Papers related to the Hopfield model (1982)

- *compiled by Wulfram Gerstner, November 2024*

Precursors

Steinbuch K (1961) Die Lernmatrix, Kybernetik 1, 3~45 (1961)

D. J. Willshaw, 0. P. Buneman, and H. C. Longuet-Higgins (1969), " Non-holographic associative memory," Nature, vol. 222, pp. 960-962. *(>1400 citations)*

T. Kohonen (1972), "Correlation matrix memories," IEEE Trans. Comput., vol. C-21, pp. 353-359, Apr. 1972.

K. Nakano (1972), "Associatron-A model of associative memory," IEEE Trans. Syst., Man, Cybern., vol. SMC-2, pp. 380-388, July 1972.

Sun-Ichi Amari (1972) Learning Patterns and Pattern Sequences by Self-Organizing Nets of Threshold Elements. IEEE Trans. Comput, VOL. c-21,, Nov. 1972

Anderson, J. A. (1972). A simple neural network generating an interactive memory, Mathem. Biosci. 14:197-220

Little WA (1974) The existence of persistent states in the brain. Math Biosci 19:101-120

Willwacher G (1976) Fahigkeiten eines assoziativen Speichersystems im Vergleich zu Gehirnfunktionen. Biol Cybern 24:181-198

Gunther Palm (1980) On associative memory. Biol. Cybern. 36 :19–31

Hopfield (1982) triggered a wave in physics:

HOPFIELD 1982 Neural networks and physical systems with emergent collective computational abilities, PNAS 79: 2554-2558*,*

Peretto (1984) Collective Properties of Neural Networks: A statistical Mechanics Approach Biol. Cybern. 50: 51-62 (received November 1983).

Amit-Gutfreund-Sompolinsky (1985) Spin-glass models of neural network Phys. Rev. A. 32: 1007-1018

Up to here: models with binary neurons. Next two are rate neurons

Cohen and Grossberg (1983) Absolute Stability of Global Pattern Formation and Parallel Memory Storage by Competitive Neural Network in IEEE Trans. Systems, Man, Cybernetics

Hopfield (1984) , Neurons with graded response have collective computational properties like those of two-state neurons. PNAS 81: 3088-3092

One aspect of Hopfield models is low-dimensional dynamics: This aspect is now studied under the terms of 'Neural Manifolds' and 'Low-rank networks'. Representative examples:

Friedrich, R.W., Laurent, G. (2001): Dynamic optimization of odor representations by slow temporal patterning of mitral cell activity. Science 291, 889–894

Shenoy, K.V., Sahani, M., Churchland, M.M. (2013): Cortical control of arm movements: A dynamical systems perspective. Annual Review of Neuroscience 36, 337–359

Mante, V., Sussillo, D., Shenoy, K.V., Newsome, W.T. (2013): Context-dependent computation by recurrent dynamics in prefrontal cortex. Nature 503, 78–84

Gallego, J.A., Perich, M.G., Miller, L.E., Solla, S.A. (2017): Neural manifolds for the control of movement. Neuron 94, 978–984

Mastrogiuseppe, F, Ostojic, S (2018).: Linking connectivity, dynamics, and computations in low-rank recurrent neural networks. Neuron 99, 609–62329

Vyas, S., Golub, M.D., Sussillo (2020), D., Shenoy, K.V.: Computation through neural population dynamics. Annual Review of Neuroscience 43, 249–275

Khona, M., Fiete, I.R (2022).: Attractor and integrator networks in the brain. Nature Reviews Neuroscience 23, 744–766 (2022)

Langdon, C., Genkin, M., Engel, T.A. (2023): A unifying perspective on neural manifolds and circuits for cognition. Nature Reviews Neuroscience 24, 363–377

DePasquale, B., Sussillo, D., Abbott, L.F., Churchland, M.M. (2023): The centrality of population- level factors to network computation is demonstrated by a versatile approach for training spiking networks. Neuron 111, 631–64910