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Differential Spatial Representations in Hippocampal CA1 and Subiculum Emerge in Evolved Spiking Neural Networks

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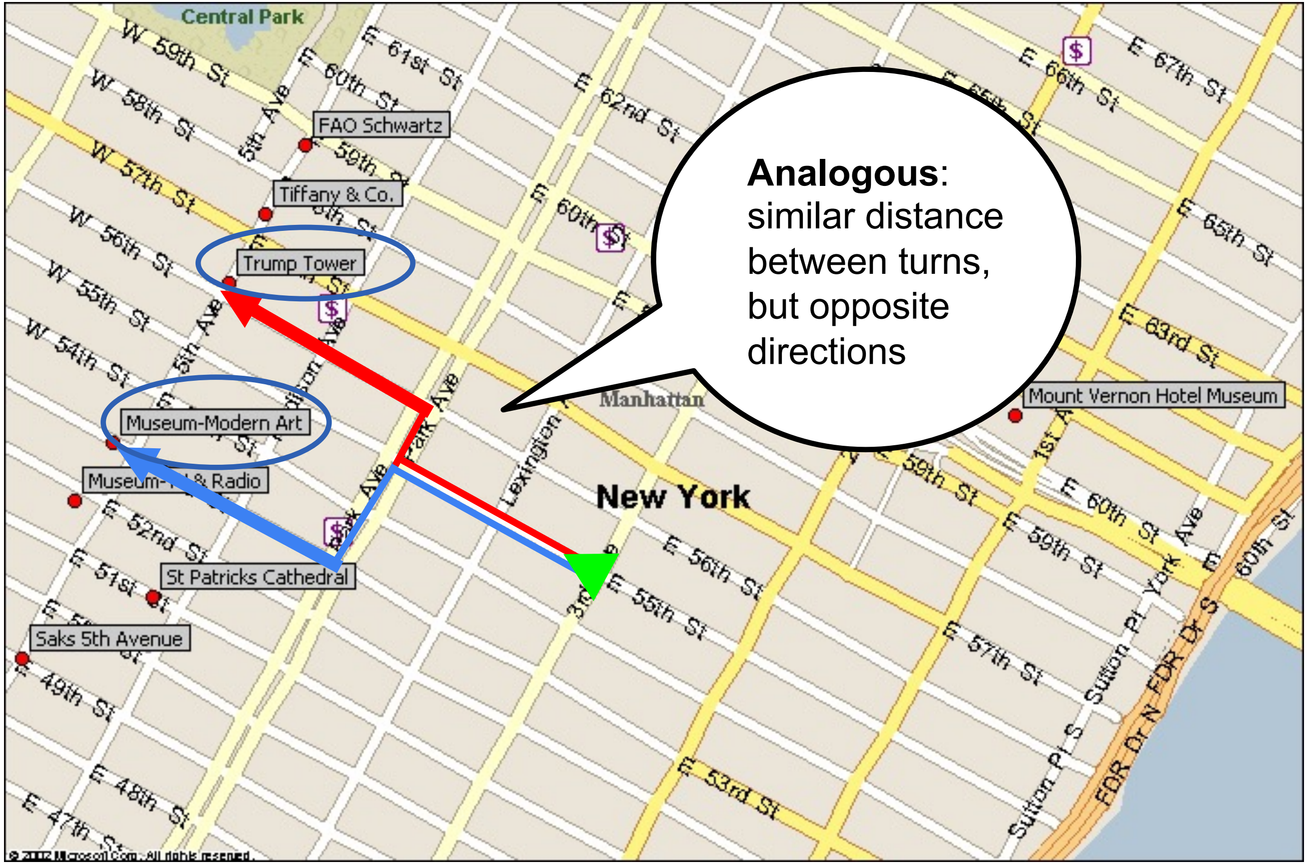
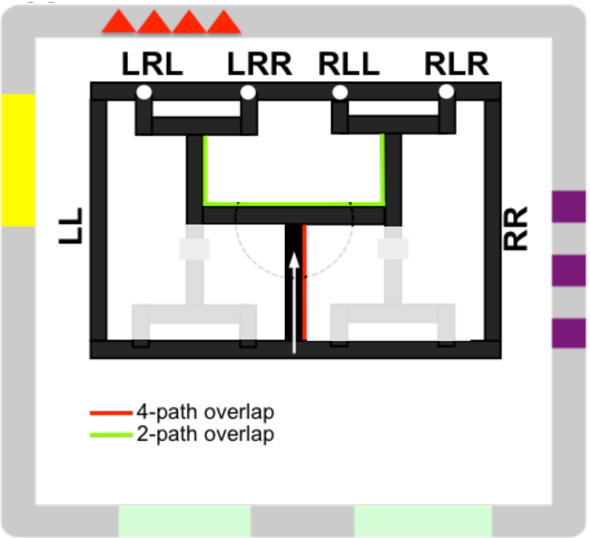
Navigation in the World



Navigation in the Lab

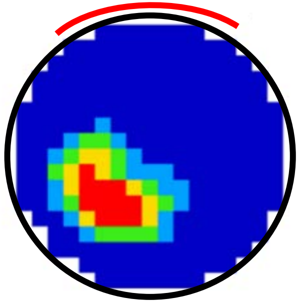


Behavioral and neural data (CA1 and SUB) being recorded.

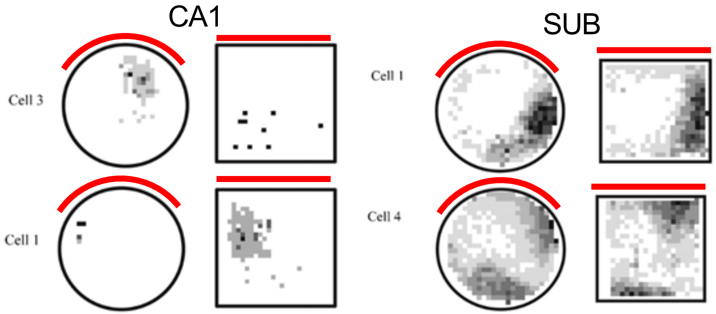
Olson et al. (2021)

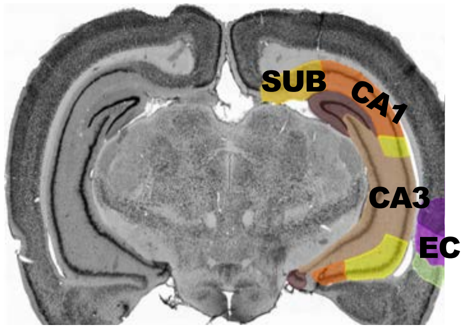
Hippocampus and Subiculum (SUB) as a Cognitive Map

Place Cells
(O'Keefe 1976)

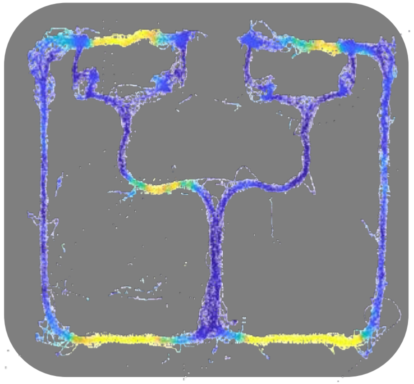


Place Activity (Sharp 1997)

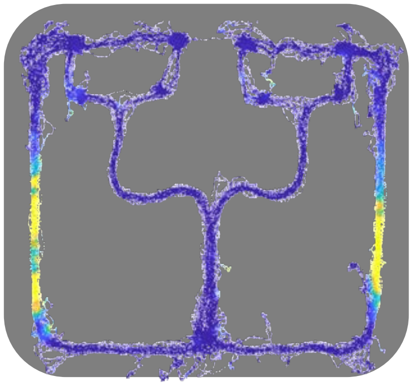




SUB Axis-tuned Activity
(Olson et al. 2017)

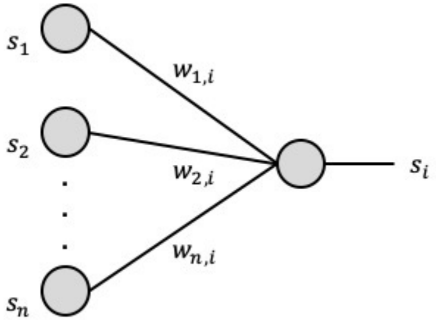


SUB Analogy Activity
(Olson et al. 2021)

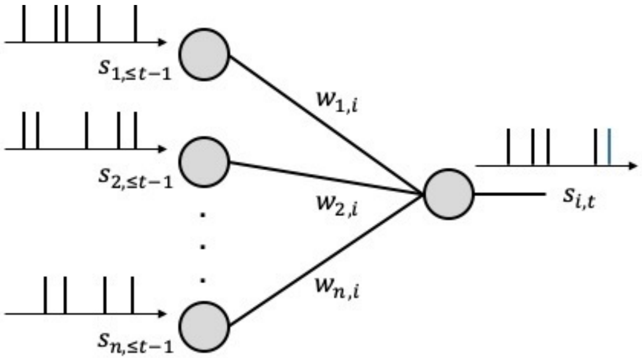


Background: Spiking Neural Networks (SNNs)

Real value Artificial Neural Network (ANN)

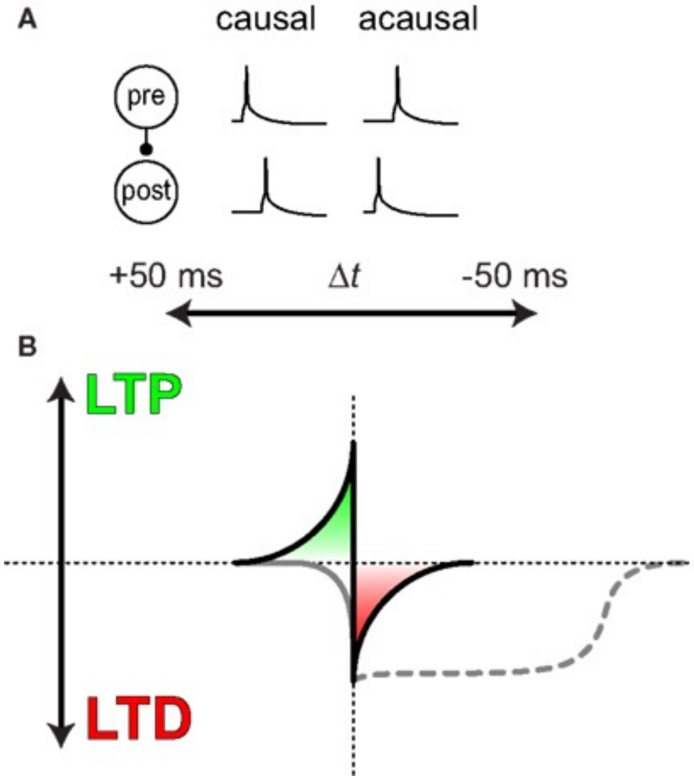


Spiking Neural Network (SNN)



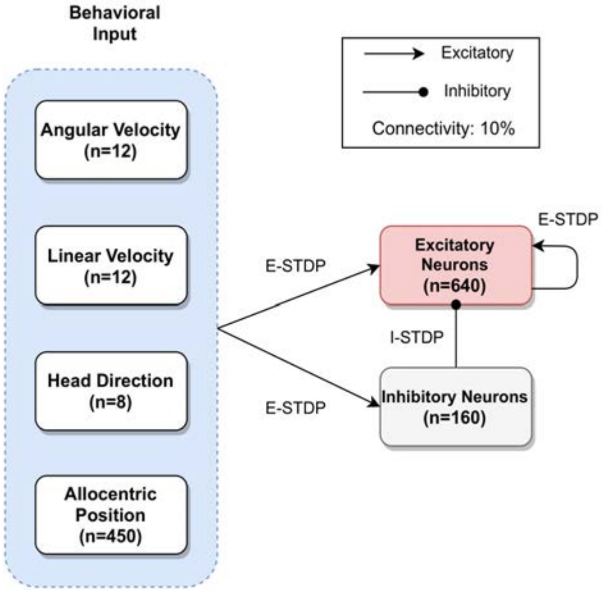
Jang et al. (2019)

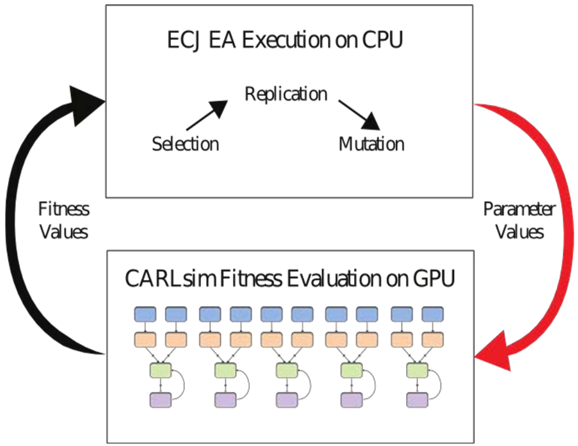
Spike-Timing Dependent Plasticity (STDP)



Markram et al. (2011)

Methods: Evolving Spiking Neural Networks





$$y = \sum_{i}^{N} \rho(\bar{R}^{i}_{real}, \bar{R}^{i}_{match}) - L$$

$$L = \begin{cases} max(\bar{R}_{exc}) - R_t & ,\text{if} \quad max(\bar{R}_{exc}) > R_t \\ 0 & ,otherwise \end{cases},$$

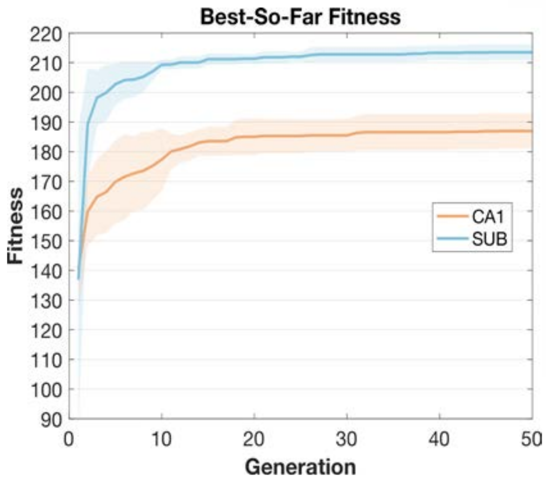
Spiking Neural Network Model

- Behavioral variables recorded from rat: converted to spike trains
- Recurrently connected excitatory and inhibitory neurons.

Evolutionary Computation

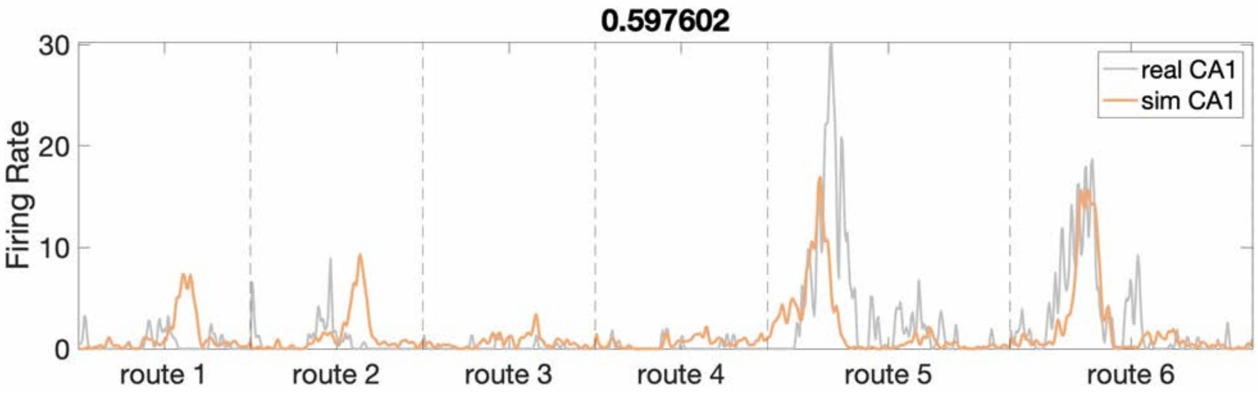
- Evolving parameters of Spike Timing Dependent Plasticity + Homeostasis (STDP-H)
- Objective: reproduce neuronal activity observed in CA1 and SUB

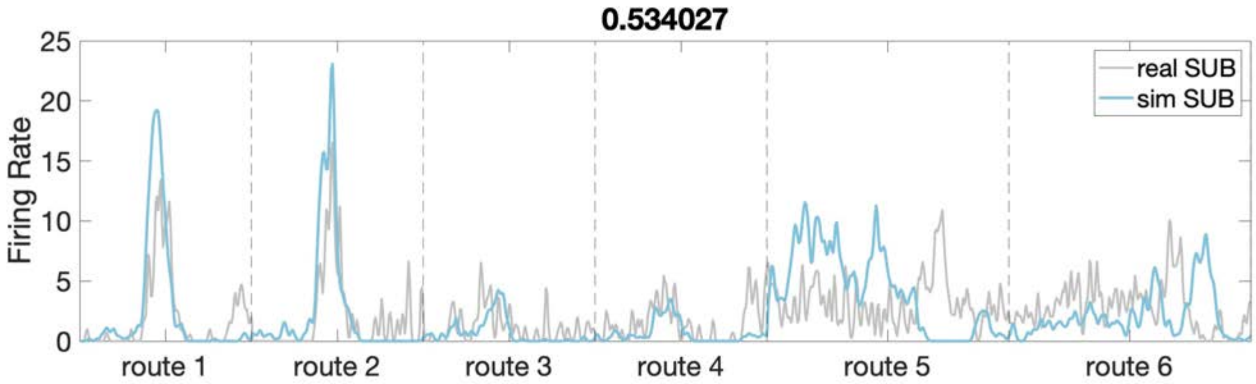
Results: SNN Neuron Activity Matched to Real Neuron Activity



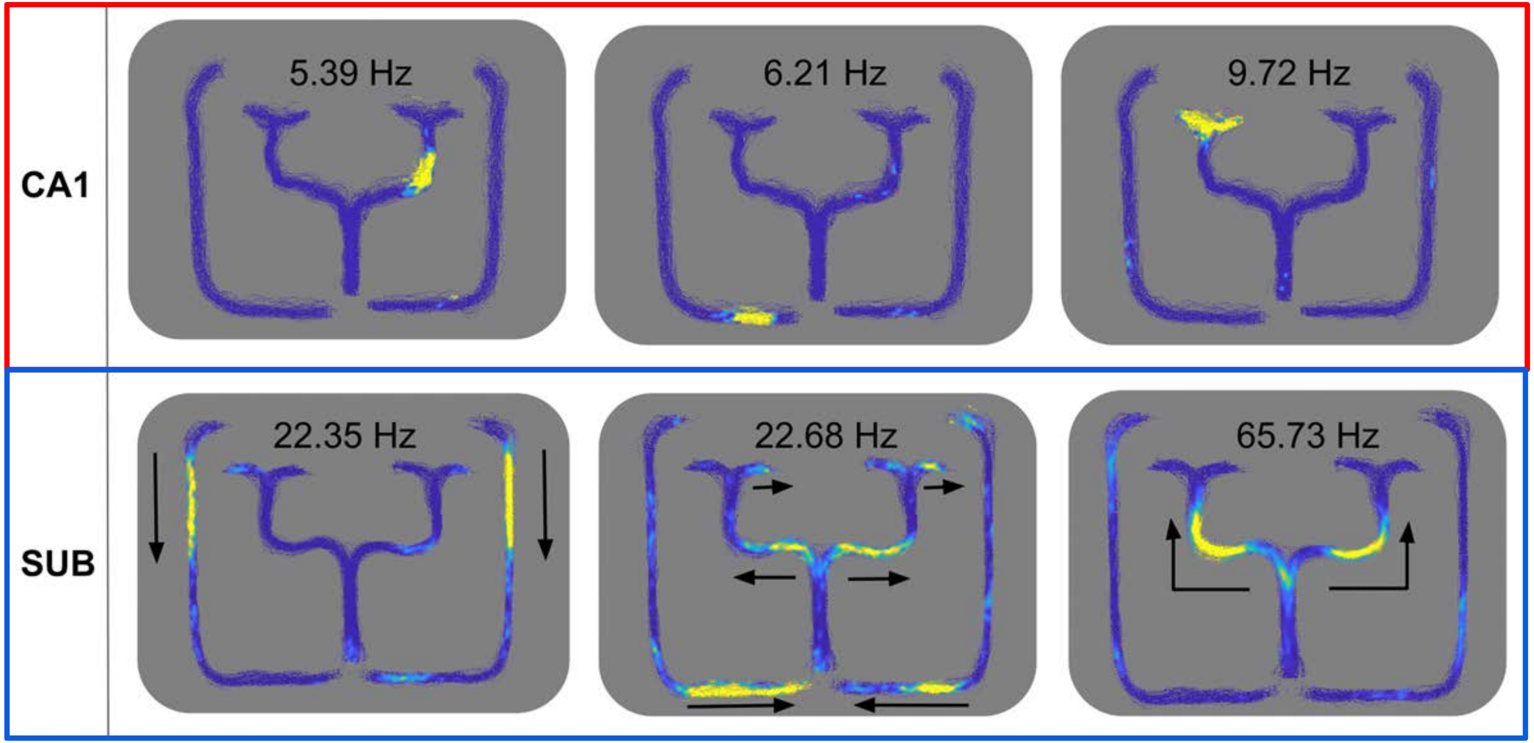
Fitness Values at Generation 50

- CA1: 187 (295 neurons in the dataset, mean correlation of 0.63)
- SUB: 213 (382 neurons in the dataset, mean correlation 0.56)



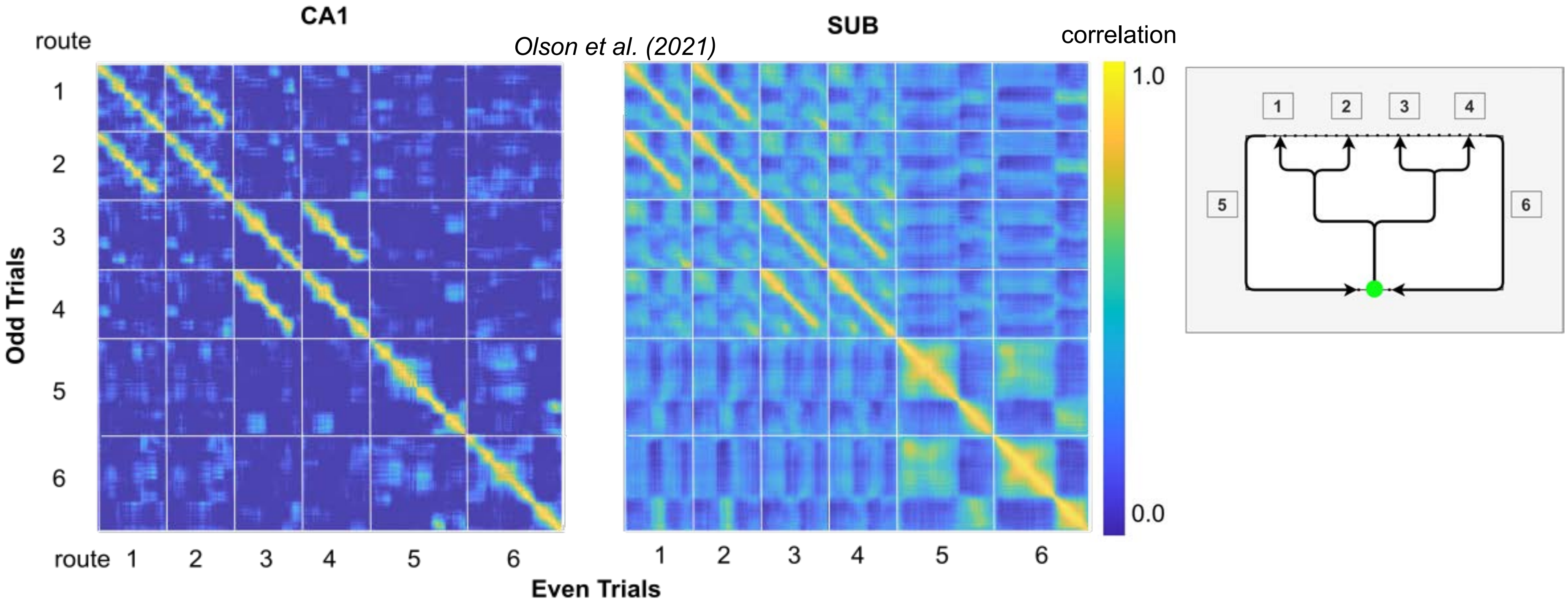


Results: Differential Firing Properties of Simulated CA1 and SUB



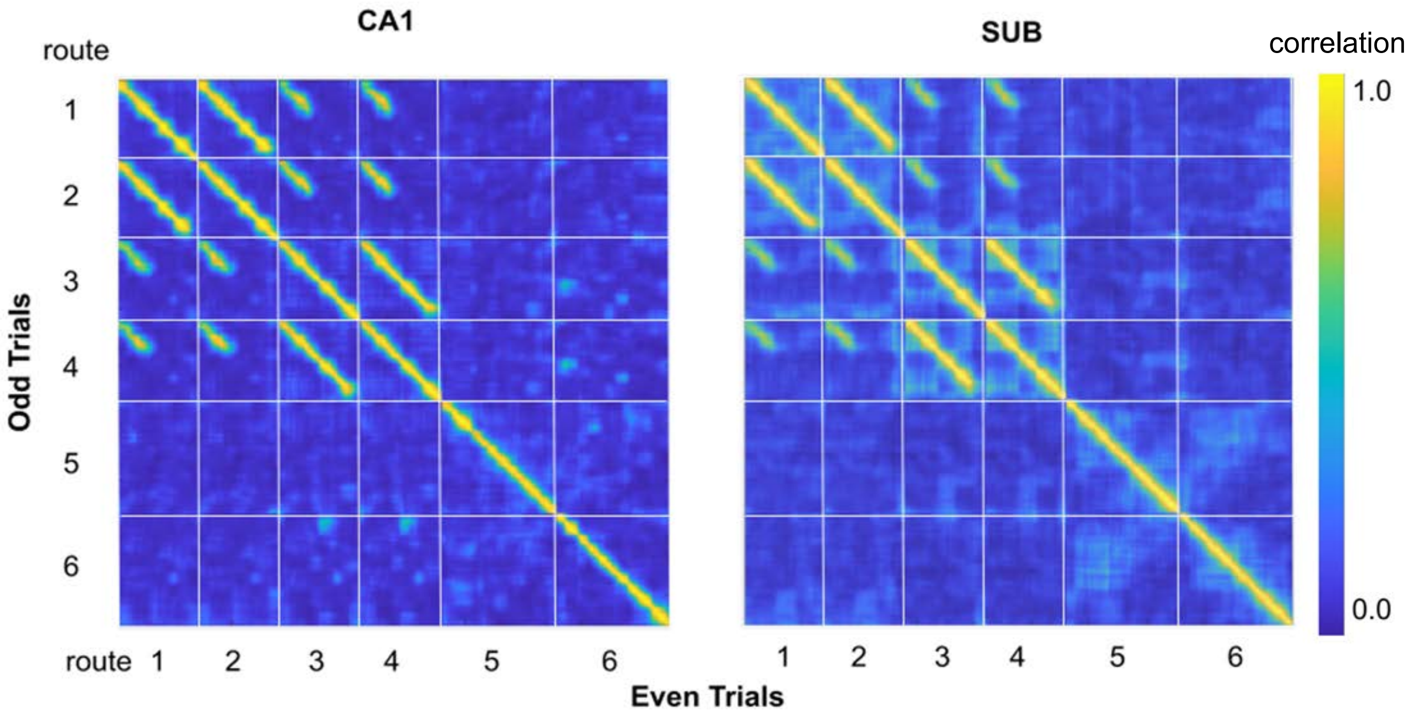
- CA1: single place fields
- SUB: firing at multiple locations; axis-tuned; analogy responses

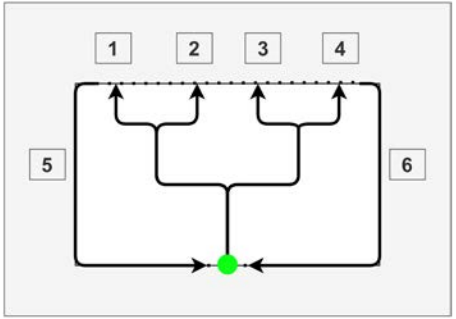
Results: Differential Spatial Representations in Population Activity



- Correlation matrix of odd and even trials for **real** neuron activity
- Provides a nice visualization of how the population encodes position and direction
- High correlation values on the diagonal line indicate consistent firing for the same locations

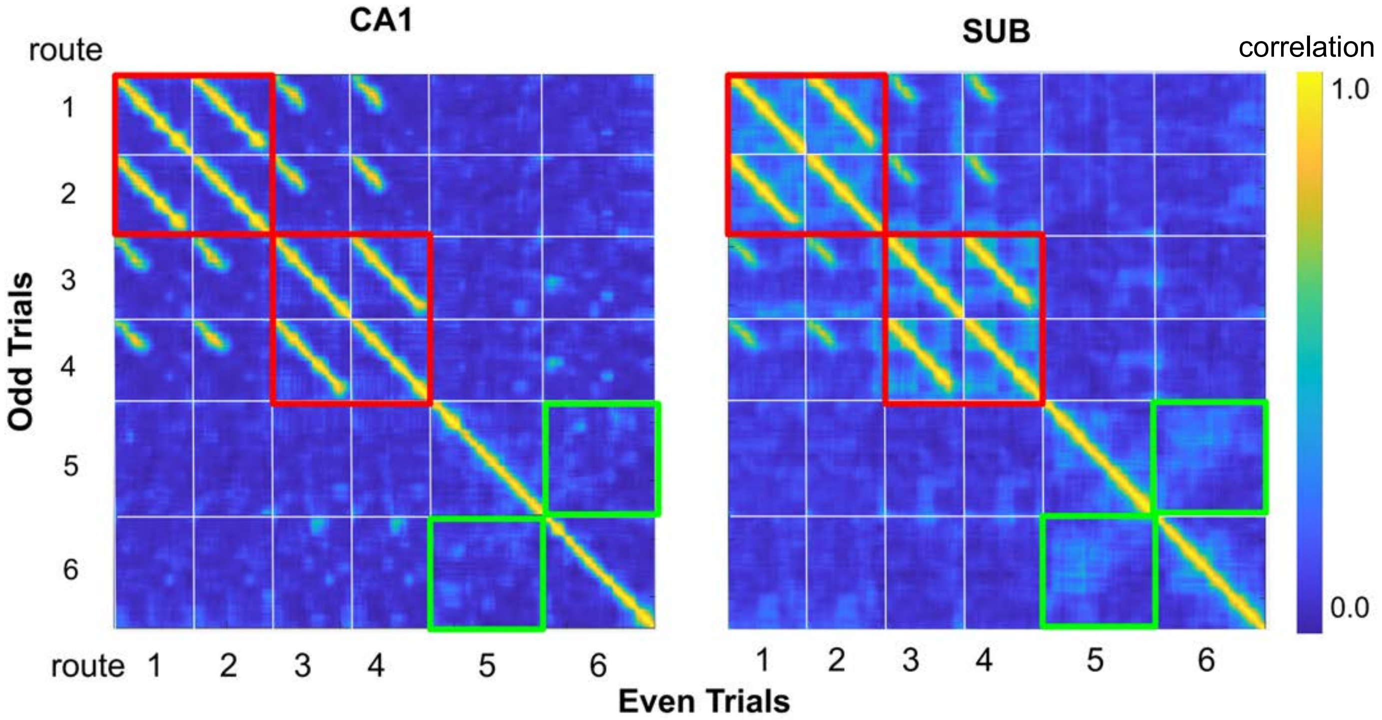
Results: Differential Spatial Representations in Population Activity

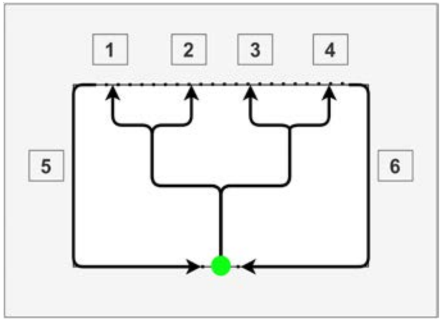




- Correlation matrix of odd and even trials for **simulated** neuron activity
- **Both models reliably encoded positions**

Results: Differential Spatial Representations in Population Activity





- Red: internal paths
- Green: return paths

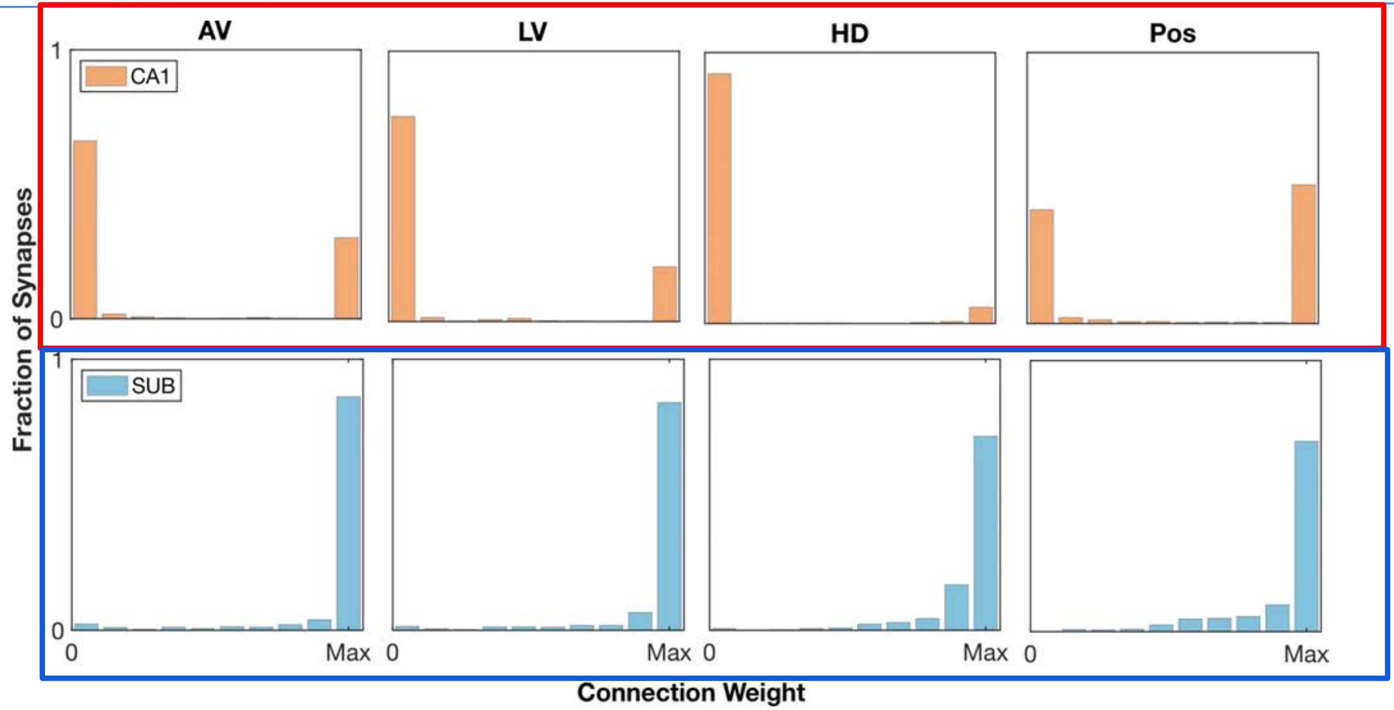
- SUB activity showed more modulation of head direction

Results: Spatial Metrics of Simulated Neurons

SpatialMetrics	CA1 (sim)	SUB (sim)	CA1 (recorded)	SUB (recorded)
meanFR (Hz)	0.85 ± 0.87	**2.16 ± 2.00**	0.88 ± 1.42	**3.62 ± 4.23**
maxFR (Hz)	27.66 ± 18.78	**41.75 ± 33.35**	31.57 ± 14.91	**38.86 ± 21.35**
spatialIfo (bits)	**2.87 ± 1.04**	1.92 ± 0.69	**2.97 ± 1.19**	1.56 ± 1.21
sparsity	0.12 ± 0.08	**0.20 ± 0.10**	0.12 ± 0.13	**0.35 ± 0.25**
selectivity	**64.53 ± 74.53**	27.29 ± 21.47	**63.76 ± 50.79**	31.18 ± 38.84
spatialCoherence	**0.83 ± 0.05**	0.81 ± 0.05	0.48 ± 0.12	0.49 ± 0.14

- Simulated neurons have similar spatial measurements to real neurons
- Bold text shows significantly larger values comparing CA1 and SUB
  - CA1 neurons encoded more spatial information, fired more sparsely and selectively

Results: Connection Weights Reflected Functions of CA1 and SUB



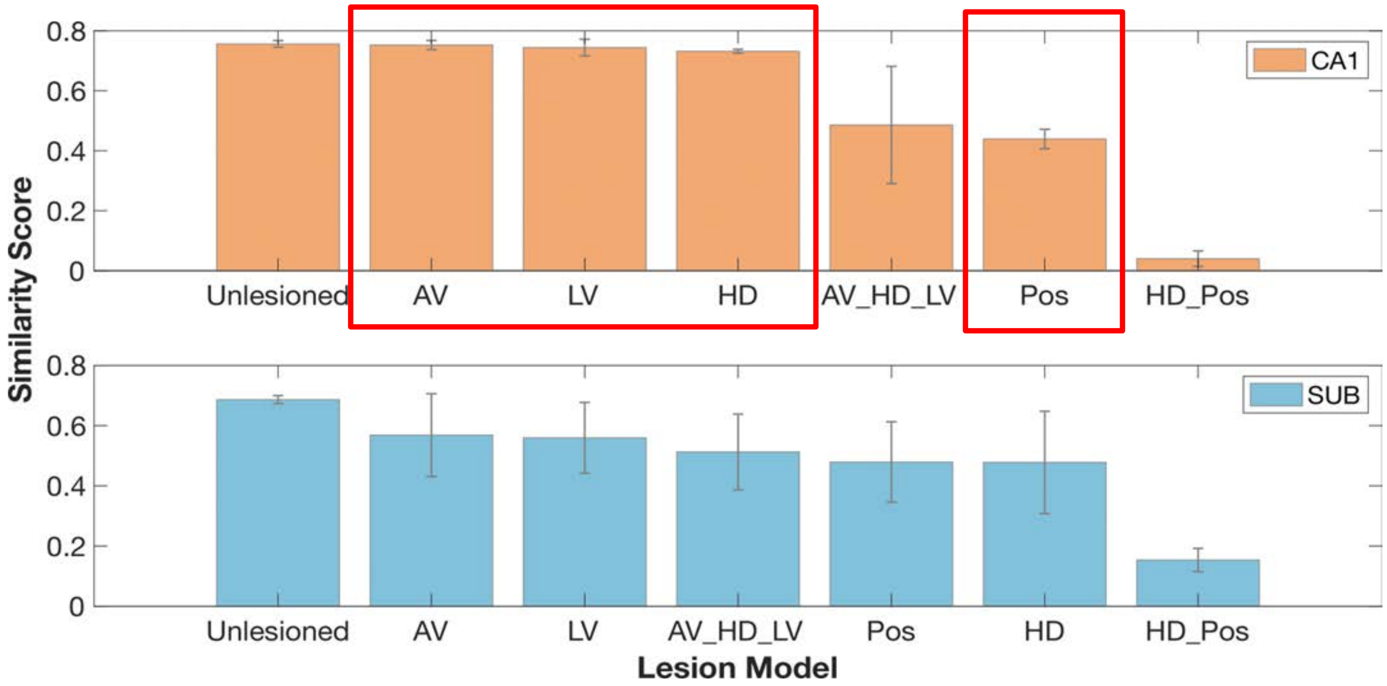
Input -> CA1

- Clustered near 0 except for positional input
- CA1 activity largely relied on positional input

Input -> SUB

- Clustered near max weight
- SUB neurons integrate position, head direction, and self-motion to encode multiple locations

Results: Effects of Input Stream Lesions

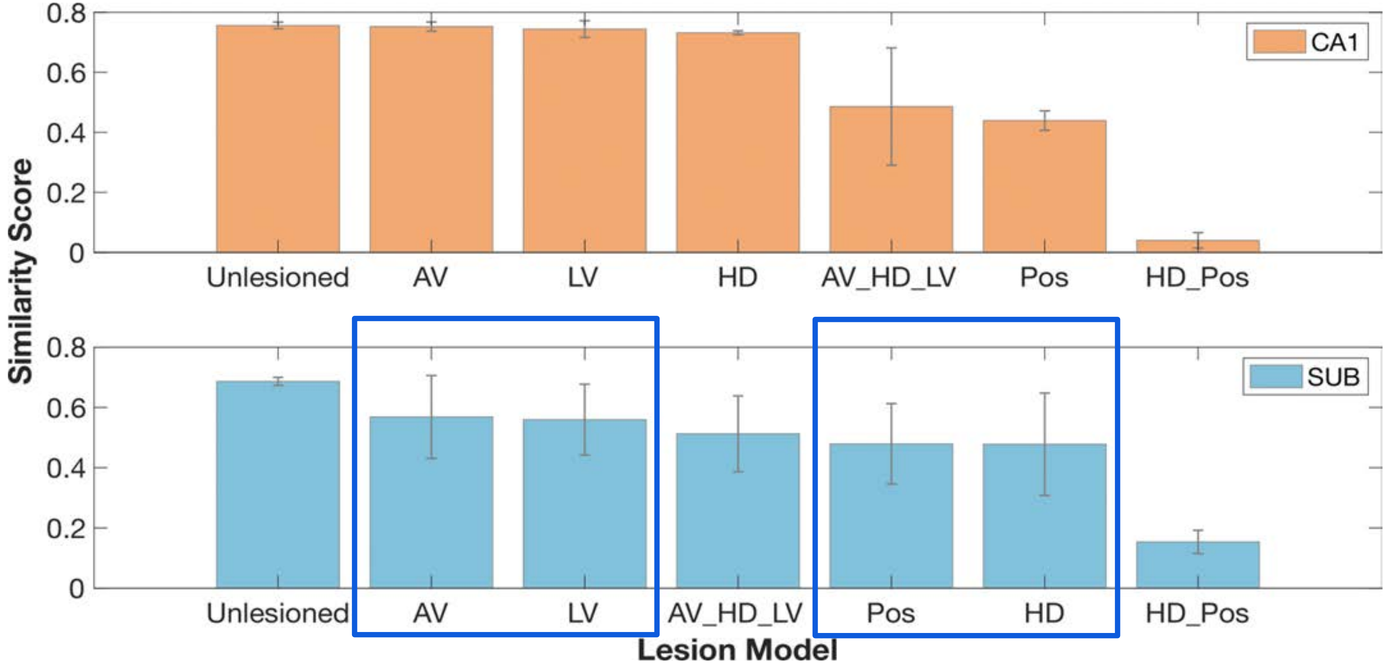


Similarity Score: correlation of real and simulated neurons on the population level

CA1

- Removing positional input had a strong impact than the other three inputs on the performance
- More reliant on the CA3 input to CA1 than self-motion signals

Results: Effects of Input Stream Lesions



Similarity Score: correlation of real and simulated neurons on the population level

SUB
- Lesions of any input had a moderate impact on network performance
- SUB model utilized different input information more equally

Conclusion

- Models faithfully reproduced neurophysiological data from CA1 and SUB

- Connection weight analysis and lesion studies showed that:
  - CA1 activity pattern mainly driven by positional input
  - SUB conjunctively encodes position, head direction, and running velocity

- Evolving learning rules in SNNs to fit neurophysiological data may be a general-purpose means to building high-fidelity models of brain regions

Thank you!

For more information, please contact:

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References

- O'Keefe J. (1976). Place units in the hippocampus of the freely moving rat. *Experimental neurology*, *51*(1), 78–109. https://doi.org/10.1016/0014-4886(76)90055-8
- Sharp P. E. (1997). Subicular cells generate similar spatial firing patterns in two geometrically and visually distinctive environments: comparison with hippocampal place cells. *Behavioural brain research*, *85*(1), 71–92. https://doi.org/10.1016/s0166-4328(96)00165-9
- Olson, J. M., Tongprasearth, K., & Nitz, D. A. (2017). Subiculum neurons map the current axis of travel. *Nature neuroscience*, *20*(2), 170–172. https://doi.org/10.1038/nn.4464
- Olson, J. M., Johnson, A. , Chang, L., Tao, E., Wang, X., & Nitz, D. A. (2021). Complementary Maps for Location and Environmental Structure in CA1 and Subiculum. 10.1101/2021.02.01.428537.
- Jang , H., Simeone O., Gardner, B., & Gruning , A. (2019). An Introduction to Probabilistic Spiking Neural Networks: Probabilistic Models, Learning Rules, and Applications. *IEEE Signal Processing Magazine*. https://doi: 10.1109/MSP.2019.2935234.
- Markram, H., Gerstner, W., & Sjöström, P. J. (2011). A history of spike-timing-dependent plasticity. *Frontiers in synaptic neuroscience*, *3*, 4. https://doi.org/10.3389/fnsyn.2011.00004