. Unsupervised learning in NN SOM (Self-Organising Maps)

- Learning of data without desired outputs, e.g.: clustering; vector quantisation .
- SOM Teuvo Kohonen, TU Helsinki
- Each output neuron specializes during the training to react to similar input vectors from a group (cluster) of the input space.
- Neurons in output layer are competitive
- SOMs preserve similarity between input vectors from the input space as *topological closeness of neurons* in the output space represented as a topological map.



A schematic diagram of a simple, hypothetical two-input, 2D output SOM system (Fig.2.2)



Clusters - SOMann1lbl.som

SOM trained on macro-economic data of EU countries, Fig.2.3



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The SOM learning algorithm (Box 2.1)

- K0. Assign small random numbers to the initial weight vectors $w_j(t=0)$, for every neuron j from the output map.
- K1. Apply an input vector **x** at the consecutive time moment t.
- K2. Calculate the distance d_i (in n-dimensional space) between x and the weight vectors $w_j(t)$ of each neuron j. In Euclidean space this is calculated as follows: $d_j = sqrt((\Sigma((x_i - w_{ij})^2))))$
- K3. The neuron k which is closest to x is declared the winner. It becomes a centre of a neighbourhood area Nt.
- K4. Change all the weight vectors within the neighbourhood area: $\mathbf{w}_{j}(t+1) = \mathbf{w}_{j}(t) + \alpha.(\mathbf{x} - \mathbf{w}_{i}(t)), \text{ if } j \in Nt,$ $\mathbf{w}_{j}(t+1) = \mathbf{w}_{j}(t), \text{ if } j \text{ is not from the area Nt of neighbours.}$

All of the steps from K1 to K4 are repeated for all the training instances. Nt and α decrease in time. The same training procedure is repeated again with the same training instances until convergence.



3. Supervised learning with NN.

MLP and the backpropagation training algorithm - Fig.2.5 and Box 2.2.







The MLP learning algorithm (Box.2.2)

Forward pass:

- BF1. Apply an input vector **x** and its corresponding output vector **y** (the desired output).
- BF2. Propagate forward the input signals through all the neurons in all the layers and calculate the output signals.
- BF3. Calculate the Err_j for every output neuron j as for example: Err_j = y_j - o_j, where y_j is the jth element of the desired output vector y.

Backward pass:

- BB1. Adjust the weights between the intermediate neurons i and output neurons j according to the calculated error: $\Delta w_{ij}(t+1) = lrate. o_j(1 - o_j). Err_j. o_i + momentum. \Delta w_{ij}(t)$
- BB2. Calculate the error Err_i for neurons i in the intermediate layer: $Err_i = \sum Err_j$. w_{ij}
- BB3. Propagate the error back to the neurons k of lower level: $\Delta w_{ki}(t+1) = lrate.o_i(1 - o_i). Err_i.x_k + momentum. \Delta w_{ki}(t)$



Artificial neural networks (ANN) can learn from data and then generalise on new data – inspiration from the brain

- ANN mimic the nervous system in its main functions of *adaptive learning* and *generalisation.*
- ANN can learn to "speak" (e.g. NetTalk by T.Sejnowsky)
- ANN can learn music as a time series and generate (predict) next musical segments (e.g.:
- Bach music:

4E

- Heavy Metal :
- ANN can learn a style of painting and recognise a true van Gogh from a fake one (Uni Maasatricht, Postma and Herik).





4. Computational modelling with NN. The NeuCom software environment (www.theneucom.com)

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: <u>www.theneucom.com</u>





MLP for classification

- The outputs are class labels
- Calculating the confusion matrix:
 - True-positive (sensitivity)
 - True negative (specificity)
- Iris data
- Comparison between different methods in NeuCom

J NeuCom - Multi-Layer Perceptron for Classification							
File Help							
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MLP for regression

- Time series prediction
- Choosing the time-lags and the features
- Case studies using NeuCom
- Training on data
- Model verification
- Gas furnice time series prediction
- Stock index time series prediction





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)
- 3. N.Kasabov, Evolving connectionist systems, Springer 2003 and 2007 (additional reading)
- 4. Kasabov, N. (ed) (2014) The Springer Handbook of Bio- and Neuroinformatics, Springer. (additional reading)
- 5. NeuCube: http://www.kedri.aut.ac.nz/neucube/
- 6. NeuCom: https://theneucom.com
- 7. KEDRI R&D Systems available from: http://www.kedri.aut.ac.nz
- 8. N. Kasabov, et al, 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.
- 9. Furber, S., To Build a Brain, IEEE Spectrum, vol.49, Number 8, 39-41, 2012.
- 10. Benuskova, L., N.Kasabov (2007) Computational Neurogenetic Modelling, Springer, New York
- 11. Indiveri, G. et al, Neuromorphic silicon neuron circuits, Frontiers in Neuroscience, 5, 2011.
- 12. Kasabov, N. (2014) NeuCube: A Spiking Neural Network Architecture for Mapping, Learning and Understanding of Spatio-Temporal Brain Data, Neural Networks, 52, 62-76.
- 13. Kasabov (2010) To spike or not to spike: A probabilistic spiking neural model, Neural Networks, v.23,1, 16-19
- 14. Merolla, P.A., J.V. Arhur, R. Alvarez-Icaza, A.S.Cassidy, J.Sawada, F.Akopyan et al, "A million spiking neuron integrated circuit with a scalable communication networks and interface", Science, vol.345, no.6197, pp. 668-673, Aug. 2014.
- 15. Wysoski, S., L.Benuskova, N.Kasabov (2007) Evolving Spiking Neural Networks for Audio-Visual Information Processing, Neural Networks, vol 23, issue 7, pp 819-835.
- 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. <u>https://techrxiv.org</u>), <u>https://doi.org/10.36227/techrxiv.21781103.v1</u>, 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: <u>https://doi.org/10.21203/rs.3.rs-2262084/v1</u>, licence CC BY 4.0,
- <u>https://orcid.org/0000-0003-4433-7521</u>
- <u>https://knowledgeengineering.ai</u>
- <u>http://scholar.google.com/citations?hl=en&user=YTa9Dz4AAAAJ&view_op=list_works</u>
- <u>https://www.scopus.com/authid/detail.uri?authorId=35585005300</u>



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Questions, exercises, assignments and project work

1. What are neural networks?

2. What is unsupervised learning with NN? Name one method and describe in your words the principle of learning. Can you find on the WWW a software, implementing this NN?

3. What is supervised learning in NN? Name one methods and describe in your words the principle of learning. Can you find a software on the WWW that implements this NN?

4. Download and learn how to use NeuCom.



