Modelling of gamma oscillations

By: Daniela Monje, Lorenzo Gutierrez, Alex Legaria, Yeselth Angarita (Pod046: Fantastic Marmoset Team: Learning Marmosets)

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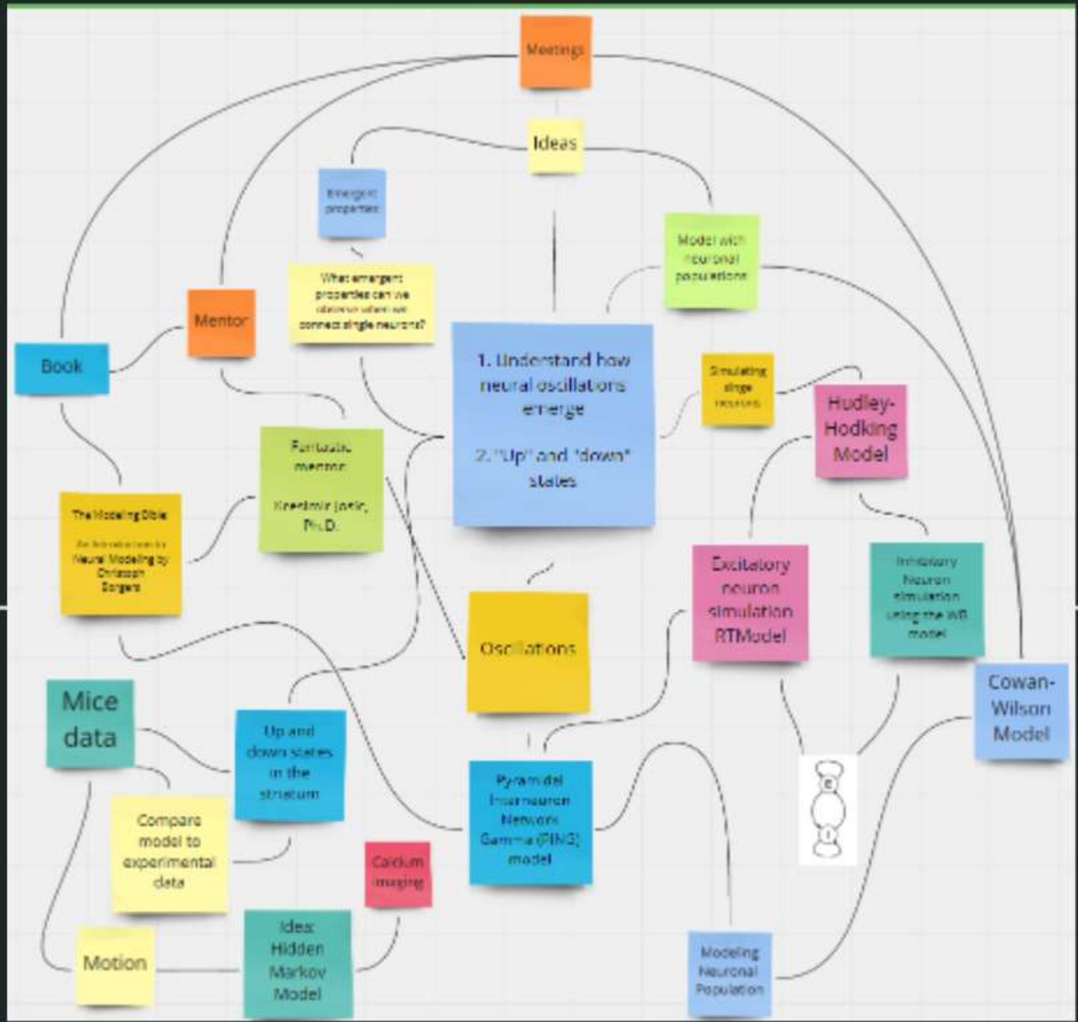
Ideas

Understand emergent network properties:

- How do neuronal oscillations emerge?
- Up and down states in the striatum



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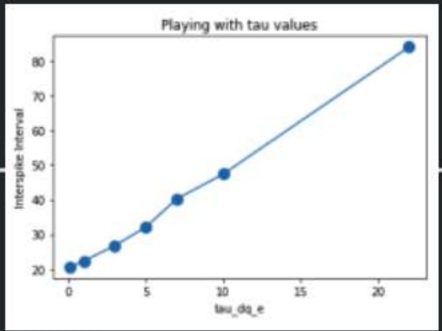
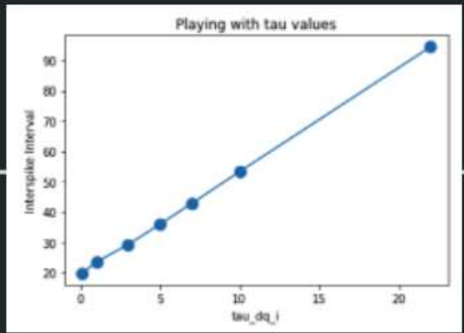
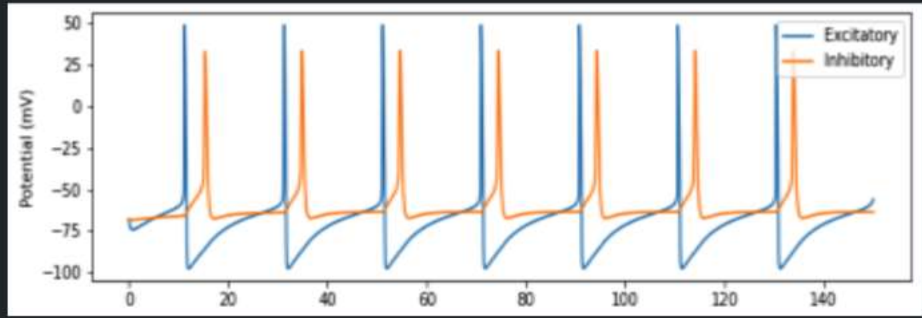
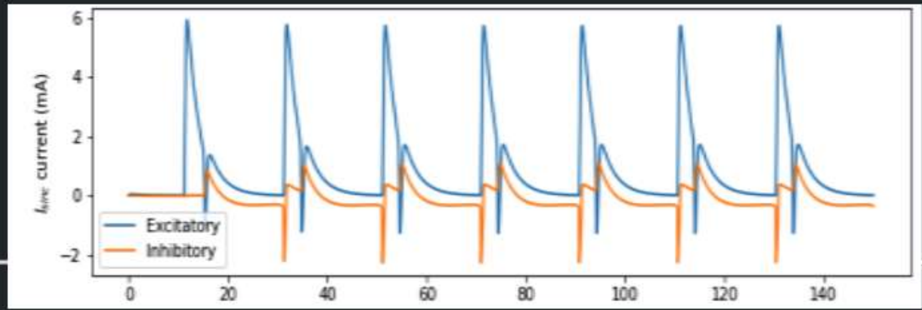
Results

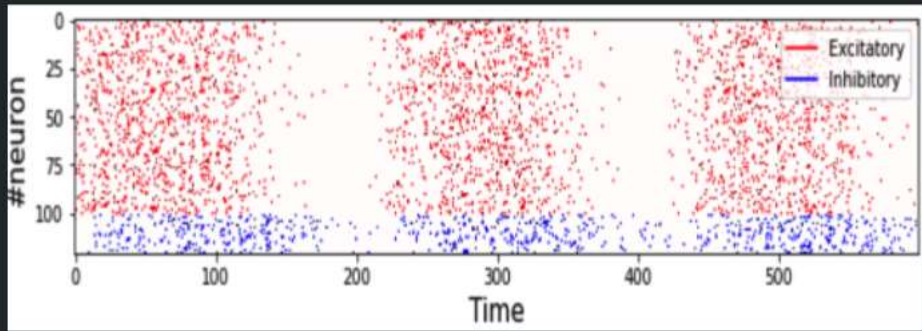
- We simulated a gamma oscillation by connecting an excitatory and an inhibitory cell using the Hodgkin and Huxley model.











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Our experience!

- Lots of meetings!
- Hard to pin down a specific question (we learned so much in NMA!)
- We were able to implement models that initially seemed really daunting

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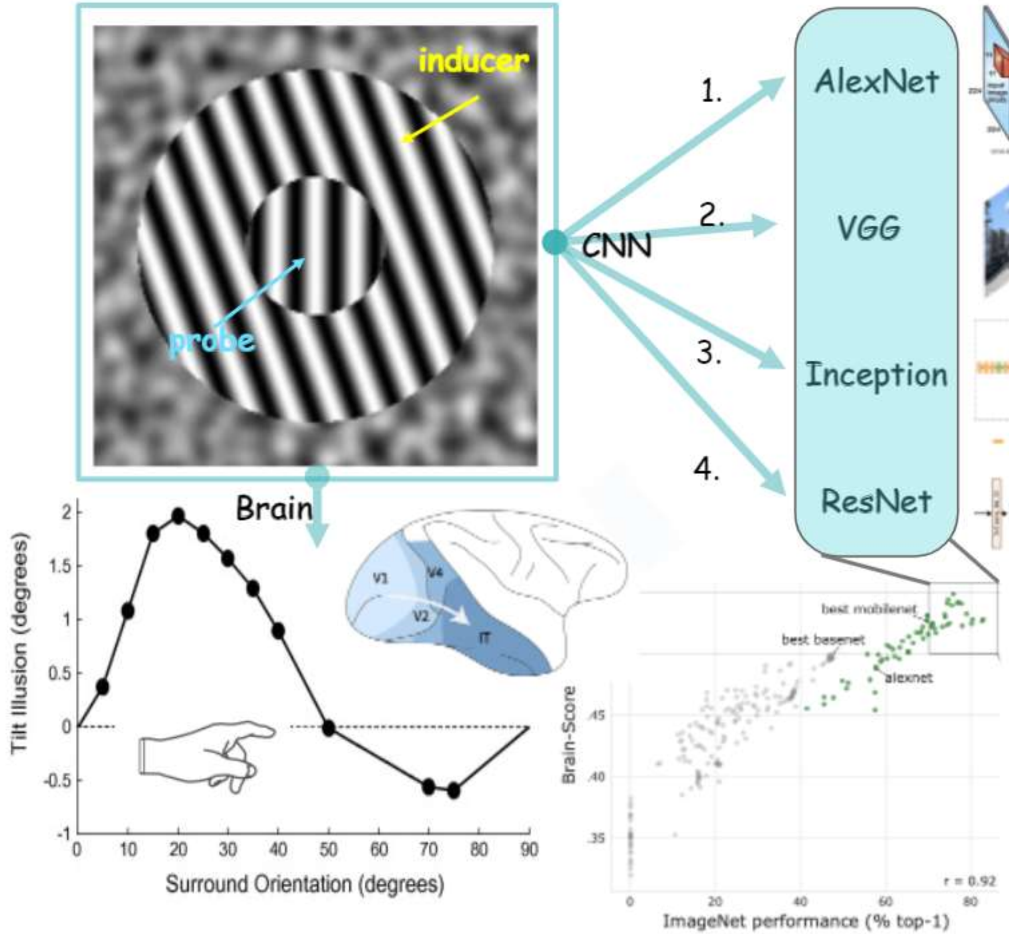
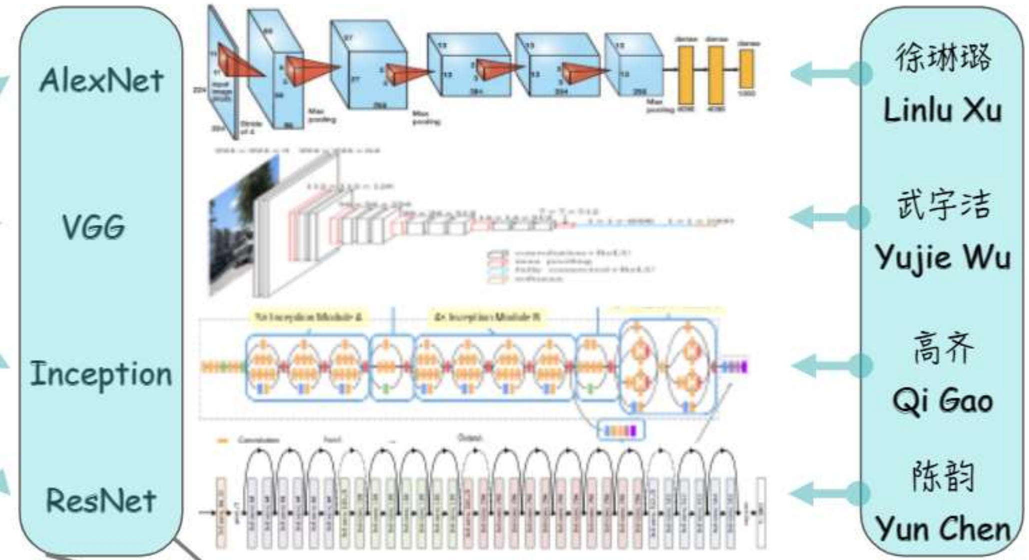
#---Can CNN See Illusions ? ---- by illusorybeing ----Pod-068





Current Question:

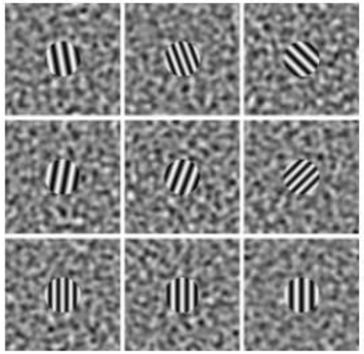
1. Can CNNs see illusions ?
2. Does CNNs with better performance exhibite stronger visual illusion ?

----Hypothesis and Method ----------------- Pod-068

Method:

orientation: -45°~45 °
bar width: [8, 9, 10, 11]
phase: 0° ~ 180°
background: band-limited Gaussian random noise

Train set:



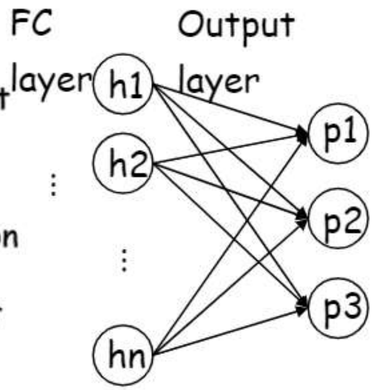
left

right

vertical

CNN structures modified

AlexNet
VGG
Inception
ResNet



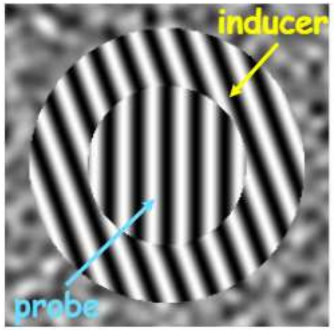
probability of left tilt

probability of right tilt

probability of vertical orientation

a sample of test set:

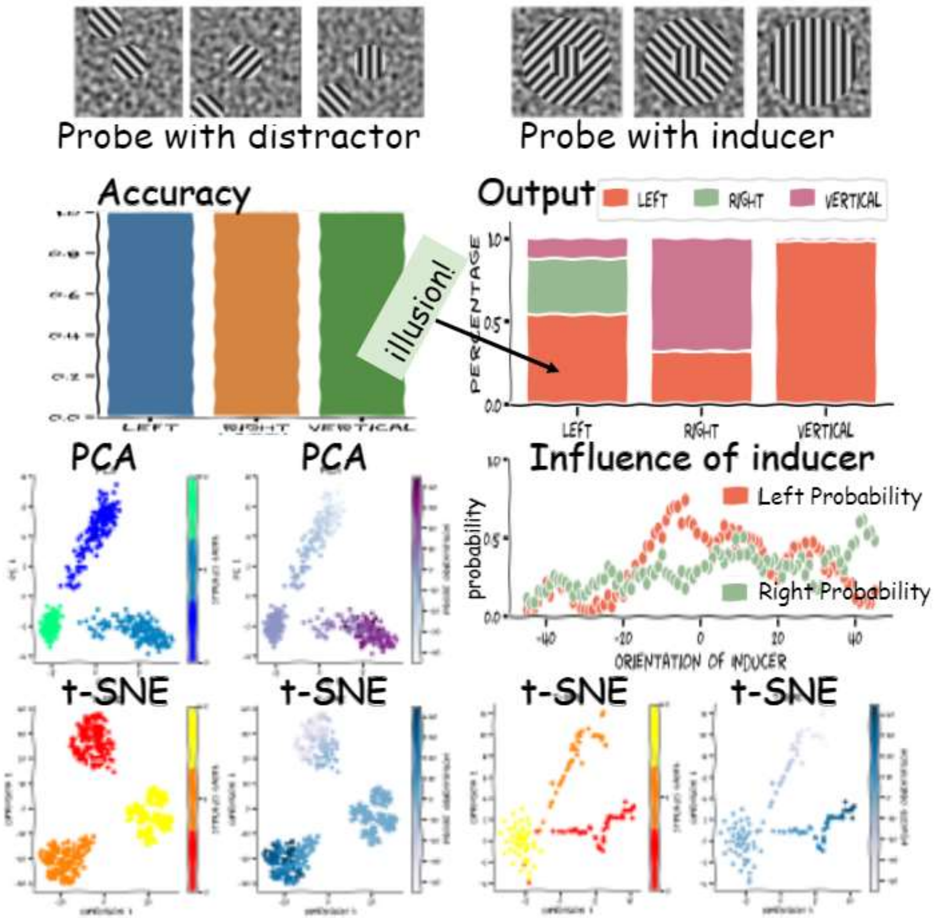
human see a rightward tilt illusion



Hypothesis:

```
if CNN see tilt illusion similar to human == True:
    report tilted probe (opposite to the inducer, in this case is right)
elif CNN see tilt illusion == False:
    report vertical probe
else:
    report others
```

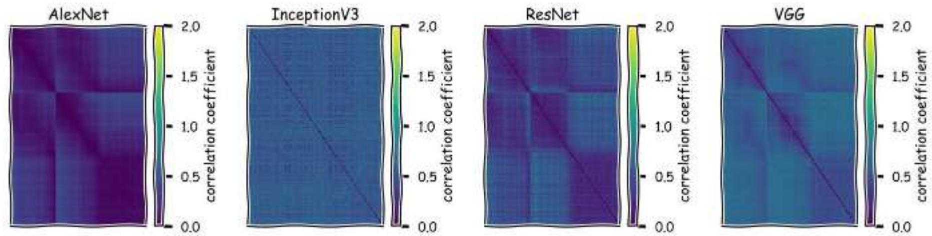
----Result and Inspiration ---------------------- Pod-068



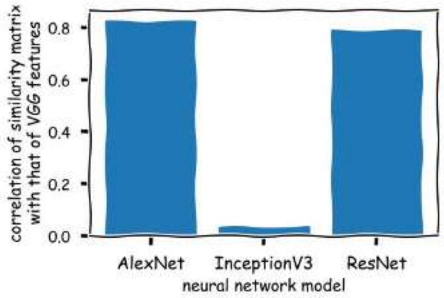
Performance on Probe with Distractor

	AlexNet	Inception V3	ResNet	VGG
Mean	0.9	0.7	0.7	1.0

Representational Dissimilarity Matrix for FC Layers



Correlation for RDMs with VGG



For more results 👇

----Experience and Feelings ----------------

Pod-068

人间真实VGG
左灯右行AlexNet
我就是我Inception
二泉映月ResNet

Different CNN, different "illusions"

The "illusion" here may be:

center-surround interaction
response bias of system

- Future Question
  - Why CNNs shows different "illusions"
- Some explorations
  - build our own CNN...
  - add "lateral inhibition" mechanism...
  - learn more about RNN[AlexNet-fc7-hopfield].
- Regular meeting and self learning
  - Meeting: 1~2 h / day
  - Self learning: 2~3 h / day
- We are a team😘🥳🤗😇
  - positive, efficient, supportive, exploration spirit...
  - ❤️ love you guys

----Project Team ----------------------------------

Pod-068

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The Brain Train : An attempt to train a CNN into developing a "Halle Berry" neuron

neuromatch academy

By: Sunisth Kumar, Md Ashiqur Rahman, Tanya Rubinstein
From pod Pumpkin Groundhog

Background

Grandma or "Halle Berry" neurons in humans:

Respond to a specific stimuli

Respond to variations of stimuli depicting the same subject (Halle Berry in various orientations or even the text "Halle Berry")

(Quiroga, Reddy, Kreiman, Koch & Fried, 2005)

We **hypothesized** that an object with emotional salience (e.g an image of Halle Berry shown to a Halle Berry fan), will likely produce dedicated neurons that respond to different representations of that object in Deep Neural Networks similarly to how they do in the human brain.

Method, or: Lets try creating a Halle Berry neuron!

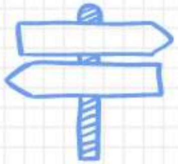
CNNs

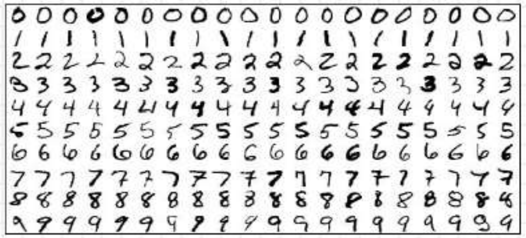
Convolutional Neural Network

Good at recognizing images

Easy to train

For simplicity, we trained our model to recognize a set of hand written digits: MNIST





How did we model emotional salience in a CNN?

Over-representation of a single digit

Maybe, if we show one digit a lot more than others when training our model, this could simulate increased exposure to an object of emotional importance.

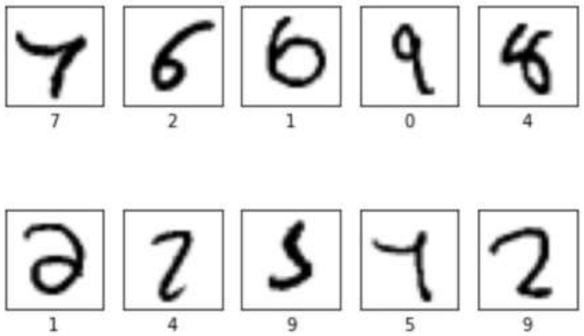
Weights

Maybe, if we train our model with different weights for different digits, this could simulate a variation in emotional salience for different stimuli.

Results

In the differential exposure model, we got some interesting results:

We analyzed the digits that were wrongly categorized.



For the varied weights model, we did not reach a high enough accuracy rate, so it needs more work.

Test Data										
0	0.002	0.009	0.007	0.003	0.006	0.009	0.007	0.008	0.008	0.006
1	0.004	0.001	0.009	0.004	0.007	0.007	0.004	0.011	0.009	0.003
2	0.014	0.017	0.003	0.021	0.013	0.011	0.016	0.024	0.016	0.009
3	0.009	0.012	0.019	0.000	0.010	0.021	0.010	0.016	0.015	0.011
4	0.015	0.012	0.011	0.009	0.000	0.010	0.025	0.012	0.017	0.025
5	0.018	0.020	0.010	0.035	0.017	0.003	0.021	0.016	0.019	0.021
6	0.026	0.010	0.018	0.013	0.022	0.021	0.003	0.010	0.014	0.018
7	0.016	0.028	0.030	0.014	0.014	0.024	0.027	0.000	0.015	0.019
8	0.031	0.016	0.028	0.033	0.027	0.022	0.023	0.018	0.002	0.020
9	0.022	0.034	0.032	0.026	0.044	0.036	0.021	0.041	0.028	0.001
Training data - over represented digit	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Overall Accuracy	0.985	0.984	0.983	0.985	0.984	0.984	0.984	0.984	0.986	0.987

Columns show which digit was over-represented in the training set, while the other digits were chosen randomly. Rows represent the digit displayed in the test set, results showing average failure rate.

Discussion

As we can see in the previous slide, indeed, the network displayed lower inaccuracy rates for each digit when it was over represented in the training trials.

Furthermore, we can see a low inaccuracy rate across trials for the digits 1 and 0. We suggest, this could be due to an intrinsic distinctive traits of these two digits compared to others.

More possible results for the future?

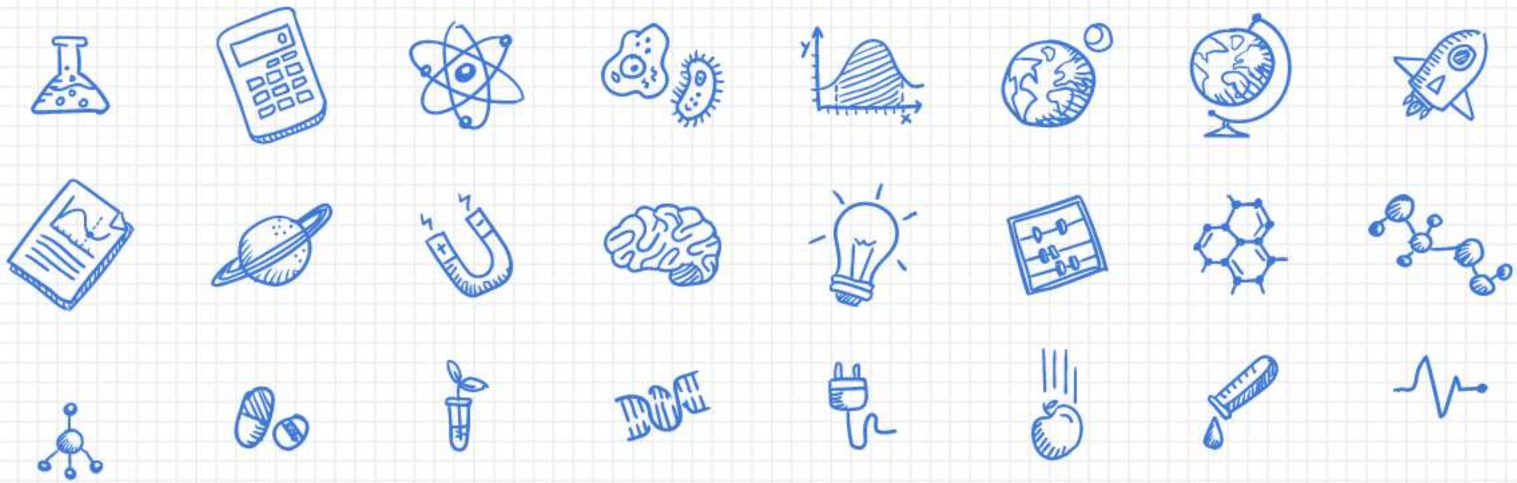
Next we would like to analyze the neuron activation in every layer, especially the last layers, to see whether certain neurons have developed specificity.

We would also like to try to work a spiking neural network into the model.

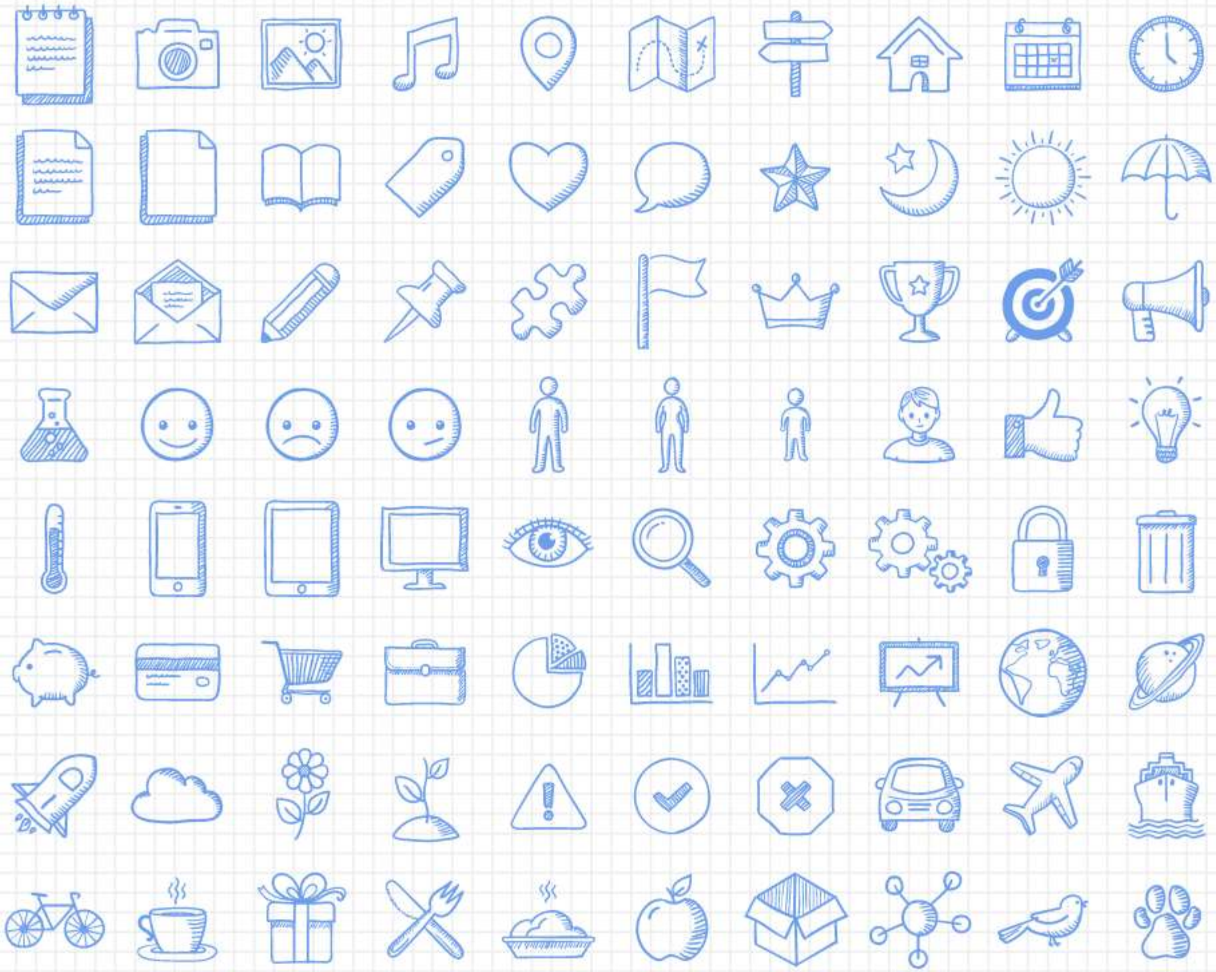
Credits

- Our mentor: Prof. Krešimir Josić
- Sunisth Kumar
- Md Ashiqur Rahman
- Tanya Rubinstein

Extra resources



π $\sqrt{2}$ $E = mc^2$ H_2O



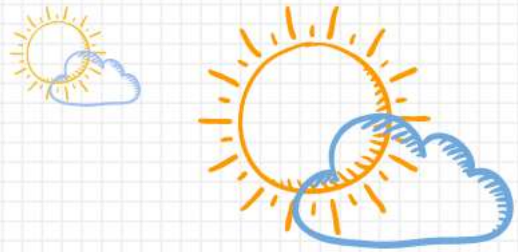
SlidesCarnival icons are editable shapes.

This means that you can:

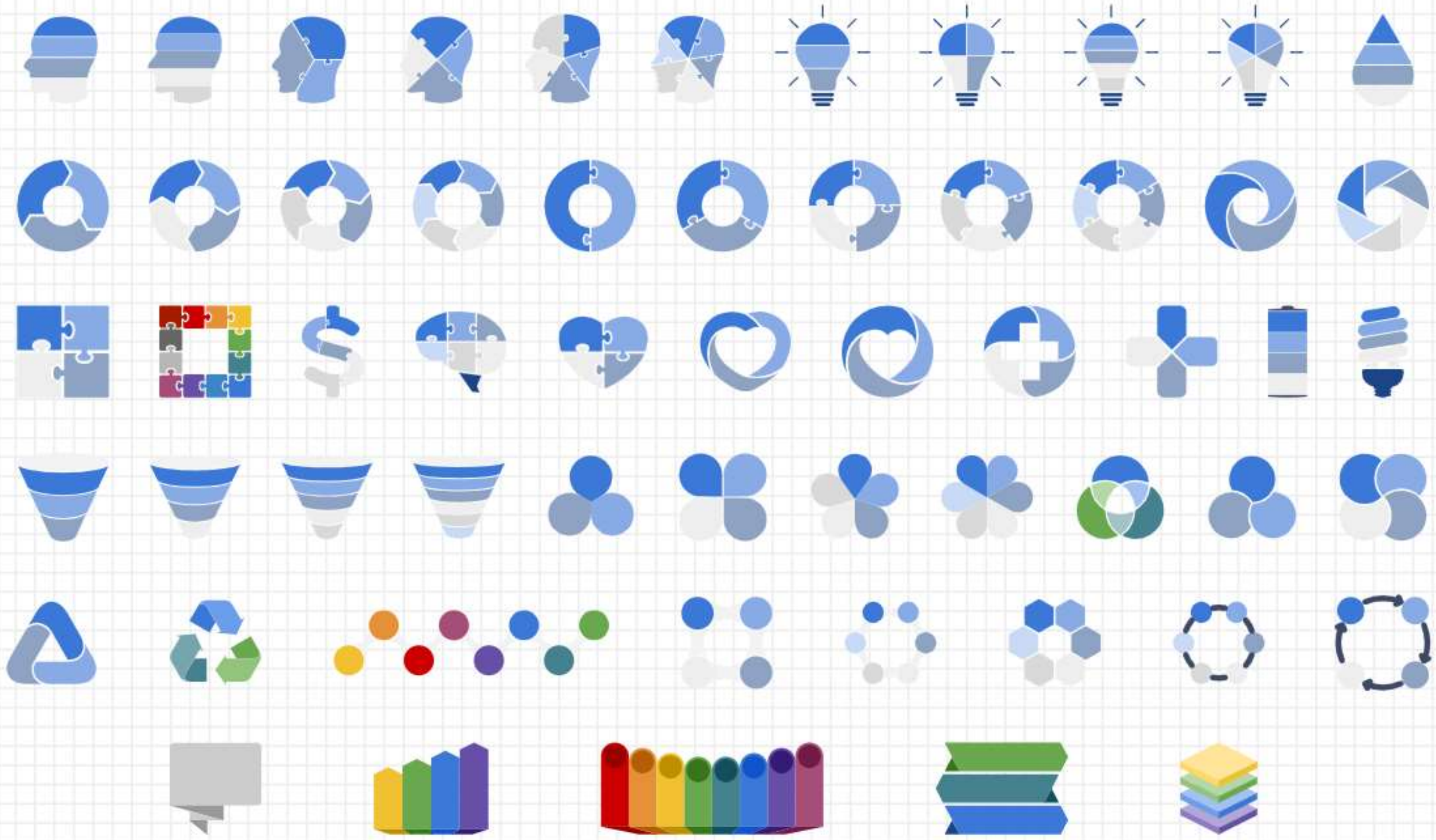
- Resize them without losing quality.
- Change fill color and opacity.

Isn't that nice? :)

Examples:

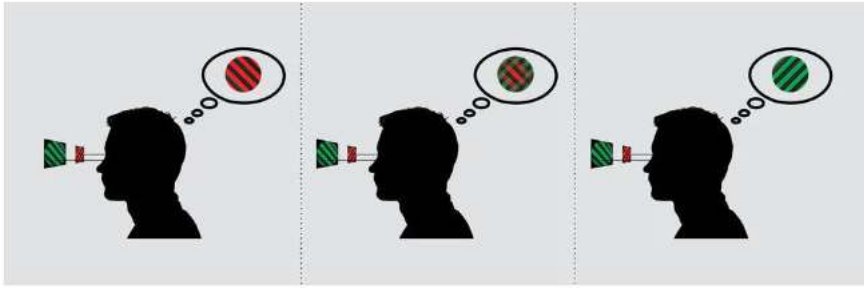


Diagrams and infographics



The role of attention in a computational model of binocular rivalry

- **Binocular rivalry** is the alternation between incompatible monocular images presented to the two eyes.

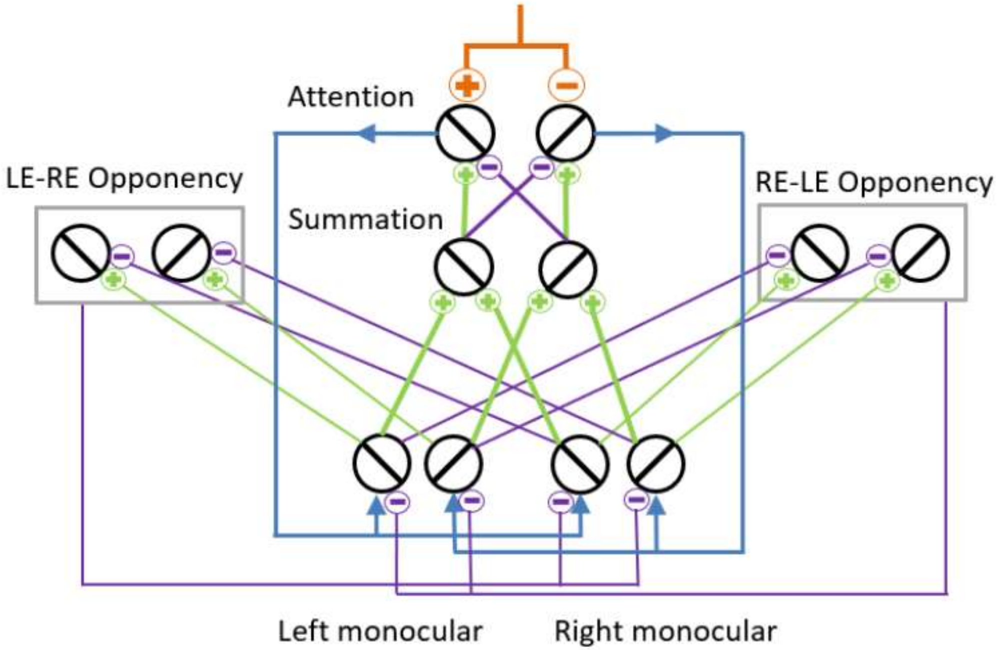


Luke Smillie (2017): People with creative personalities really do see the world differently

- Binocular rivalry depends on attention.

- Li et al. (2016) modelled binocular rivalry as an interplay of mutual inhibition and saliency driven attention.

- **Can voluntary attention be incorporated into this model?**

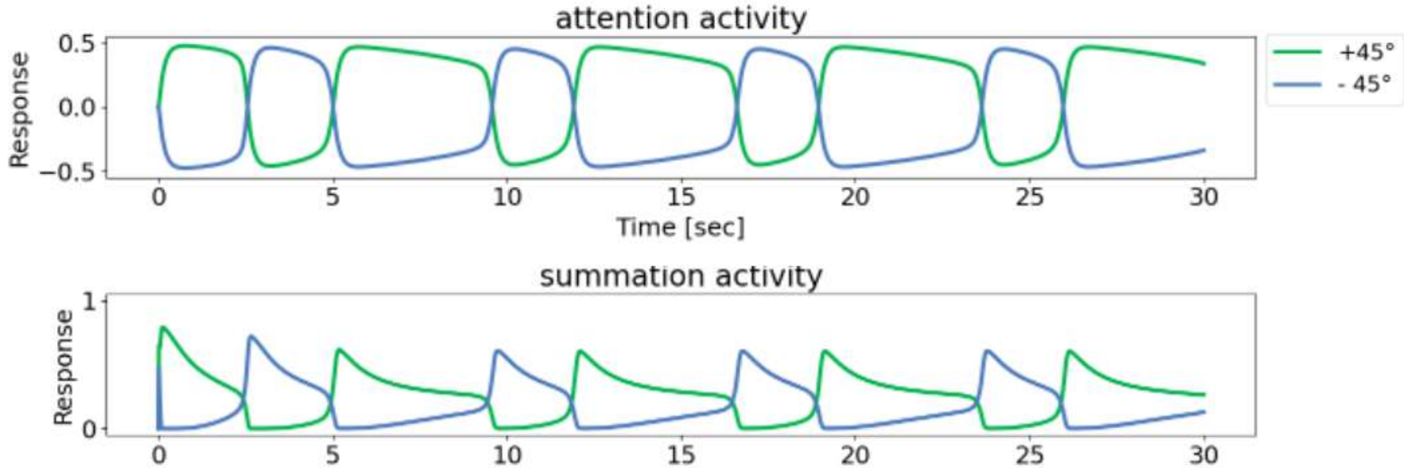


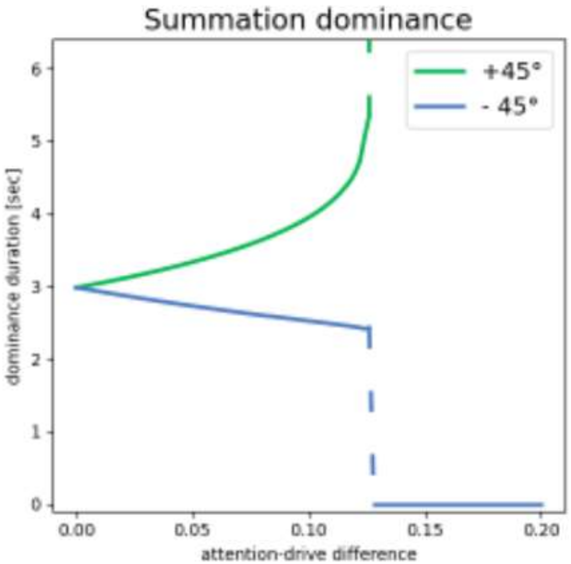
Model Alteration: External input to attention population

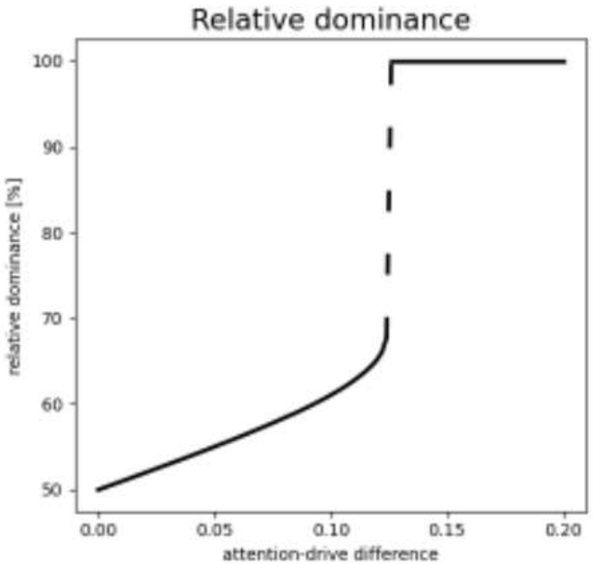
Change in the excitatory drive of the attention population:

$$E_{a1} = (Rb_1 - Rb_2 + \textit{external drive})^n$$

$$E_{a2} = (Rb_2 - Rb_1 - \textit{external drive})^n$$







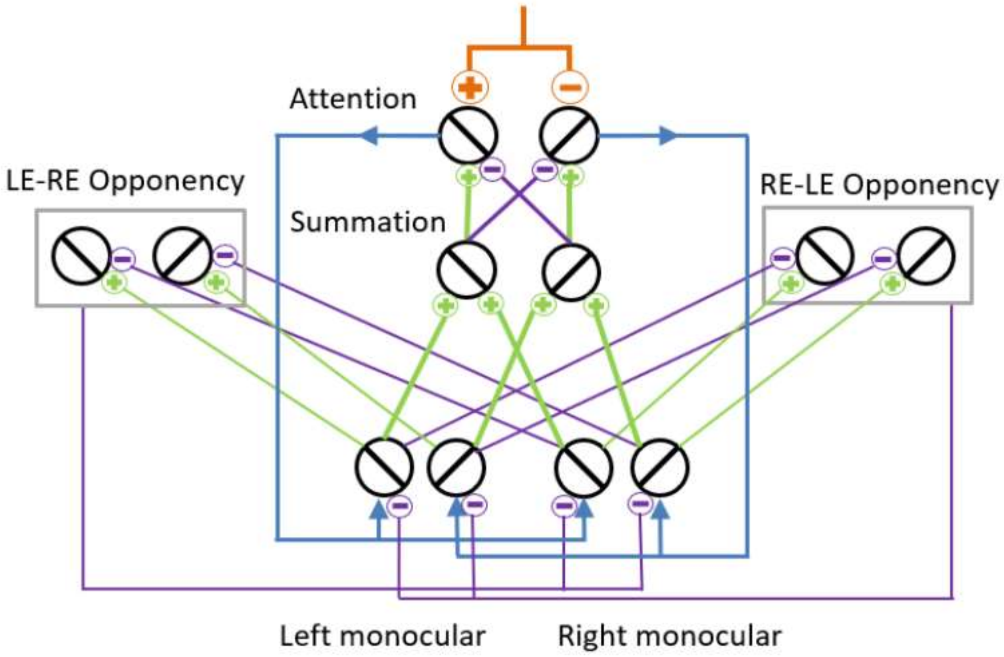
Results

Adding external input to attention neurons **prolonged** dominance periods of the **excited representation** and **shortened** periods of the **suppressed** ones.

Conclusion

General:

- We were able to reimplement the model in an object-oriented framework in python



Model alteration:

- Direct excitatory input to attention neurons prolongs dominance durations
- For input strengths of > ~12.4% of normal excitatory drive leads to a **Winner-takes-all** condition

Outlook:

- Compare the observed changes in dominance duration to experimental findings
- Test alternative alteration by weight changes

Neuromatch summer school project TEAM:

"We're usually modelling for Victoria's secret"

I really enjoyed this project work. It took use some time to find a project everyone was interested in, but once we had a plan it was pretty straight forward.

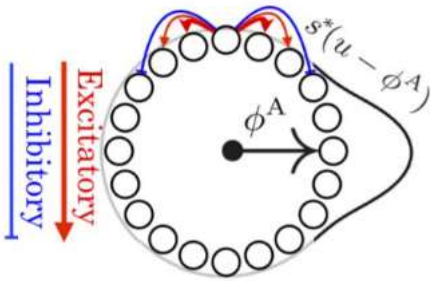
The project work was an inspiring adventure for me with the exploration how to implement object-based programming in python and how a well-defined scope of a project improves motivation and success. It was fun working in an interdisciplinary team and in the end, my dream to explore a cortical mechanism without data became true.

While it has been really interesting to implement a model that goes a lot deeper than I'm used to as a cognitive neuroscientist, the most helpful aspect for me has been the project-based work in a team. It's been a really enjoyable journey and I take a lot away from it.

We would like to thank our mentor, Xaq Pitkow for his time and his great explanations and drawings to bifurcation.

Introduction

- The ring attractor (a class of recurrent networks) with bump-like neural activity has been hypothesised to work as a biologically plausible model for memory.
- One example is the naturalistic dynamics of head direction, encoded by E-PG neurons of Ellipsoid Body (EB) in *Drosophilla melanogoster* (fruit flies) for spatial memory, have been proved useful to study navigation in fruit flies[1].
- Besides for spatial memory, ring attractors can also be used to model memory of other cyclic parameters such as colours.



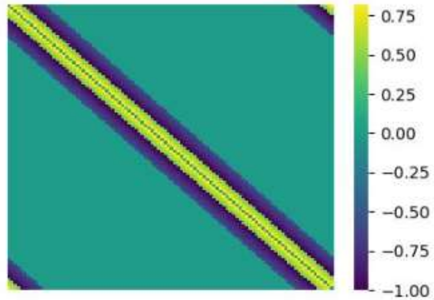
Representation of the bump in the ring attractor with excitatory and inhibitory dynamics[2]

1- Kim, S.S., Rouault, H., Druckmann, S. and Jayaraman, V., 2017. Ring attractor dynamics in the Drosophila central brain. Science, 356(6340), pp.849-853.
2-.Ocko, S., Hardcastle, K., Giocomo, L., & Ganguli, S. (2018). Emergent elasticity in the neural code for space. *Proceedings Of The National Academy Of Sciences*, *115*(50), E11798-E11806.

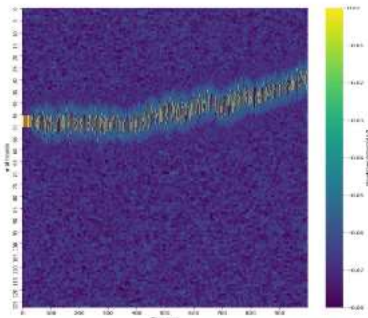
Methods

- ➢ Leaky-integrate-and-fire neurons modelled using methods described in this paper[1]
- ➢ Connectivity matrix used to describe a 4-7 topology to structure the ring attractor network
- ➢ Added fix points to correct for the drift from white noise

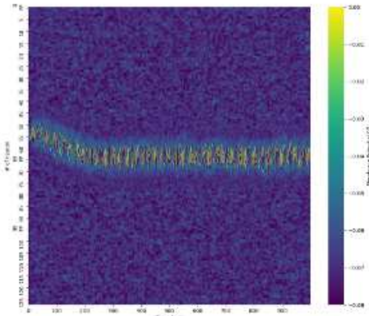
Connectivity Matrix Without Fixed Points



Drift caused by noise, without fixed points



Drift caused by noise, with fixed points



Theoretical formulation of the implemented neurons

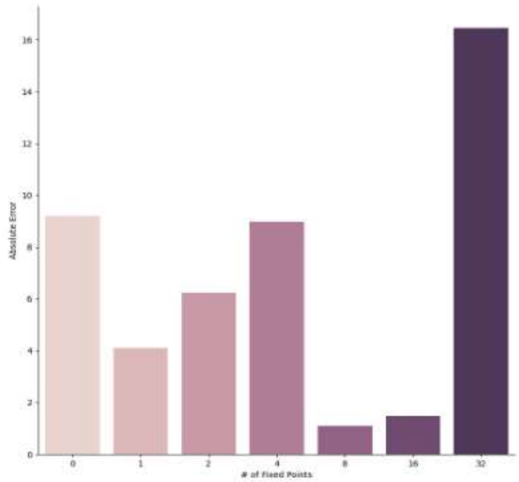
[1] Critical Limits in a Bump Attractor Network of Spiking Neurons, Alberto Arturo Vergani, Christian Robert Huyck 2003 - arXiv:2003.13365

Pranjal, Stefano, Nikitas, Angela

Final Thoughts

Conclusions

- ➢ Successful construction of a working model of ring attractor which behaves like a working memory device for continuous cyclic variables
- ➢ Dynamics of the network are determined by parameters such as the balance between inhibitory and excitatory neurons
- ➢ Fixed points must be included to prevent drift by noise



Experiences

- ★ Remote collaboration on ideas and codes
- ★ Building complex neural network using leaky-integrate-and-fire neuron models from the ground up
- ★ Extensive literature search for methodologies and results.

pod-109
PINK VICUÑA

Pranjal, Stefano, Nikitas, Angela

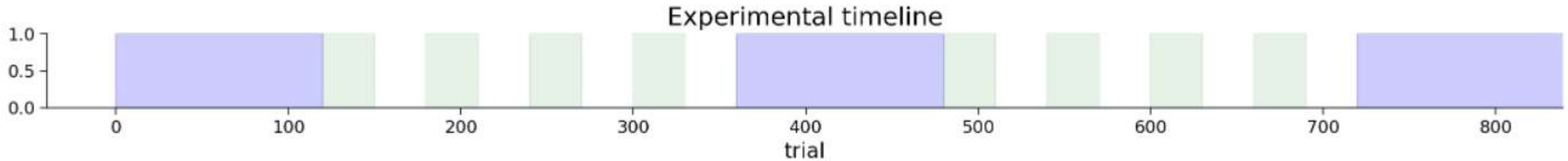
Neuromatch Academy 2020 Project

Team Members: Cristian Tatarau, Martyna Plomecka, Deepak Kumar Ravi, Nils Nyberg

Reinforcement Learning in behavior modeling - Learning the value of information in an uncertain world

GOALS:

- Test hypothesis about behavior
- Link **internal model variables** of the RL model to possibly human "internal states". Here, these variables are Q values and prediction errors

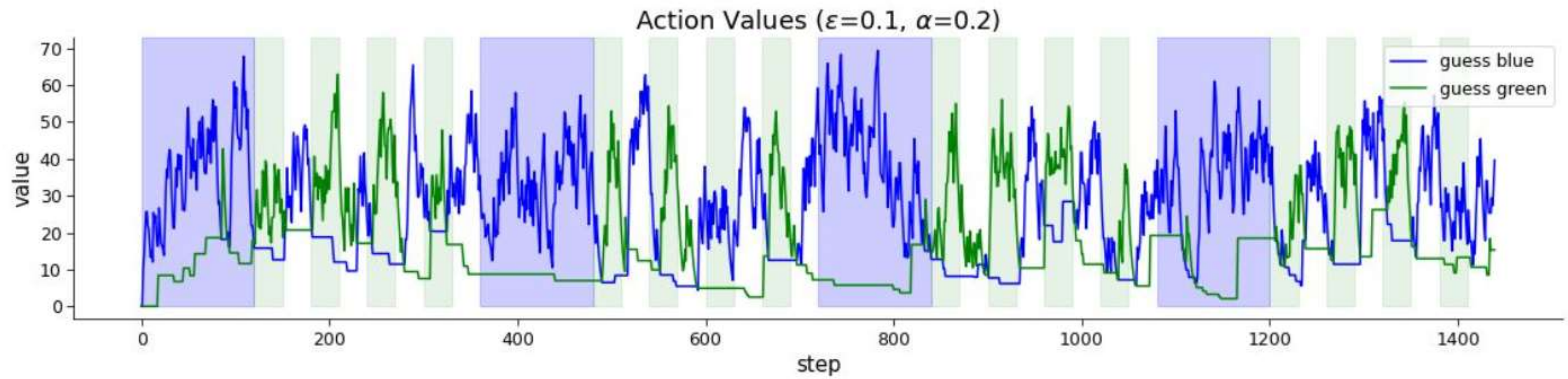


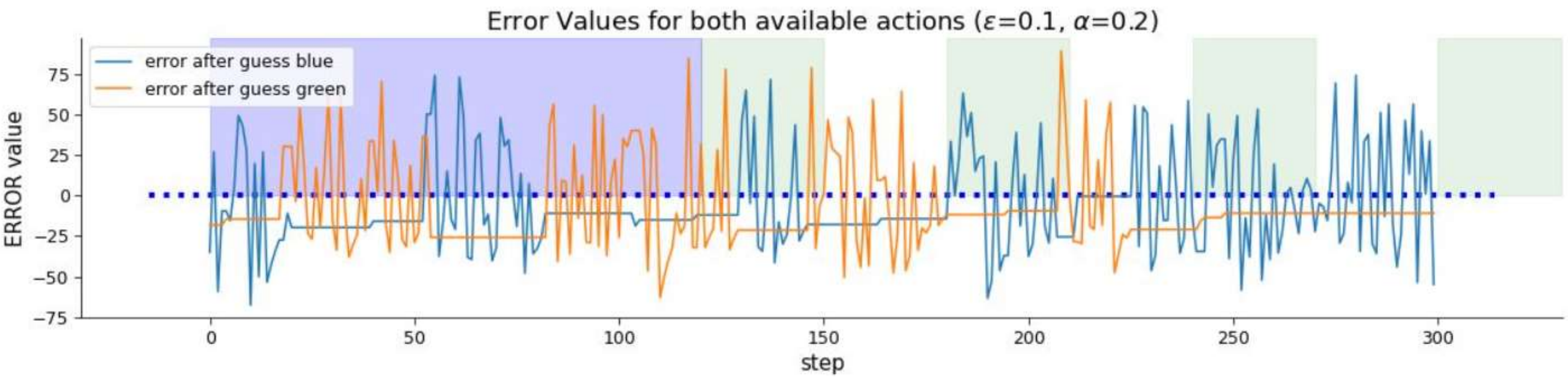
A constant environment (120 trials) with 70% blue cards, followed by a variable environment (170 trials) where probabilities for blue and green change (80% on either changed every 30 or 40 trials). Task adopted from Behrens et al, 2007.

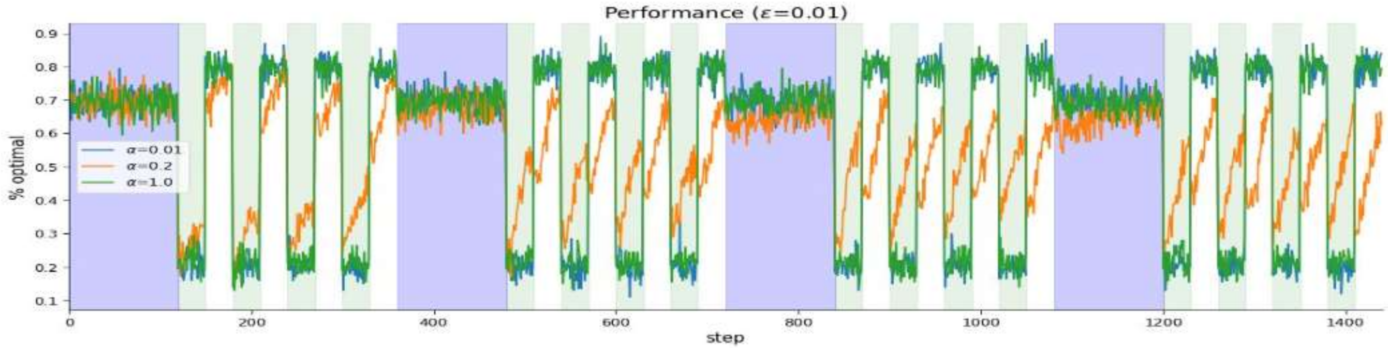
Finding an appropriate dataset to use RL model

Dataset	Reasons
Steinmetz Dataset (Visual contrast detection)	One learning task with fast learning
Stringer Dataset (Spontaneous behavior)	No learning tasks
HCP Dataset (Gambling task)	Random rewards
Behren's et al 2007 (Probability tracking)	Prediction of subject decisions

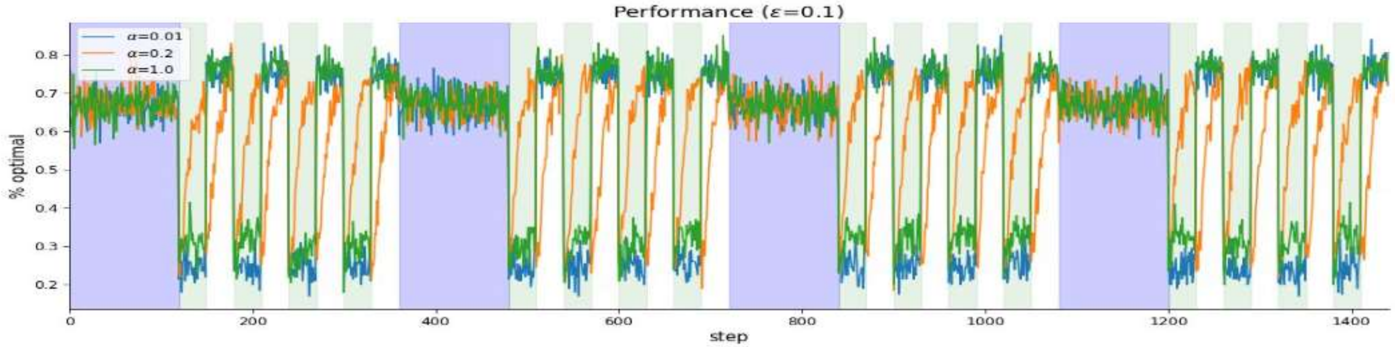
RL Model: Epsilon-Greedy 2-Armed Bandit



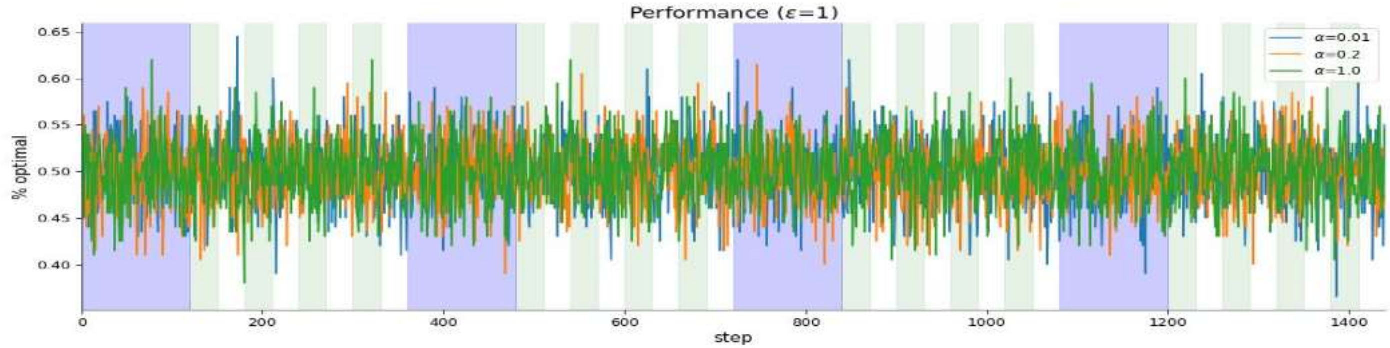




A very low exploration rate results in sticking with the same strategy. The agent does not discover that after reversal, green gets rewarded. Only later, in the 2nd block, the agent with alpha = 0.2 starts reversing decisions.



A very low and a very high learning rate lead to suboptimal results.



Complete random choice of actions in the epsilon greedy policy.

Experience of working as a group

- Deciding on question and dataset
  - Challenging finding appropriate research question, but we had many rewarding discussions
- Debugging existing codes and trying to adapt them to our task
  - Adjusting parameters for the Q-learning model, like ε and α, we simulated some previously-published findings in our model
- Discussions with mentors (Matthijs van der Meer and Helen Motanis)
  - Helped us decide on a research question and choose a novel method for replicating some previous findings
- Fun with plotting :)
- Fun with furry friends :)

THANK YOU NEUROMATCH ACADEMY!

Drift-diffusion Model in Working Memory





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Brown University

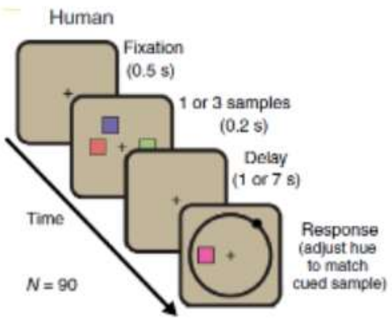
Shuyuan Xu
Shaanxi Normal University

Ying Fan
Peking University

Jie Gao
South China Normal University

Xinge Liu
Sun Yat-sen University

NMA pod-068-silver-goose Attractor Group



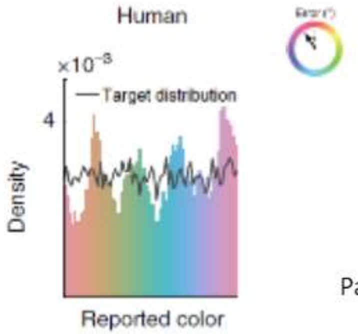
Task:

Delayed match to sample color working memory task. Adjust hue to match cued sample

Design:

Sample size: 1, 3

Delay: 1s, 7s



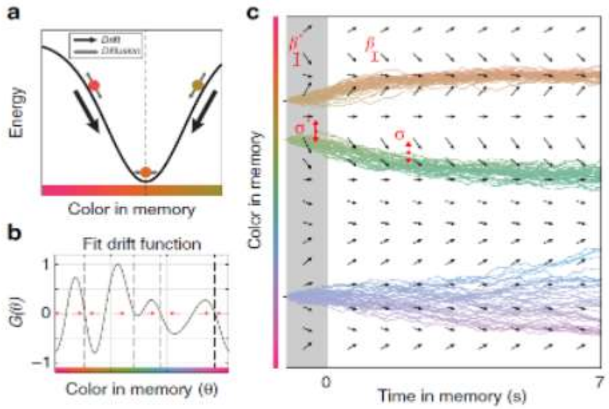
Results:

Target colors distributed uniformly, however **reports clustered around specific colors**

Panichello et al., Nature Communications, 2019

What Question:
How do the clusters emerge in participants' report for a color working memory task?

How to answer:
Attractor model



$$d\theta = \boxed{\beta_L G(\theta) dt} + \boxed{\sigma_L dW}.$$

drift towards attractor states

noise **diffusion**

Drift-diffusion model (W2D2)

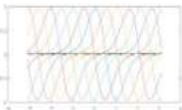
What we did: (1) understand attractor model

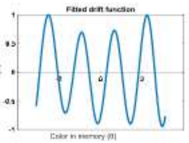
- Attractor model (drift and diffusion)

$$d\theta = \beta_L G(\theta)dt + \sigma_L dW. \quad (1)$$

- How to describe the drift function G(θ) ?

$$G(\theta) = \sum_{j=1}^{12} w_j \frac{d}{d\theta}\phi\left(\frac{2\pi}{12}j, \frac{2\pi}{12}\right)$$





- How fit the model described in Eq (1) ?

p(θ, t): the pdf of the color in memory θ at time t

$$\frac{\partial}{\partial t}p(\theta,t) = -\frac{\partial}{\partial\theta}\beta_L G(\theta)p(\theta,t) + \frac{\sigma_L^2}{2}\frac{\partial^2}{\partial\theta^2}p(\theta,t). \quad (2)$$

$$\frac{\partial}{\partial t}p(\theta,t) = M_L p(\theta,t). \quad (3)$$

$$p(\theta,t) = e^{M_L t}p(\theta,0), \quad (4)$$

Dataset:

200 sample trials

delayTime	report	target
7	-1.7907	-2.1936
7	1.0996	1.0264
7	-1.9792	-2.7365
7	0.8482	0.9625
1	-0.4712	0.1414
1	2.7332	1.9210
1	-2.1677	-1.5936

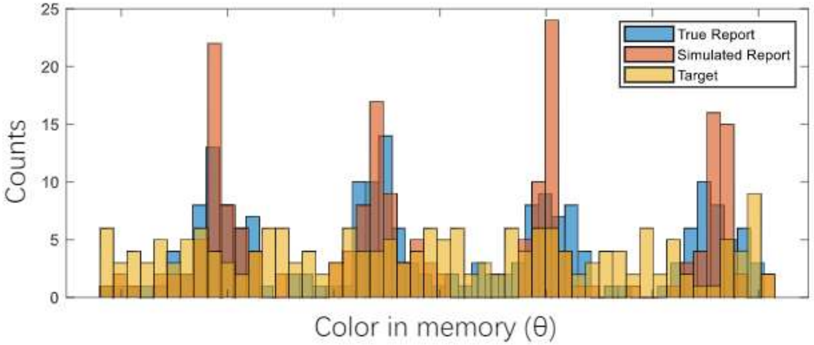
Parameter estimation (MLE)

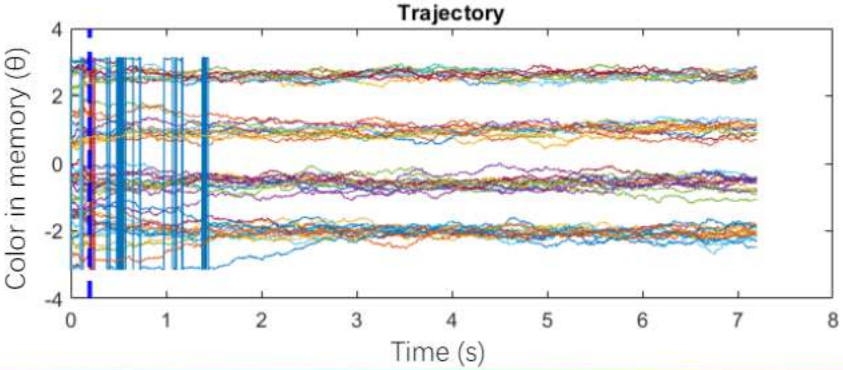
Model fitting（W1D3）

What we did:

(2) Simulation results from target to report

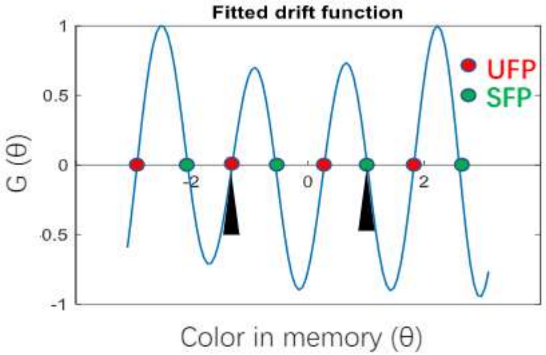
$$d\theta = \beta_L G(\theta)dt + \sigma_L dW.$$

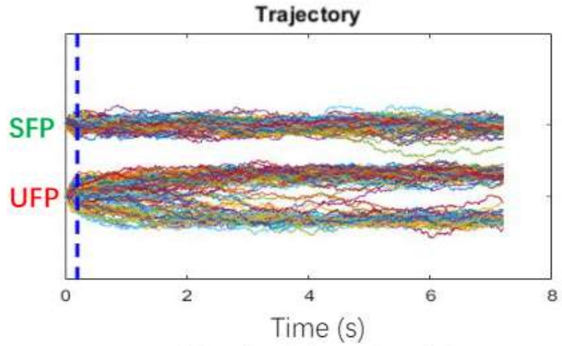




What we did:

(3) Simulation results stable fixed point(SFP) and unstable fixed point (UFP)





Fixed point and working memory (W3D2)

Summary

Two forces drive the evolution of visual representations in a working memory process

(1) random diffusion
(2) drift towards discrete attractor states

Future work

Expand this to why model

whether there exist neuro-foundations or biological constraints leading to the existence of attractors

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