Hierarchical architectures for spiking Winner-Take-All networks

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Outline

Goals

- Further the understanding of the network model
- Simulate feedback found in the visual cortex
- Show connection between Bayesian inference and network model

Biological background

- Spiking neural networks
- Winner-Take-All networks
- Modular structure of the brain
- Hierarchical structure of the brain
- Feedback mechanisms in cortical hierarchies

Kanizsa square, Lee TS (2003)

Biological background

- Probabilistic brain
- Synaptic plasticity
- Spiking neural networks
- Winner-Take-All networks

Theoretical background

- Bayesian inference and its relevance to neural networks
- Explain model... (input image, input neurons, output neurons, prior neurons, spikes, doubleexpo kernel, membrane potential, firing rates (poisson, e hoch u - i(t)), adaptive inhibition... !!!AM BESTEN MIT DER ZEICHNUNG ERKLÄREN!
- Nessler said that: Every synaptic weight converges to the log of the conditional probability that the presynaptic neuron has fired just before the postsynaptic neuron, given that the postsynaptic neuron fires.... Proven later in Experiment
- g(k) P(Y|X,Z) Mathematically proven

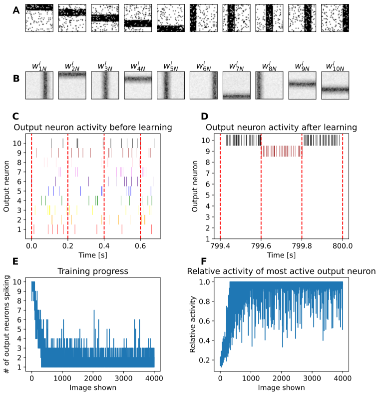
Methodology

- Simulation was performed in Python
- Simulation step size was 1 ms
- Pixels of input images and the prior had a noise level of 10%

Ambiguous visual stimuli 1

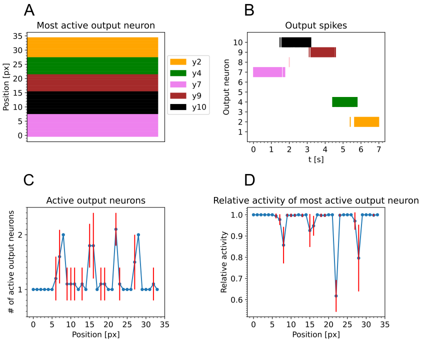
- Network learned to group horizontal and vertical bars into 10 groups
- After training ambiguous images with 1 horizontal and 1 vertical bar were shown
- Network was able to focus on individual bars, due to prior neurons

Ambiguous visual stimuli 2

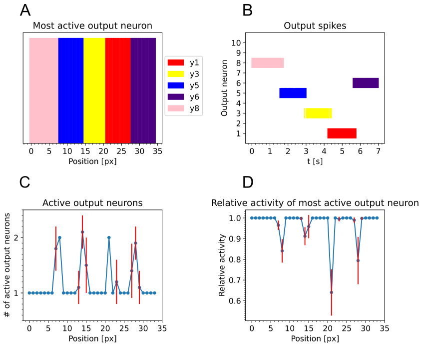


Training plot

Ambiguous visual stimuli 3

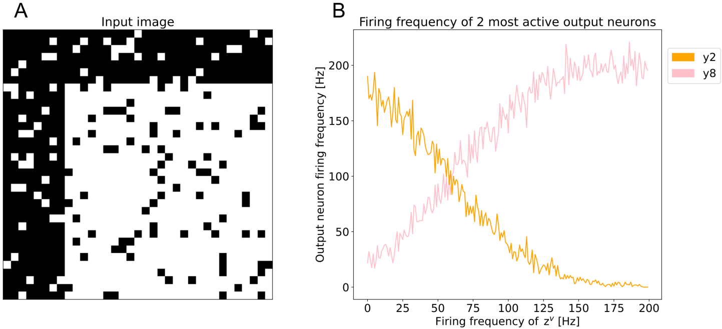


Horizontal validation



Vertical validation

Ambiguous visual stimuli 4

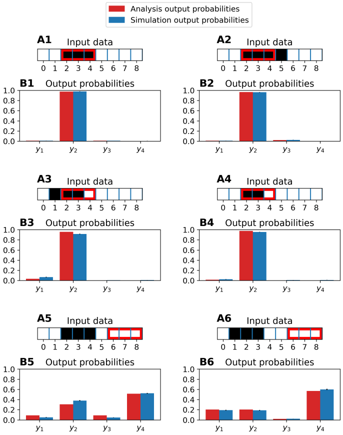


Variable prior activity

Analysis and simulation of the network 1

- usage of smaller 1-D images to make network easier to analyse
- Mathematical derivation of Bayesian likelihood, prior and posterior
- Derived synaptic weights from Bayesian likelihood and prior
- Simulated network with those weights and fitted hyperparameters
- Compared Bayesian posterior to output of the simulation

Analysis and simulation of the network 2

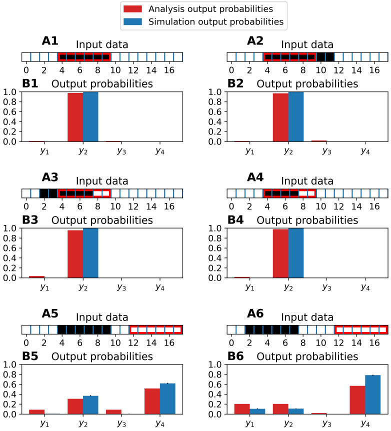


Kullback–Leibler divergence = 0.0101 ± 0.0009

Transferability of hyperparameters 1

- Input size and prior neuron firing rate was doubled
- Network was simulated with same hyperparameters of smaller network, to check if they are applicable to any network size

Transferability of hyperparameters 2



Kullback–Leibler divergence = 0.2392 ± 0

Training with predetermined hyperparameters 1

- Determined hyperparameters were used to train weights
- Trained weights were compared to analytically determined weights

Training with predetermined hyperparameters 2

A Learned $P^{X|Y}$

0.52	0.49	0.53	0.06	0.1	0.08	0.12	0.11	0.06
0.09	0.07	0.49	0.49	0.51	0.09	0.09	0.09	0.06
0.07	0.08	0.08	0.06	0.51	0.5	0.52	0.07	0.1
0.11	0.1	0.12	0.07	0.09	0.06	0.53	0.46	0.51

B Calculated $P^{X|Y}$

0.9	0.9	0.9	0.1	0.1	0.1	0.1	0.1	0.1
0.1	0.1	0.9	0.9	0.9	0.1	0.1	0.1	0.1
0.1	0.1	0.1	0.1	0.9	0.9	0.9	0.1	0.1
0.1	0.1	0.1	0.1	0.1	0.1	0.9	0.9	0.9

C Learned $P^{Y|Z}$

1.14	0.02	0.02	0.02
0.03	1.17	0.03	0.01
0.02	0.02	1.15	0.02
0.02	0.03	0.03	1.17

D Calculated $P^{Y|Z}$

0.9	0.03	0.03	0.03
0.03	0.9	0.03	0.03
0.03	0.03	0.9	0.03
0.03	0.03	0.03	0.9

Analysis of model

- Analysed impact of hyperparameters
  - fiNPUT
  - fPrior
  - tau decay
- Connection between model and Bayesian inference was shown
- Importance of neural feedback was shown for
  - Attention / Ambiguity resolution
  - Illusory contour effect

Conclusion

- Thesis provided insight to hierarchical spiking Winner-Take-All network model
- Showed that the network model can simulate effects like attention and changing beliefs through feedback
- Provided ideas on how to further analyse and improve the model

Sources

- Lee TS, Mumford D. (July 2003). “Hierarchical Bayesian inference in the visual cortex.” In: J Opt Soc Am A Opt Image Sci Vis. DOI: doi:10.1364/josaa.20.001434
- Nessler, Bernhard et al. (Apr. 2013). “Bayesian Computation Emerges in Generic Cortical Microcircuits through Spike-Timing-Dependent Plastic ity.” In: PLOS Computational Biology 9.4, pp. 1–30. doi: 10.1371/journal. pcbi.1003037. url: https://doi.org/10.1371/journal.pcbi.1003037