Cognitive System Engineering

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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. Experimental results and discoveries
5. Future work to be done for this problem
6. Questions for individual work for those interested

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, Springe-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.

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.

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*

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CogSysEn: Lecture Topics

Part II. Associative memories

9. Spatio-Temporal Associative Memories in brains and in SNN

- *Kasabov, Nikola (2023). STAM-SNN: Spatio-Temporal Associative Memories in Brain-inspired Spiking Neural Networks: Concepts and Perspectives. TechRxiv. Preprint.* https://doi.org/10.36227/techrxiv.23723208.v1

10. Associative memories for neuroimaging data: EEG and fMRI

- *N K. Kasabov, H Bahrami, M Doborjeh, A Wang, Brain Inspired Spatio-Temporal Associative Memories for Neuroimaging Data: EEG and fMRI, Bioengineering 2023, MDPI 10(12), 1341 https://doi.org/10.3390/bioengineering10121341, www.mdpi.com/journal/bioengineering*

11. Audio-visual associative memories

- *N Kasabov, B Sen Bhattacharya, D Patel, N Aggarwal, T Bankar, IAbouHassan, Cognitive Audio-Visual Associative Memories using Brain-inspired Spiking Neural Networks with Case Studies on Moving Object Recognition (subm. IEEE Trans. Cognitive and Developm. Systems, 2023).*

12. Predictive associative memories for time series

- *AbouHassan, I; Kasabov, N; Bankar, T; Garg, R; Sen Bhattacharya, B (2023). PAMeT-SNN: Predictive Associative Memory for Multiple Time Series based on Spiking Neural Networks with Case Studies in Economics and Finance. TechRxiv. Preprint. https://doi.org/10.36227/techrxiv.24063975.v1, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4665533*

Part III. Software and Hardware Implementation of CogSys.

13. Software implementation of CogSys in Python

- *NeuCubePy*

14. Neuromorphic implementation of CogSys. China neuromorphic hardware systems for CogSys.

- *J. Behrenbeck, Z. Tayeb, C. Bhiri, C. Richter, O. Rhodes, N. Kasabov, S. Furber, J. Conrad, Classification and Regression of Spatio-Temporal EMG Signals using NeuCube Spiking Neural Network and its implementation on SpiNNaker Neuromorphic Hardware. J. Neural Eng. (IOP Press, Article reference: JNE-102499) (2018). http://iopscience.iop.org/journal/1741-2552.*
  - *paper for CogSys on Loihi chip and on China neuromorphic chips*

15. Quantum computation

- *Ravi , N. Kasabov et al, (2023). From Quantum Computing to Quantum-inspired Computation for Neuromorphic Advancement – A Survey. TechRxiv. Preprint. https://doi.org/10.36227/techrxiv.24053250.v1*

16. Revision of the course

Lecture 3.Modelling brain dynamics

- Problem specification:

General problem: How to model a complex dynamical system, which consists of several dynamical sub-systems, each working at different time scale?

Specific problem: How to model brain dynamical system, which consists of a gene regulatory network (working in minutes and hours time scale) and neuronal activities (in milliseconds)?

- Paper to discuss - *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*

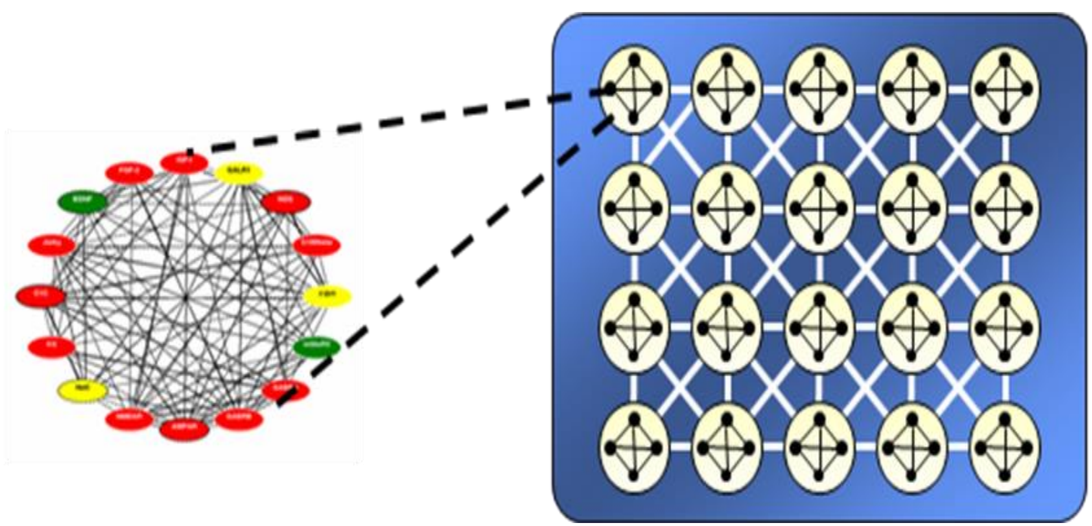
- *Other readings: Chapter 16.Computational neurogenetic modelling, in:* Kasabov, N., Time-Space, Spiking Neural Networks and Brain-Inspired Artificial Intelligence, Springer Nature (2019) 750p., https://www.springer.com/gp/book/9783662577134

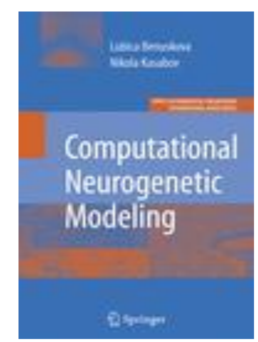
Chapter 16. Computational Neuro-Genetic Modelling (CNGM)

- Benuskova and Kasabov (2007)

SNN that incorporate a gene regulatory network (GRN) as a dynamic parameter systems to capture dynamic interaction of genes (parameters) related to neuronal activities of the SNN.

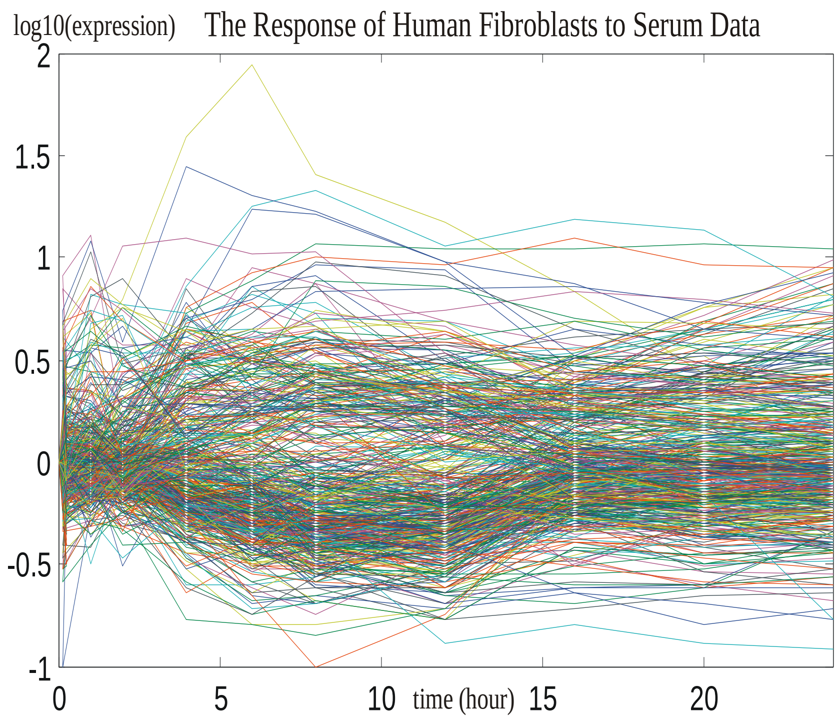
- Functions of neurons and neural networks are influenced by internal networks of interacting genes and proteins forming an abstract GRN model.
- The GRN and the SNN function at different time scales.

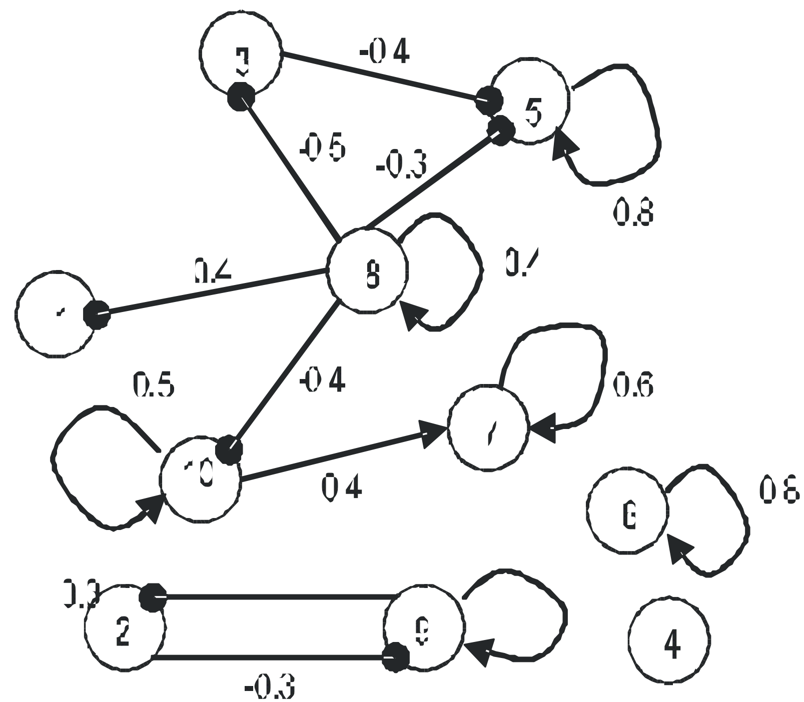




Example of a GRN derived from gene expression time course data

(Chan, Collins and Kasabov, JBCB, 2005)





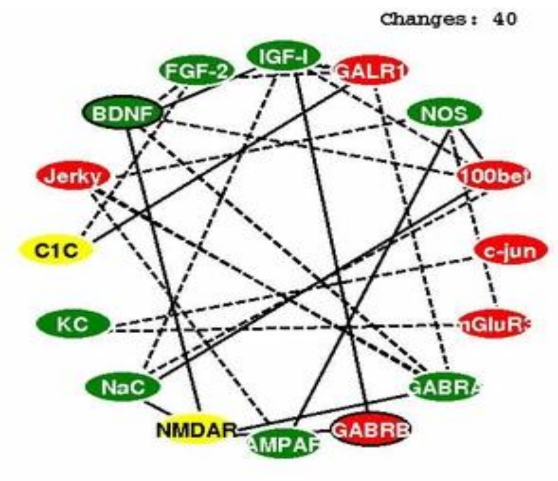
A neurogenetic model of a spiking neuron

(Kasabov, Benuskova, Wysoski, 2005)

- Four types of synapses: fast excitation; slow_excitation; fast_inhibition; slow_inhibition
- A Gene Regulatory Network (GRN) as a dynamical parameter system of the neuron

Table. Neuronal Parameters and Related Proteins

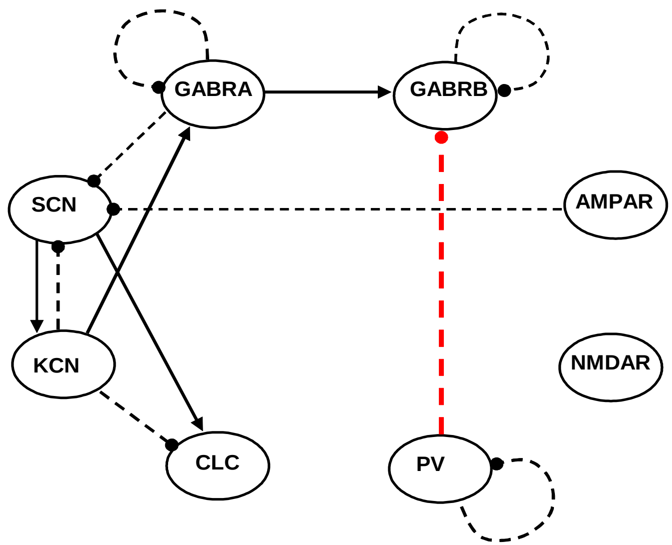
Neuronal parameter Amplitude and time constants of	Protein
Fast excitation PSP	AMPAR
Slow excitation PSP	NMDAR
Fast inhibition PSP	GABRA
Slow inhibition PSP	GABRB
Firing threshold	SCN, KCN, CLC
Late excitatory PSP through GABRA	PV



$$PSP_{ij}^{type}(t - t_j - \Delta_{ij}^{ax}) = A^{type}\left(\exp\left(-\frac{t - t_j - \Delta_{ij}^{ax}}{\tau_{decay}^{type}}\right) - \exp\left(-\frac{t - t_j - \Delta_{ij}^{ax}}{\tau_{rise}^{type}}\right)\right)$$

type = fast excitation; slow_excitation; fast_inhibition; slow_inhibition

An example of a derived GRN through CNGM: A case study on epilepsy (with A. Villa et al, 2006))



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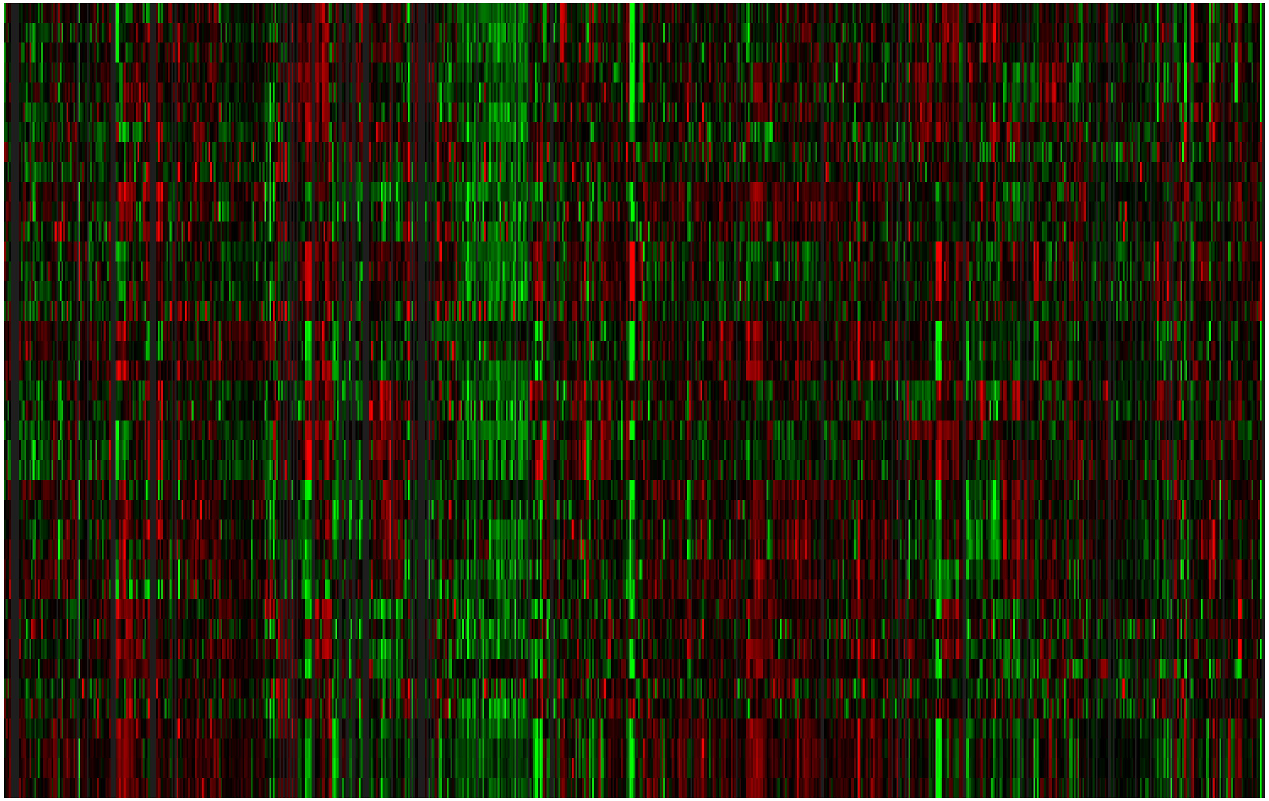
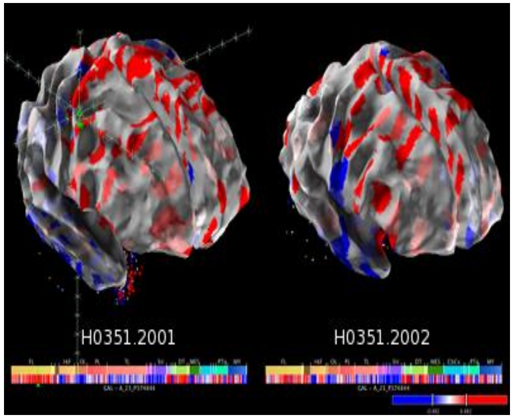
- The strongest interactions between genes in the evolved abstract GRN (left picture)
- The GRN can be used to predict gene knock-out consequences
- Predicted consequence of PV gene knock-out upon expression of GABRB – stronger slow inhibition
- Predicted consequence of PV gene knock-out upon local field potential – shift to lower frequencies of oscillations
- Potential for modeling of epilepsy and other genetic diseases manifested by the change of EEG/LFP

Neurogenetic STBD: The Allen Brain Institute Map (http://www.brain-map.org)





From the Brain Explorer: The Expression level of the genes (on the y-axis): ABAT A_23_P152505, ABAT A_24_P330684, ABAT CUST_52_PI416408490, ALDH5A1 A_24_P115007, ALDH5A1 A_24_P923353, ALDH5A1 A_24_P3761, AR A_23_P113111, AR CUST_16755_PI416261804, AR CUST_85_PI416408490, ARC A_23_P365738, ARC CUST_11672_PI416261804, ARC CUST_86_PI416408490, ARHGEF10 A_23_P216282, ARHGEF10 A_24_P283535, ARHGEF10 CUST_) at different slices of the brain (on the x-axis) (from www.brain-map.org) (http://www.alleninstitute.org)

Some applications and future challenges

- Predicting brain diseases at different time scales
- Predicting epilepsy (at a time scale of seconds)
- Predicting dementia (at a time scale of years)
- Preventing obesity , alcoholism, addiction ….
- Defining more precisely the time of death and perhaps preventing it (??).