Yapay ve Gerçek Sinir Ağları

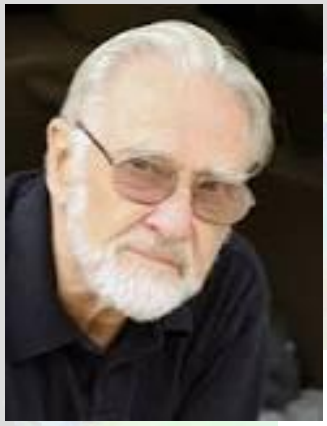
Matematik Kullanabilmenin Faydaları

Neslihan Serap ŞENGÖR

İTÜ Maslak, Ekim, 2019

İstanbul Teknik Üniversitesi
Sinirbilim Modelleme ve Araştırma Grubu

İstanbul Teknik Üniversitesi
Elektronik ve haberleşme Mühendisliği Bölümü



Bir psikolog fizikçileri niçin kıskanır.....

1964

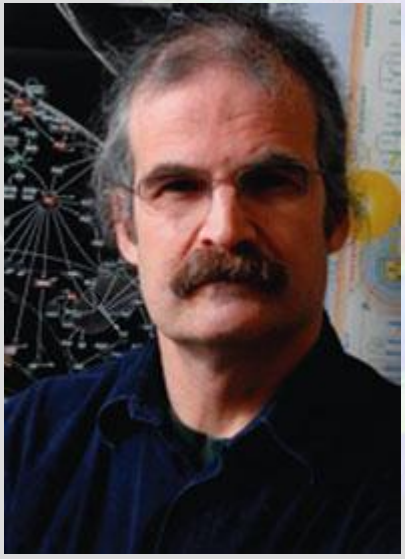
R.Duncan Luce
1925-2012

THE MATHEMATICS USED IN MATHEMATICAL PSYCHOLOGY

R. DUNCAN LUCE, University of Pennsylvania

Introduction. The main issue in applying mathematics to psychological problems today, and most likely for some time to come, is the formulation of these problems in mathematical terms. The solution of difficult but well-formulated mathematical problems and the analysis of complex applied problems in terms of precise and well-confirmed theories are more secondary efforts. We do not yet have the basic concepts and variables staked out in a way that makes the introduction of mathematics the relatively straightforward business that it has become in much of physical science. We are in a situation somewhat analogous to sixteenth, or hopefully seventeenth, century physics, but the analogy is far from complete. We resemble the early physicists in our effort, often fumbling and always slow, to isolate and purify the fundamental variables from the myriad, vague, commonsense psychological ideas and concepts. We differ in the range of techniques available to us. The modern electronics technology, including high speed computers, provides us with a control over experimental conditions and a computational capacity for data analysis incomparably more extensive and subtle than those with which the early physicists had to contend. In addition, most of the mathematics and statistics we now use was quite unknown three centuries ago.

Biyologlar da kıskanmakta....



Yuri Lazebnik

Biochemistry (Moscow), Vol. 69, No. 12, 2004, pp. 1403-1406.

DISCUSSIONS

Can a Biologist Fix a Radio? — or, What I Learned while Studying Apoptosis

Y. Lazebnik

Cold Spring Harbor Laboratory, Cold Spring Harbor, New York 11724, USA; E-mail: lazebnik@cshl.org

This article by Yu. Lazebnik, "Can a Biologist Fix a Radio? — or, What I Learned while Studying Apoptosis" has already been published in English (*Cancer Cell*, 2002, **2**, 179-182) and in Russian (*Uspekhi Gerontologii*, 2003, No. 12, 166-171). Nevertheless, we have undertaken its secondary publication in our journal for two reasons: first, our journal has different readers, and, second, the great significance of this manifest of Yuri Lazebnik. The author in bright and clever form shows the emerging necessity to create formalized language designed to describe complicated systems of regulation of biochemical processes in living cells. The article is published with permission of *Cancer Cell* and *Uspekhi Gerontologii*.

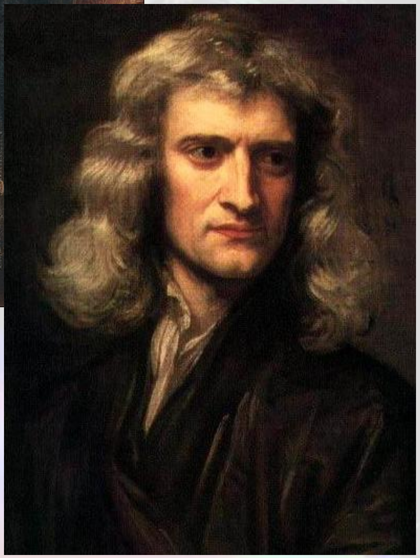
Editor-in-Chief of Biokhimiya/Biochemistry (Moscow) V. P. Skulachev

http://www.onclive.com/publications/Oncology-live/2012/january-2012/5-Questions-for-Yuri-Lazebnik-PhD

Matematik: Doğanın kitabının dili

Galileo Galilei
1564-1642

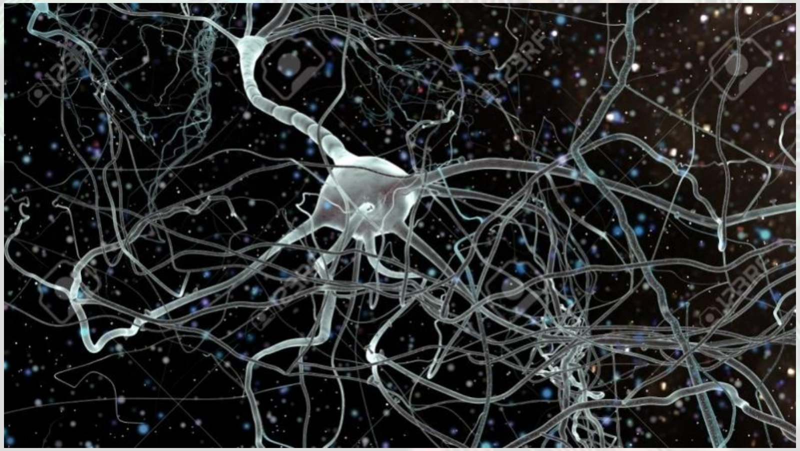
$$x = \frac{1}{2} g t^2$$

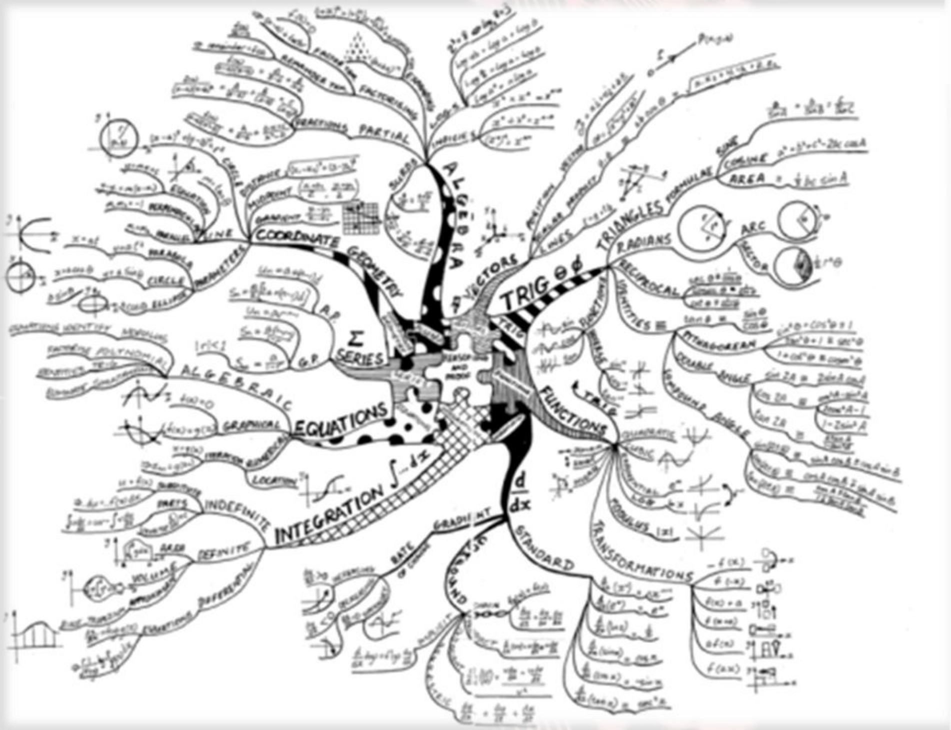


Isaac Newton
1643-1727

$$F = ma$$

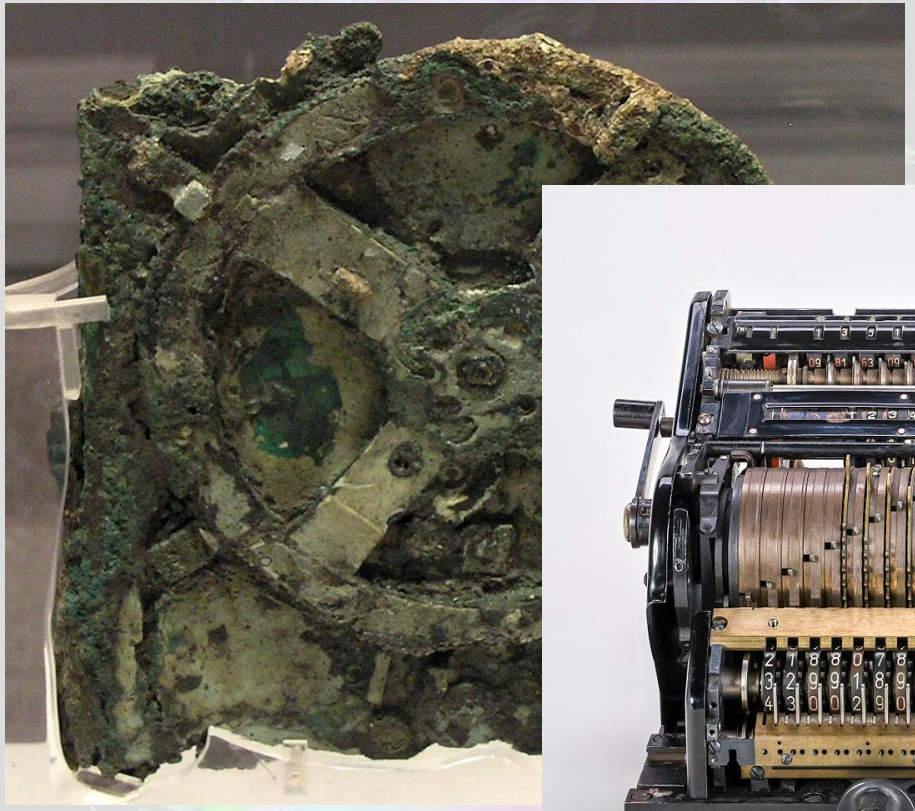
$$F = m \frac{d^2 x}{dt^2}$$



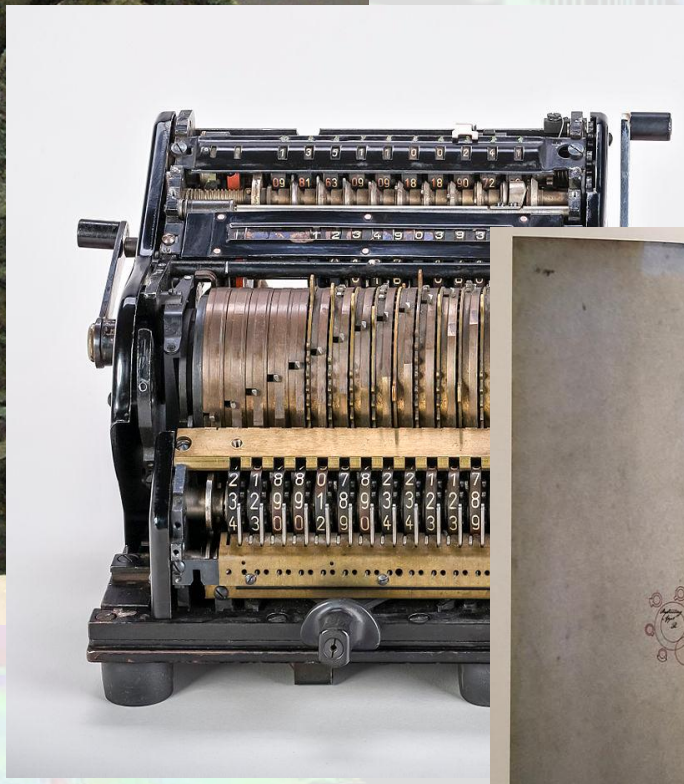


https://hdwallpapers.cat/neurons_synapse_abstract_academy_brains_3d_hd-wallpaper-1795266/

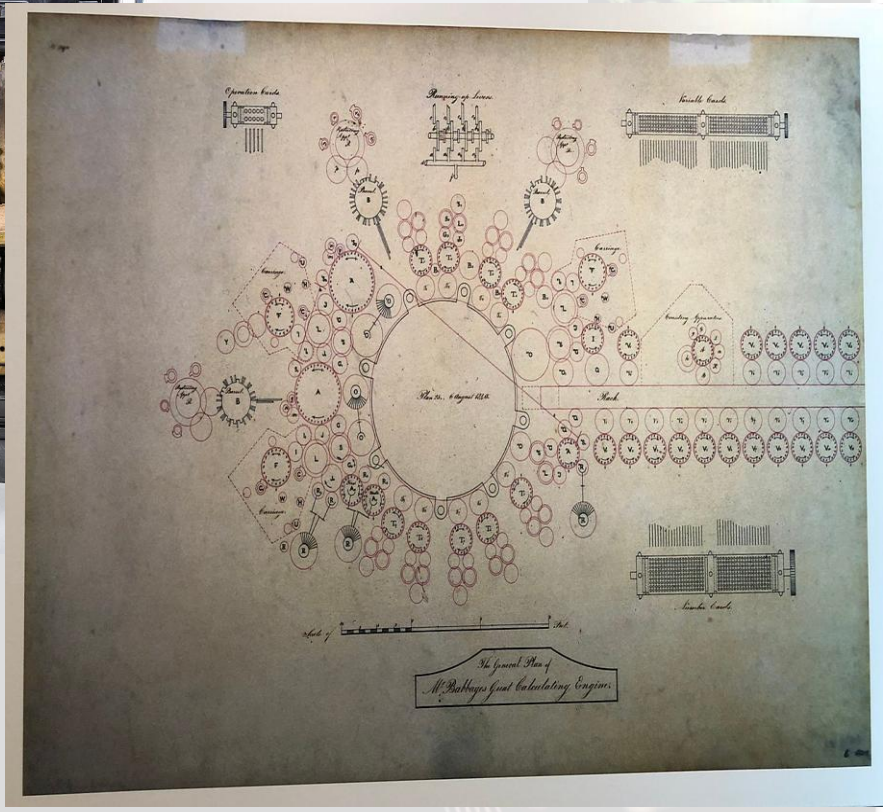
Antikythera Düzeneği MÖ 150-100



Leibniz Çarkı 1673



Analitik Makine 1833



https://en.wikipedia.org/wiki/Antikythera_mechanism https://en.wikipedia.org/wiki/Leibniz_wheel https://en.wikipedia.org/wiki/Analytical_Engine

VOL. LIX. No. 236.] [October, 1950

MIND

A QUARTERLY REVIEW

OF

PSYCHOLOGY AND PHILOSOPHY

I.—COMPUTING MACHINERY AND INTELLIGENCE

BY A. M. TURING

1. *The Imitation Game.*

I PROPOSE to consider the question, 'Can machines think?' This should begin with definitions of the meaning of the terms 'machine' and 'think'. The definitions might be framed so as to reflect so far as possible the normal use of the words, but this attitude is dangerous. If the meaning of the words 'machine' and 'think' are to be found by examining how they are commonly used it is difficult to escape the conclusion that the meaning and the answer to the question, 'Can machines think?' is to be sought in a statistical survey such as a Gallup poll. But this is absurd. Instead of attempting such a definition I shall replace the question by another, which is closely related to it and is expressed in relatively unambiguous words.

The new form of the problem can be described in terms of a game which we call the 'imitation game'. It is played with three people, a man (A), a woman (B), and an interrogator (C) who may be of either sex. The interrogator stays in a room apart from the other two. The object of the game for the interrogator is to determine which of the other two is the man and which is the woman. He knows them by labels X and Y, and at the end of the game he says either 'X is A and Y is B' or 'X is B and Y is A'. The interrogator is allowed to put questions to A and B thus:

C: Will X please tell me the length of his or her hair?

Now suppose X is actually A, then A must answer. It is A's

Alan Turing
1912-1954

İnsan tarzı zekayı mekanikleştirme olasılığı

Makineler düşünebilir mi? Sorusu yerine Turing testi

'Zeki' bilgisayara ulaşma olasığı aleyine savlar

Yetişkin zihnini taklit etme yerine çocuk zihnini taklit eden programı eğitme

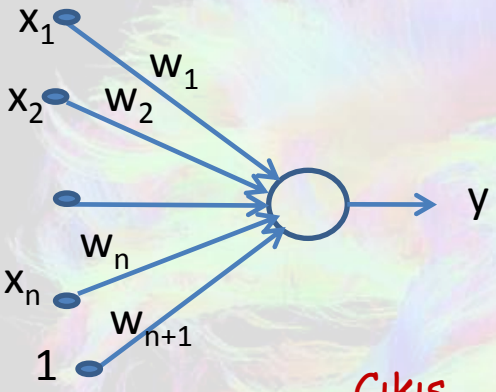
Yapay Zeka Dartmouth Yaz okulu 1956

Walter Pitts: Sayın Farley, Clark, Selfridge ve Dinneen sinir sistemini taklit ederlerken, Sayın Newell, geleneksel olarak zihin denilen, nihai sebepler, sebepler hiyerarşisini taklit etmeyi tercih ediyor. Sonunda hepsi hiç şüphesiz aynı kapıya çıkacak. *

https://medium.com/h-farm-industry/ai-glossary-1bcdd483f12a

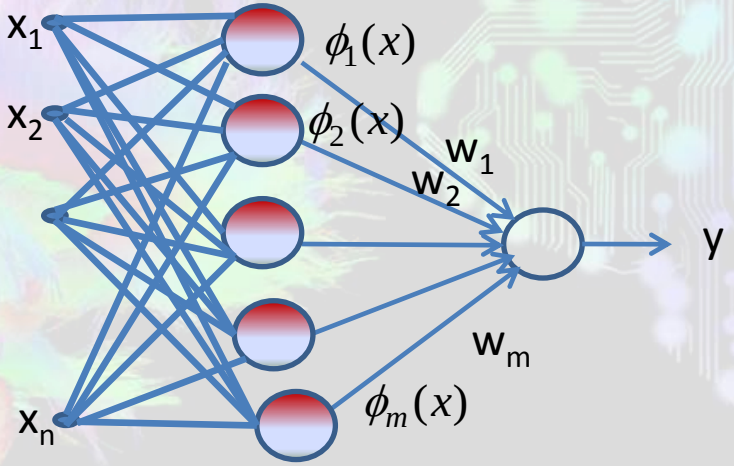
*N.J. Nilsson,'Yapay Zeka' Boğaziçi Üniversitesi Yayınları

Perceptron 1958



Giriş Katmanı

Çıkış Katmanı



Giriş Katmanı

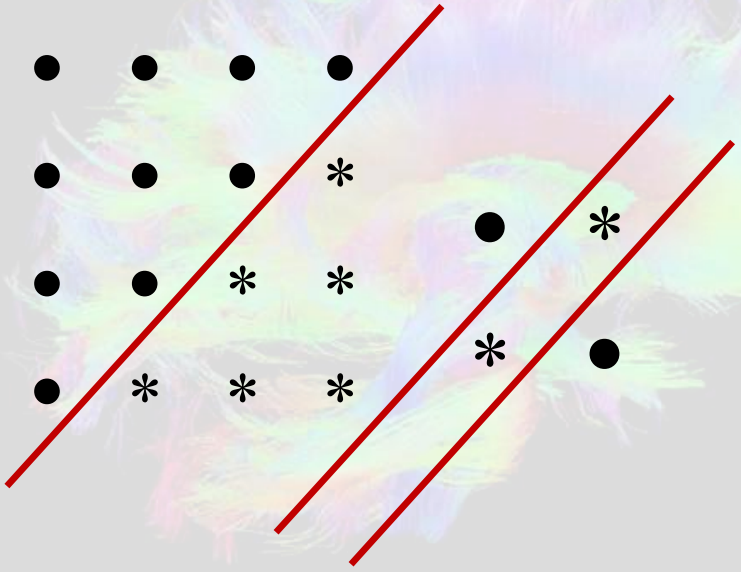
Birinci Katman

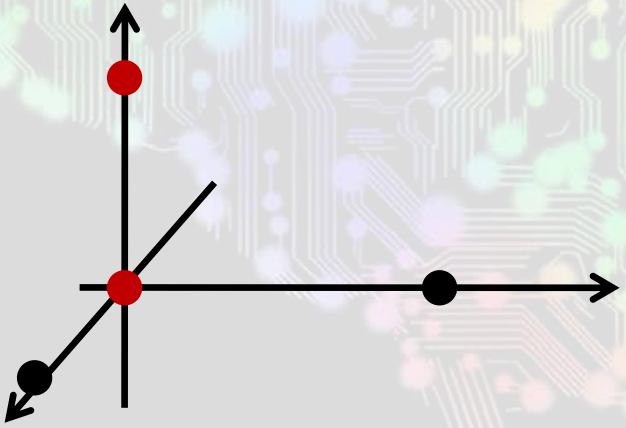
Çıkış Katmanı

Sabit ağırlıklar, sabit fonksiyonlar

Bağlantı ağırlıkları, eğitim kümesi ile belirlenen tek bir nöron

Frank Rosenblatt
1928-1971





ADALINE-MADALINE 1960

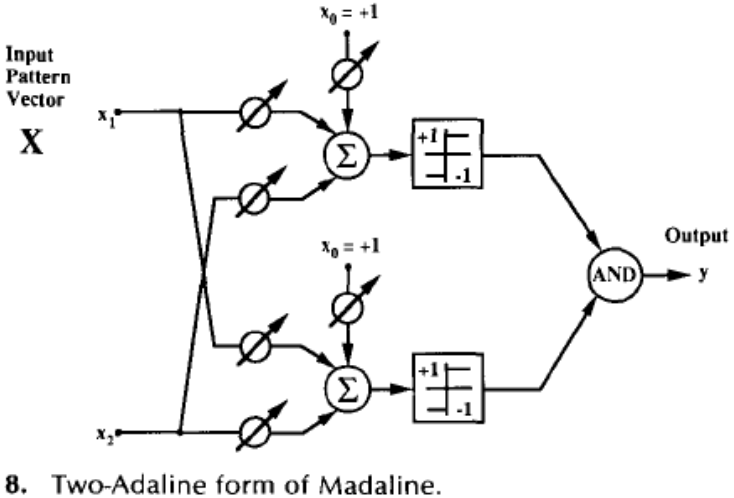
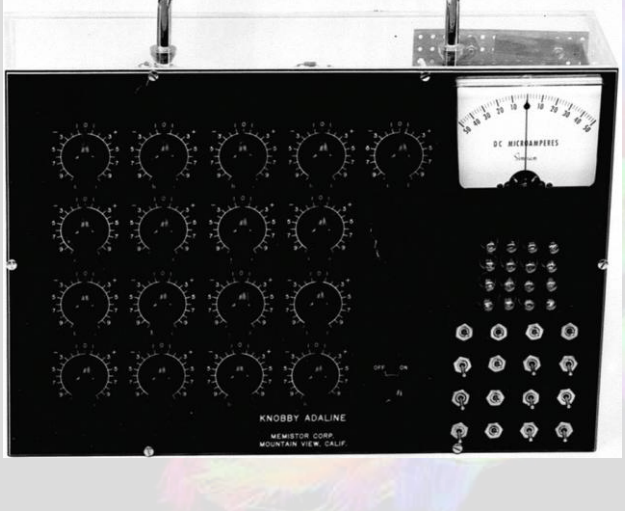
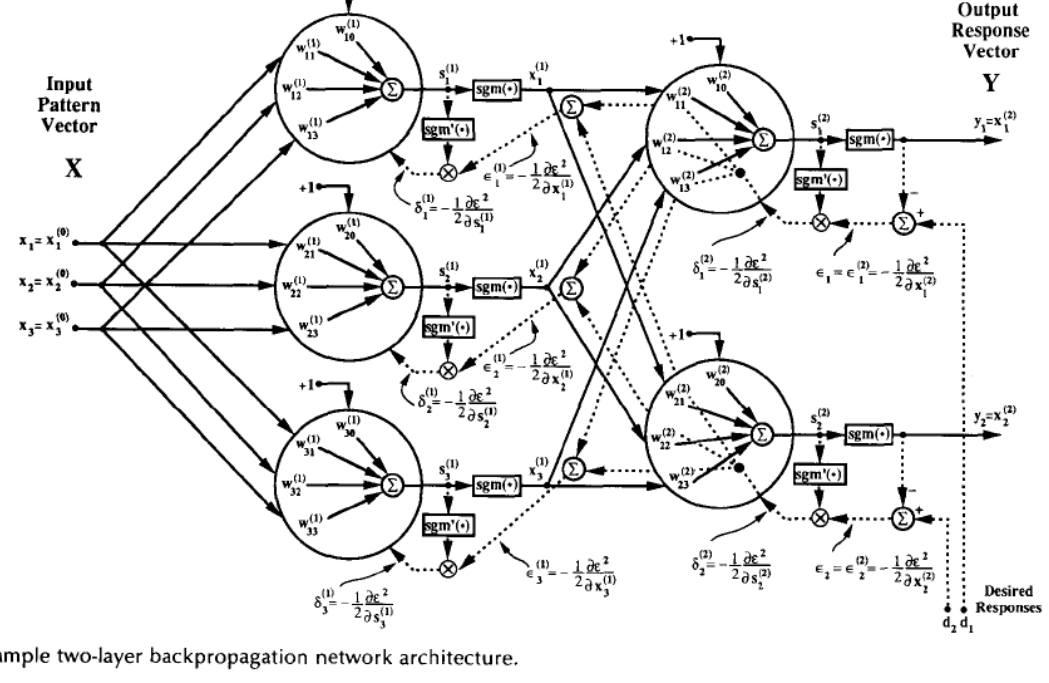


Fig. 8. Two-Adaline form of Madaline.

M.T. Hoff 1937-

Bernard Widrow 1929-





Example two-layer backpropagation network architecture.

https://www.researchgate.net/figure/ADALINE-An-adaptive-linear-neuron-Manually-adapted-synapses-Designed-and-built-by-Ted_fig2_26578943

Widrow, Lehr, 30 Years of Adaptive Neural Networks: Perceptron, Madaline, and Backpropagation, Proc. of IEEE 1990

Neocognitron 1983

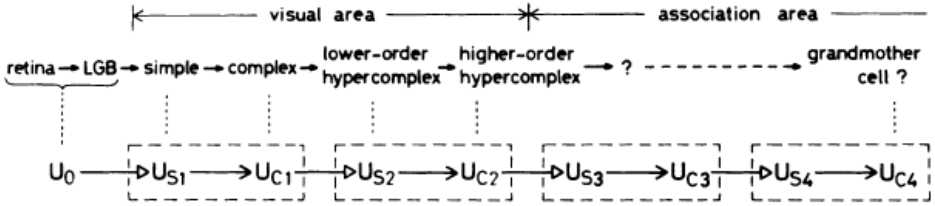


Fig. 1. Comparison between hierarchical model by Hubel and Wiesel and structure of neural network of neocognitron.

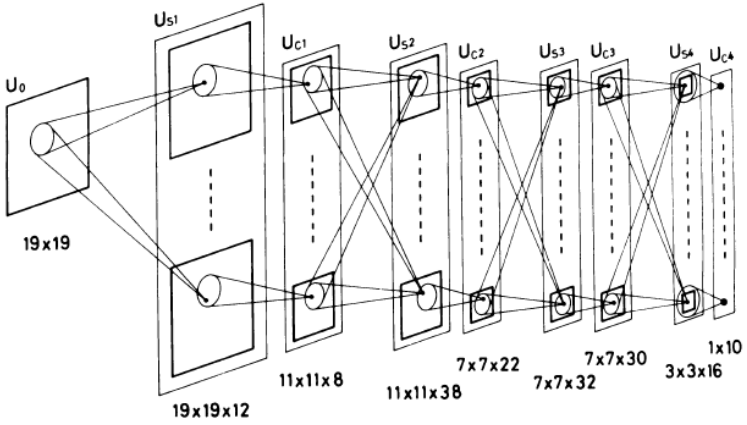


Fig. 2. Schematic diagram illustrating synaptic connections between layers in neocognitron.

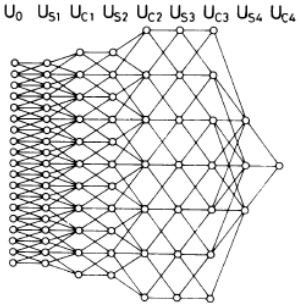


Fig. 3. One-dimensional view of interconnections between cells of different cell planes. Only one cell plane is drawn in each layer.

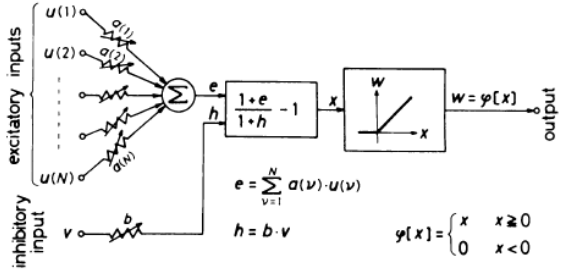


Fig. 4. Input-to-output characteristics of *S* cell: typical example of cells employed in neocognitron.

Kunihiko Fukushima

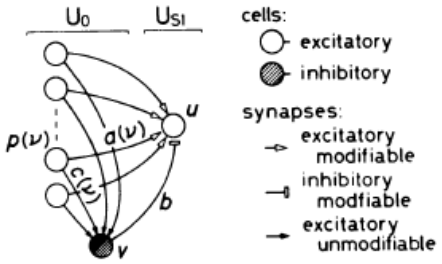


Fig. 5. Synaptic connections converging to *S* cell.

Yinelemeli Ağ- Recurrent Neural network 1990

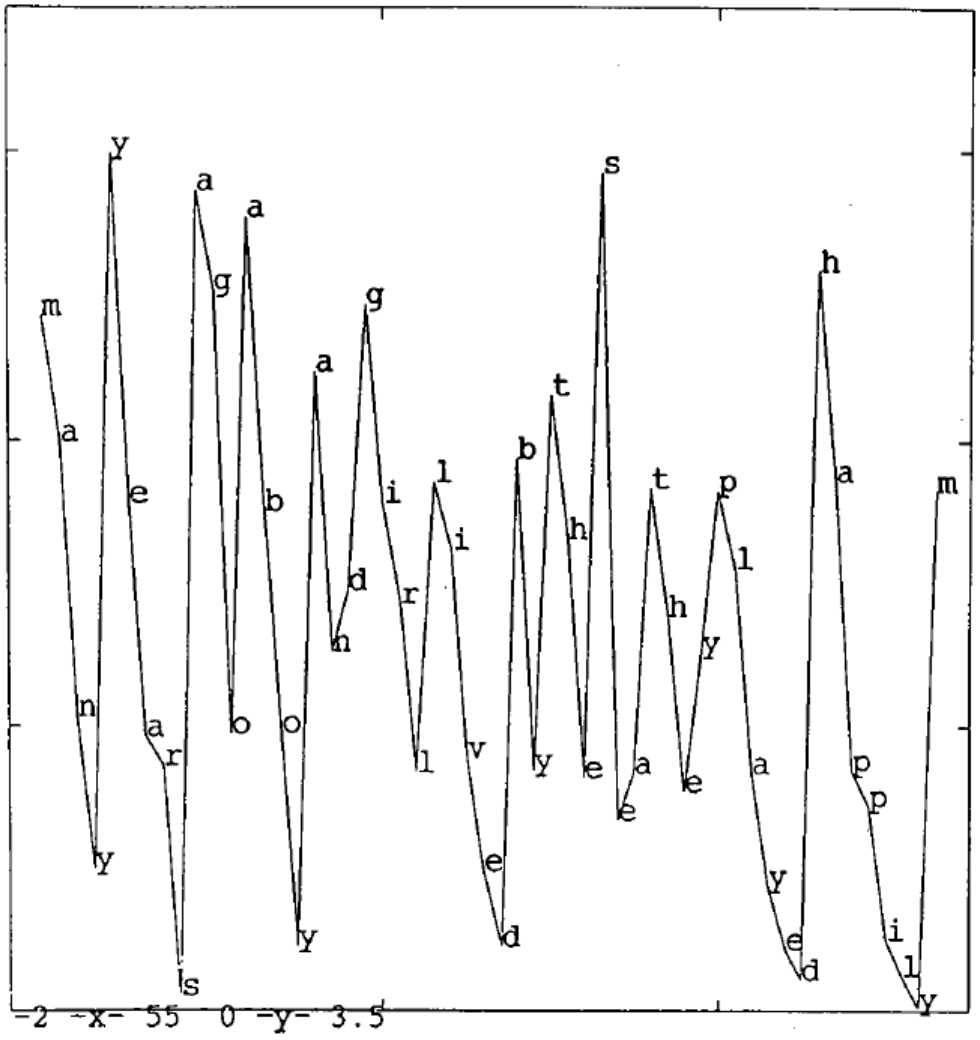
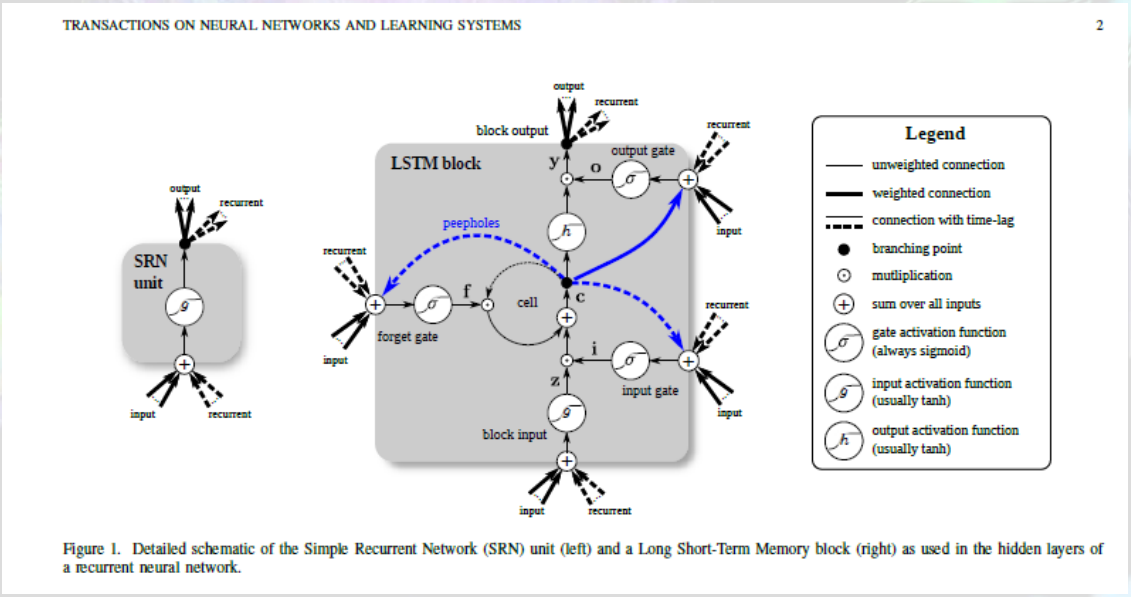


Figure 6. Graph of root mean squared error in letter-in-word precition task.

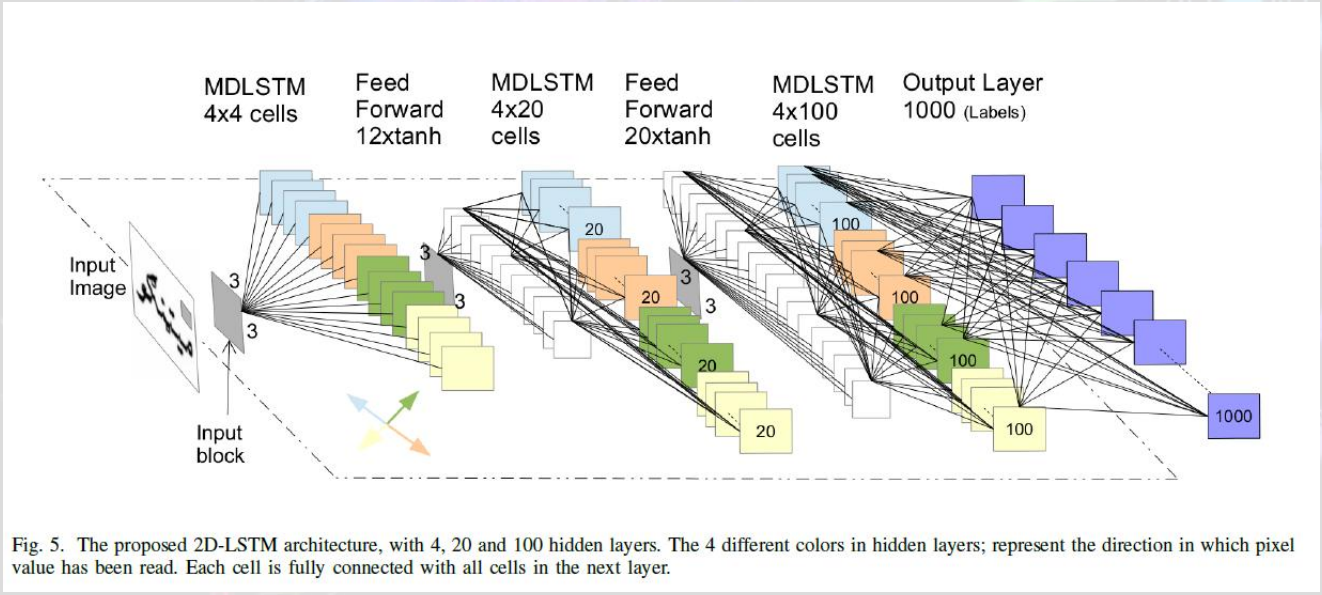
Jeffrey L. Elman
1948-2018

Long-Short Term Memory 1997



Greff, Klaus, et al. "LSTM: A search space odyssey." *IEEE neural networks and learning systems* (2017)

Jürgen Schmidhuber
1963



Ahmad, Riaz, et al. "Scale and rotation invariant OCR for Pashto cursive script using MDLSTM network." *2015*

Katlamalı Ağ Yapıları – Convolutional Neural Networks

ImageNet Classification with Deep Convolutional Neural Networks 2012

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Ilya Sutskever
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Geoffrey E. Hinton
University of Toronto
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Abstract

We trained a large, deep convolutional neural network to classify the 1.2 million high-resolution images in the ImageNet LSVRC-2010 contest into the 1000 different classes. On the test data, we achieved top-1 and top-5 error rates of 37.5% and 17.0% which is considerably better than the previous state-of-the-art. The neural network, which has 60 million parameters and 650,000 neurons, consists of five convolutional layers, some of which are followed by max-pooling layers, and three fully-connected layers with a final 1000-way softmax. To make training faster, we used non-saturating neurons and a very efficient GPU implementation of the convolution operation. To reduce overfitting in the fully-connected layers we employed a recently-developed regularization method called "dropout" that proved to be very effective. We also entered a variant of this model in the ILSVRC-2012 competition and achieved a winning top-5 test error rate of 15.3%, compared to 26.2% achieved by the second-best entry.

Geoffrey E. Hinton
1947

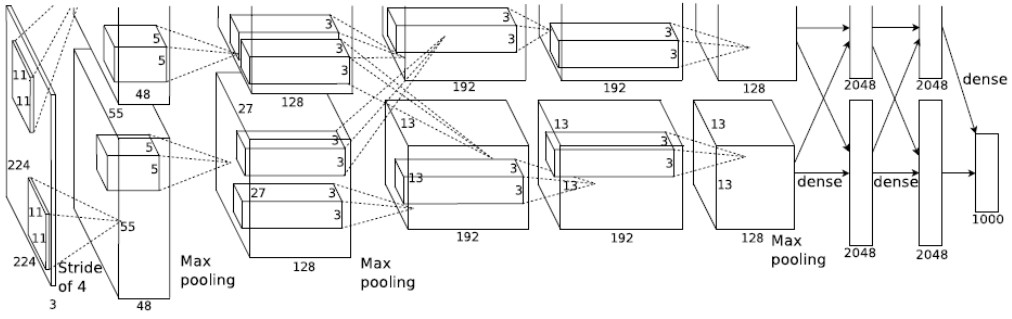


Figure 2: An illustration of the architecture of our CNN, explicitly showing the delineation of responsibilities between the two GPUs. One GPU runs the layer-parts at the top of the figure while the other runs the layer-parts at the bottom. The GPUs communicate only at certain layers. The network's input is 150,528-dimensional, and the number of neurons in the network's remaining layers is given by 253,440–186,624–64,896–64,896–43,264–4096–4096–1000.

REVIEW

doi:10.1038/nature14539

Deep learni

Yann LeCun[1,2], Yoshua Bengio[3] & Ge

Deep learning allows computati
data with multiple levels of abstr
ognition, visual object recognitio
learning discovers intricate struc
should change its internal param
the previous layer. Deep convolu
audio, whereas recurrent nets h

INSIGHT REVIEW

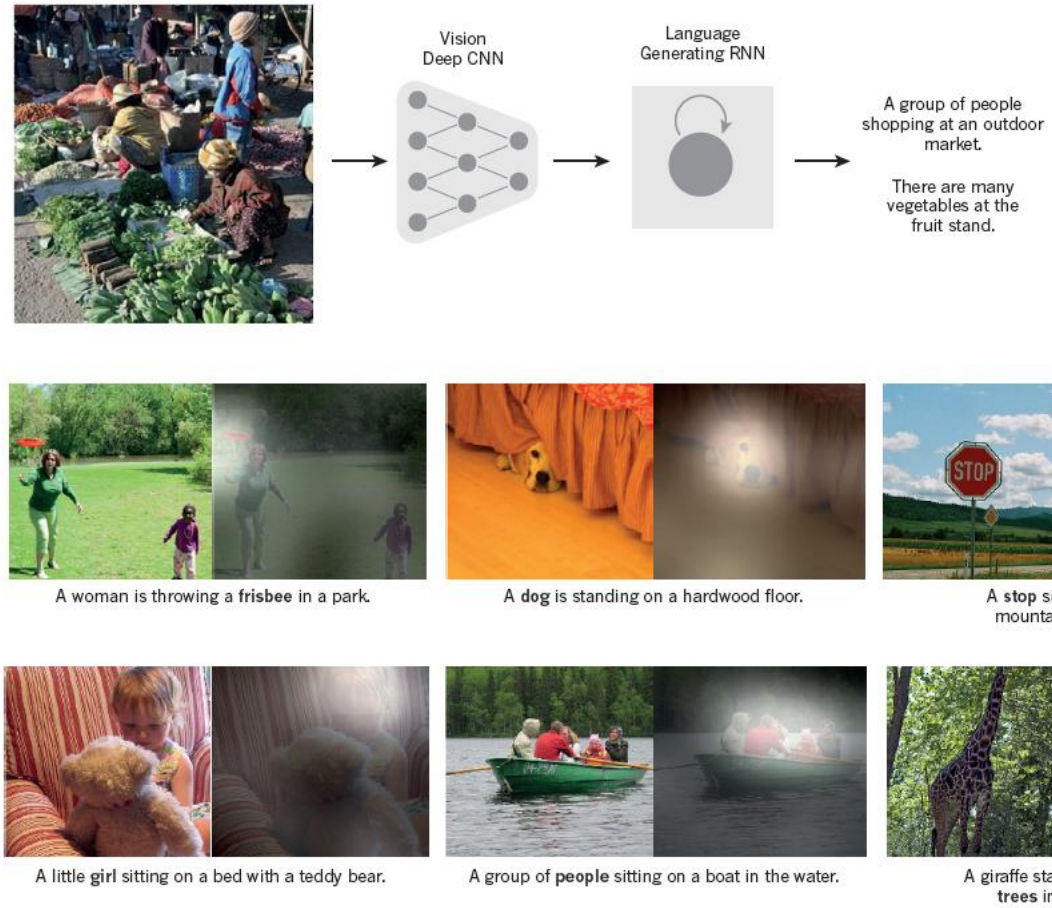


Figure 3 | From image to text. Captions generated by a recurrent neural network (RNN) taking, as extra input, the representation extracted by a deep convolution neural network (CNN) from a test image, with the RNN trained to 'translate' high-level representations of images into captions (top). Reproduced with permission from ref. 102. When the RNN is given the ability to focus its attention on a different location in the input image (middle and bottom; the lighter patches were given more attention) as it generates each word (bold), we found[86] that it exploits this to achieve better 'translation' of images into captions.

ARTICLE

doi:10.1038/nature16961

Mastering the game of Go with deep neural networks and tree search

David Silver[1]*, Aja Huang[1]*, Chris J. Maddison[1], Arthur Guez[1], Laurent Sifre[1], George van den Driessche[1], Julian Schrittwieser[1], Ioannis Antonoglou[1], Veda Panneershelvam[1], Marc Lanctot[1], Sander Dieleman[1], Dominik Grewe[1], John Nham[2], Nal Kalchbrenner[1], Ilya Sutskever[2], Timothy Lillicrap[1], Madeleine Leach[1], Koray Kavukcuoglu[1], Thore Graepel[1] & Demis Hassabis[1]

The game of Go has long been viewed as the most challenging of classic games for artificial intelligence owing to its enormous search space and the difficulty of evaluating board positions and moves. Here we introduce a new approach to computer Go that uses 'value networks' to evaluate board positions and 'policy networks' to select moves. These deep neural networks are trained by a novel combination of supervised learning from human expert games, and reinforcement learning from games of self-play. Without any lookahead search, the neural networks play Go at the level of state-of-the-art Monte Carlo tree search programs that simulate thousands of random games of self-play. We also introduce a new search algorithm that combines Monte Carlo simulation with value and policy networks. Using this search algorithm, our program AlphaGo achieved a 99.8% winning rate against other Go programs, and defeated the human European Go champion by 5 games to 0. This is the first time that a computer program has defeated a human professional player in the full-sized game of Go, a feat previously thought to be at least a decade away.

South Korean professional Go player Lee Sedol reviews the match after finishing the final match of the Google DeepMind Challenge Match against Google's artificial intelligence program, AlphaGo, in Seoul, South Korea, Tuesday, March 15, 2016. Google's Go-playing computer program again defeated its human opponent in a final match on Tuesday that sealed its 4:1 victory. (Lee Jin-man/AP)

1997'de Garry Kasparov Deep Blue'ya karşı kaybettiğinde IBM'in açıklaması: Deep Blue, yapay zeka kullanıyor mu? Kısaca yanıt 'hayır'dır. İnsan düşünüşünü taklit etmeye çalışan eski bilgisayar tasarımları, bu işte pek iyi değildi. Sezgilere karşılık gelen bir formül yok… Deep Blue daha çok hesaplama gücüne, ayrıca basit arama ve değerlendirme işlevlerine dayanır. …. Deep Blue uğraşsa bile asla bir HAL-9000 olamaz. Hatta Deep Blue, 'uğraşmak' ne demek onu da bilmez. *

*N.J. Nilsson,'Yapay Zeka' Boğaziçi Üniversitesi Yayınları

Ödüle Dayalı Öğrenme

articles

Dopamine neurons report an error in the temporal prediction of reward during learning

Jeffrey R. Hollerman[1,2] and Wolfram Schultz[1]

[1] *Institute of Physiology, University of Fribourg, CH-1700 Fribourg, Switzerland*

[2] *Present address: Department of Psychology, Allegheny College, Meadville, Pennsylvania, 16335, USA*

Correspondence should be addressed to W.S. (Wolfram.Schultz@unifr.ch)

Many behaviors are affected by rewards, undergoing long-term changes when rewards are different than predicted but remaining unchanged when rewards occur exactly as predicted. The discrepancy between reward occurrence and reward prediction is termed an 'error in reward prediction'. Dopamine neurons in the substantia nigra and the ventral tegmental area are believed to be involved in reward-dependent behaviors. Consistent with this role, they are activated by rewards, and because they are activated more strongly by unpredicted than by predicted rewards they may play a role in learning. The present study investigated whether monkey dopamine neurons code an error in reward prediction during the course of learning. Dopamine neuron responses reflected the changes in reward prediction during individual learning episodes; dopamine neurons were activated by rewards during early trials, when errors were frequent and rewards unpredictable, but activation was progressively reduced as performance was consolidated and rewards became more predictable. These neurons were also activated when rewards occurred at unpredicted times and were depressed when rewards were omitted at the predicted times. Thus, dopamine neurons code errors in the prediction of both the occurrence and the time of rewards. In this respect, their responses resemble the teaching signals that have been employed in particularly efficient computational learning models.

Received: 24 November 1997 / Accepted: 30 April 1998

Pekiştirmeli Öğrenme – Bir Hesaplamalı Model

Neuronlike Adaptive Elements That Can Solve Difficult Learning Control Problems

ANDREW G. BARTO, MEMBER, IEEE, RICHARD S. SUTTON,

Abstract—It is
adaptive elements c
to balance a pole th
cart's base. It is as
system are not knov
a failure signal that
vertical, or the cart

Manuscript recei
was supported by
Laboratory under C
The authors are
Science, University

the pole under the conditions usually assumed by control

Adaptive critic element

Associate search element

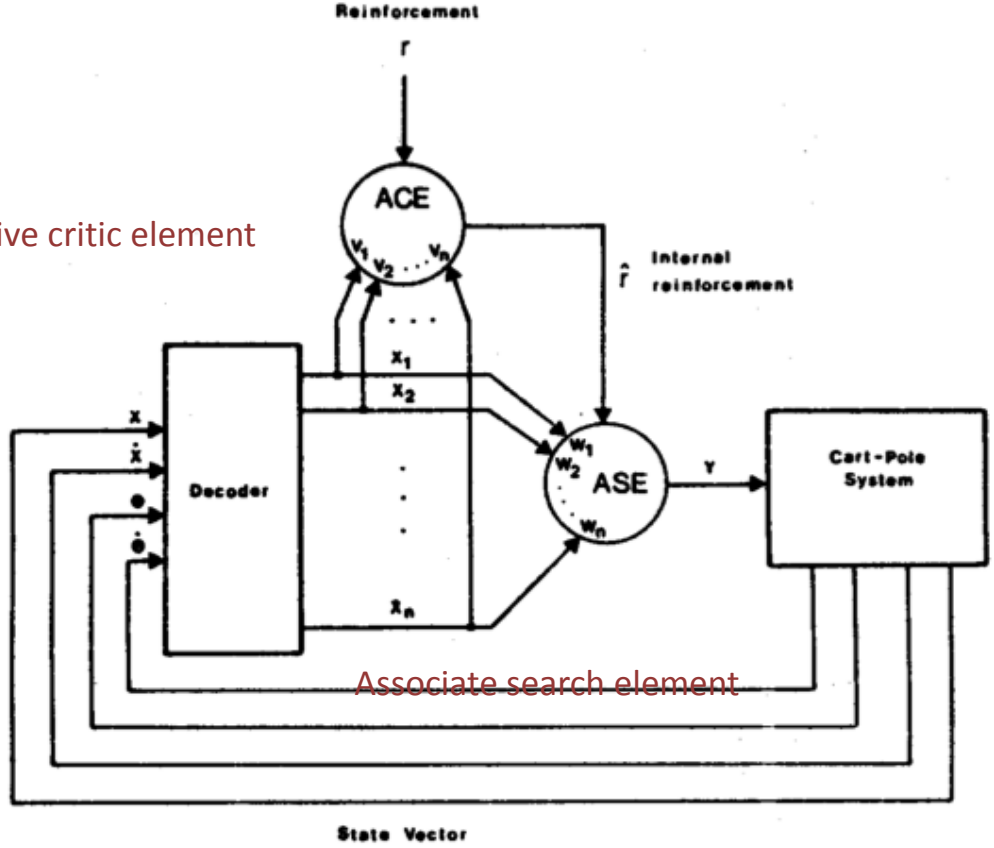
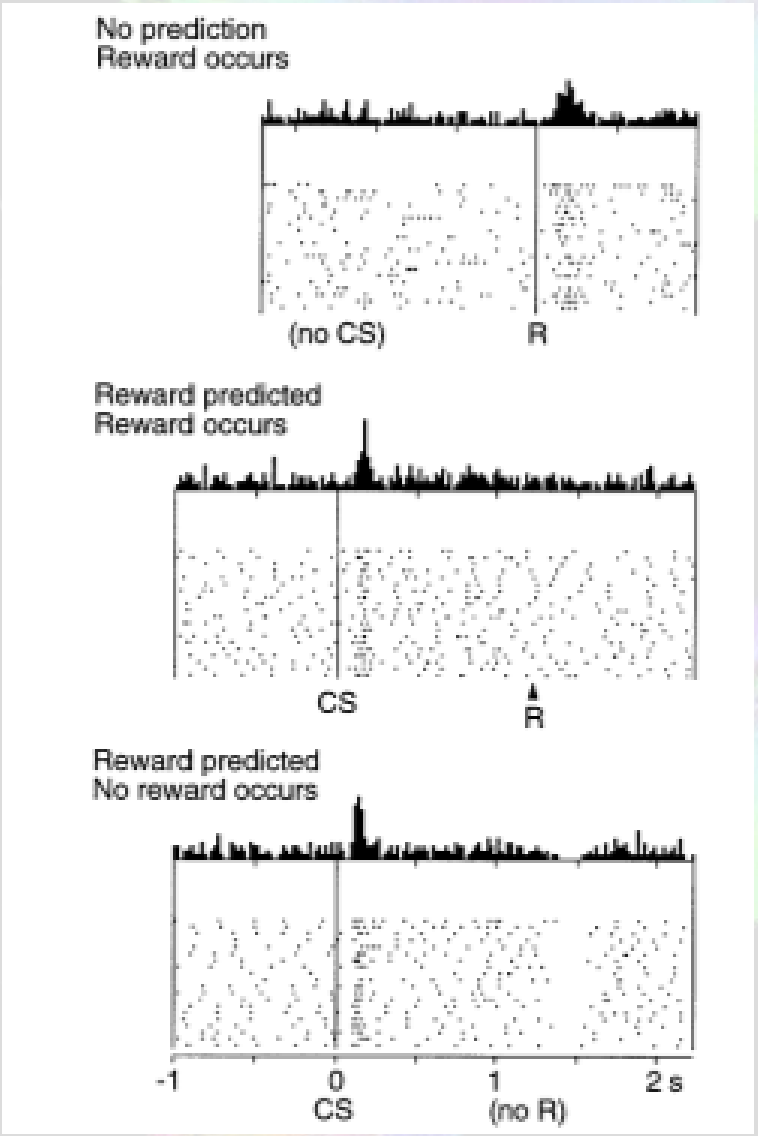
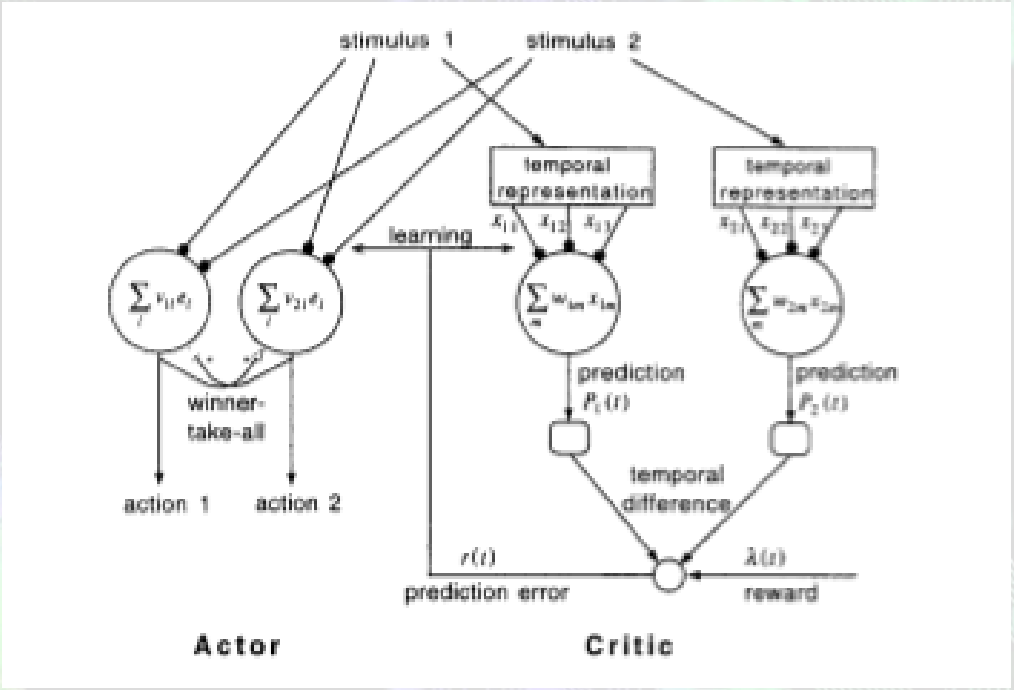


Fig. 3. ASE and ACE configured for pole-balancing task. ACE receives same nonreinforcing input as ASE and uses it to compute an improved or internal reinforcement signal to be used by ASE.

Dopamin nöronları ödülü öngörüyor – bir hesaplamalı model

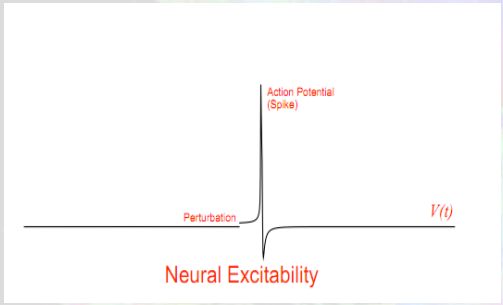


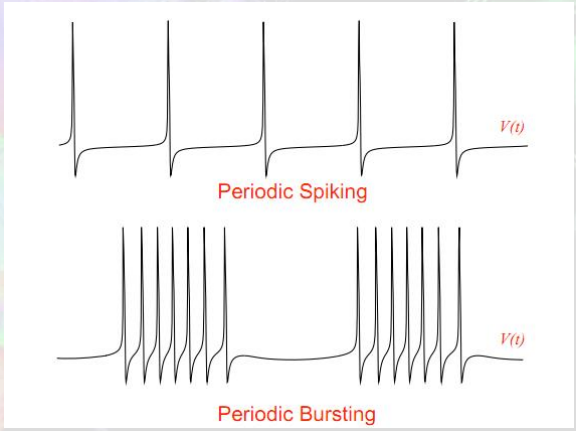


W.Schultz,P.Dayan, R.E. Montague 1997, Science

R.E. Suri, W.Schultz, 1998, Exp Brain Res

Hücre davranışlarını açıklayacağımız bir matematik araç var mı?

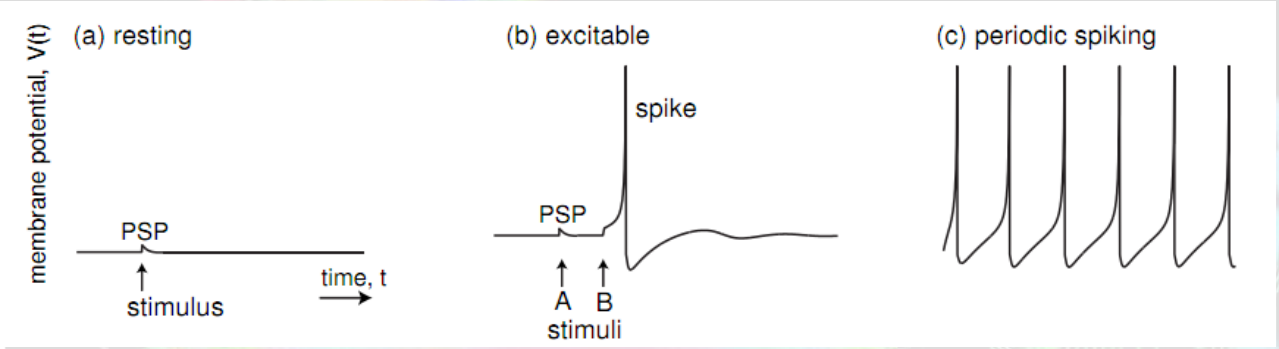


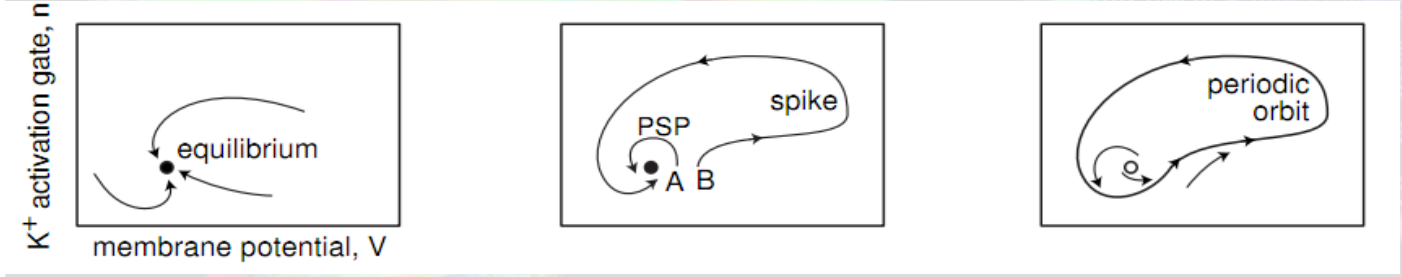


Dallanma (Bifurcation)

$$\frac{dx}{dt} = f(x), \quad x \in R^n$$

$$\frac{dx}{dt} = f(x,\alpha), \quad x \in R^n, \ \alpha \in R^m$$





Dallanma: Bir parametrenin değişimi ile topolojik olarak eşdeğer olmayan durum portresinin oluşumuna "dallanma" denir.

E.M. Izhikevich, "Neural exciability, spiking and bursting ", Int.J.Bif. and Chaos, vol. 10,no.6, 2000

Matematik sinirbilimde işe yarıyor mu, nasıl?

Activity Patterns in a Model for the Subthalar the Basal Ganglia

D. Terman,[1] J. E. Rubin,[2] A. C. Yew,[1] and C. J. Wilson[3]

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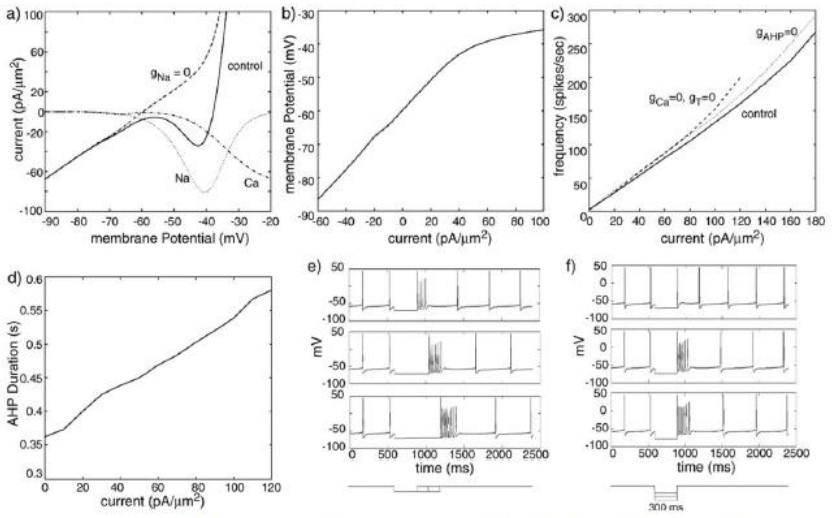

Figure 1. Properties of STN model neuron. *a*, Current as a function of voltage. For fixed voltages, steady-state currents were computed with slow gating variables set to their limiting values $[X \to X_\infty(v)$; see Materials and Methods]. In this and all subsequent figures, omitted units are as in Tables 1 and 2. *b*, Membrane potential of a model STN cell under various current injections. The parameter g_{Na} has been set to 0 to mimic the behavior of an STN cell in the presence of sufficient concentration of TTX to block spiking. *c*, Spike frequency as a function of injected current (*solid line*, full model; *dotted line*, $g_{AHP} = 0$; *dashed line*, $g_{Ca} = g_T = 0$). *d*, Duration of afterhyperpolarization after high-frequency spiking. A constant current pulse was applied to a model STN cell for 500 msec. After this, a prolonged afterhyperpolarization occurred before the cell returned to regular spiking. Its duration is plotted against the strength of applied current. *e*, *f*, STN rebound bursts after hyperpolarizing injections. *e*, Model responses of STN cell to currents of varying duration: 25 pA/μm² of current applied for 300 (*top*), 450 (*middle*), and 600 (*bottom*) msec. Longer current application augments deinactivation of I_T, enhancing rebound. *f*, Responses to currents of varying magnitude: 20 (*top*), 30 (*middle*), and 40 (*bottom*) pA/μm² of current applied for 300 msec. Stronger current application augments deinactivation of I_T, enhancing rebound.

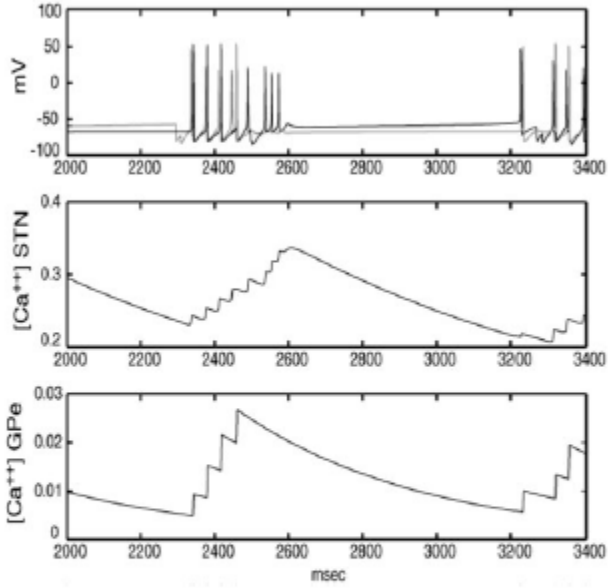

Figure 4. Mechanisms underlying episodic activity patterns. The *gray trace* in the *top box* shows the evolution of voltage over time for a single GPe cell in an episodic pattern, whereas the *black trace* shows the voltage for a single STN cell. The *boxes* below show the intracellular calcium concentration of each cell as a function of time. Initially, GPe spikes closely follow STN spikes. Here I_{app} is sufficiently strong such that the build-up of calcium terminates the GPe activity of the cell eventually, after which the STN cell fires one last volley of rebound spikes until about 2600 msec. Subsequent decay of calcium allows STN activity to resume after time 3200 msec; this recruits the GPe cell again.

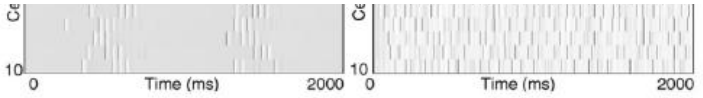

Figure 3. Activity patterns in a random, sparsely connected architecture. *a*, Arrangement of the model network. Each STN neuron excites a single GPe neuron selected at random, and each GPe neuron inhibits three randomly chosen STN cells. GPe cells also inhibit each other through all-to-all connections. *b*, Dependence of activity patterns on coupling strengths $g_{G\to G}$ and $g_{S\to G}$. Weak STN→GPe excitation or strong GPe→GPe inhibition leads to sparse irregular firing patterns. Intermediate values yield episodic patterns, whereas high levels of excitation and low levels of GPe mutual inhibition give rise to continuous uncorrelated activity. *c*, Membrane potential (in millivolts) as a function of time (milliseconds) for individual cells in each of the activity patterns: sparse activity ($g_{G\to G} = 0.06$ nS/μm²; $g_{S\to G} = 0.03$ nS/μm²; $g_{G\to S} = 2.5$ nS/μm²; $I_{app} = -1.2$ pA/μm²), episodic, almost-synchronized spiking ($g_{G\to G} = 0$ nS/μm²; $g_{S\to G} = 0.016$ nS/μm²; $g_{G\to S} = 2.5$ nS/μm²; $I_{app} = -1.2$ pA/μm²), and continuous, irregular spiking ($g_{G\to G} = 0.02$ nS/μm²; $g_{S\to G} = 0.1$ nS/μm²; $g_{G\to S} = 2.5$ nS/μm²; $I_{app} = -1.2$ pA/μm²). *d*, Network activity in various patterns. In each plot, 10 rows show the voltage traces of 10 cells, with time evolving over 2000 msec to the *right* along each row. Voltage is coded in *grayscale* as shown. Because they are so brief, individual action potentials (*dark gray line segments*) are not prominent, but are more clearly indicated by their afterhyperpolarization (*white bars*).

Striatal origin of the pathologic beta oscillations in Parkinson's disease

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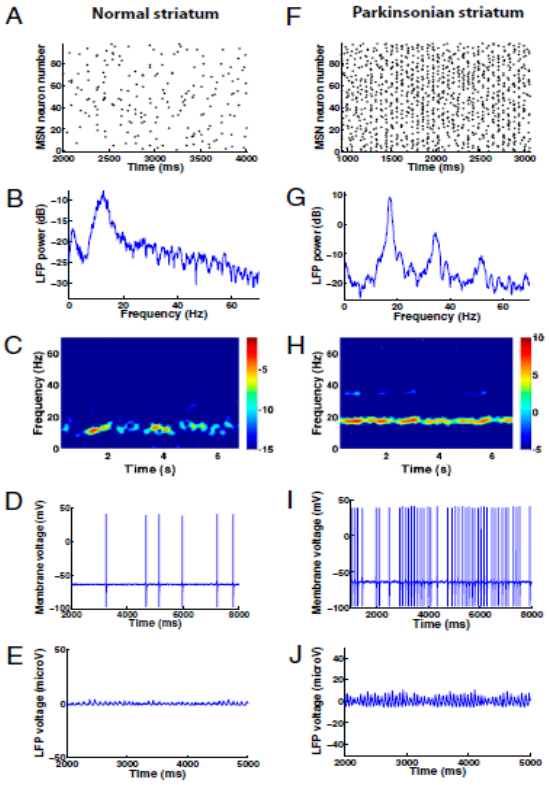

Fig. 1. Beta oscillations emerge in the model striatum under normal conditions and become enhanced under parkinsonian conditions. *A–E* are taken from the same 7-s simulation under normal conditions, and *F–J* are from the same 7-s simulation under parkinsonian conditions. (*A*) Raster plot of 100 reciprocally connected medium spiking neurons (MSNs) under normal, non-parkinsonian conditions. (*B*) Power spectral density of the model LFP. (*C*) Spectrogram of the model LFP. (*D*) Membrane voltage fluctuations from one MSN in the network. (*E*) Waxing and waning of the model LFP trace under normal conditions. (*F*) Raster plot of 100 reciprocally connected MSNs under parkinsonian conditions. (*G*) Power spectral density of the model LFP. (*H*) Spectrogram of the model LFP. (*I*) Membrane voltage fluctuations from one MSN in the parkinsonian network. (*J*) The model LFP trace under parkinsonian conditions.

The results presented here highlight the powerful combination of mathematical and experimental approaches in addressing problems in systems neuroscience. Dynamics of biological systems do not readily yield to direct observation using even the most sophisticated experimental approaches. We show here that informed biophysical modeling can be highly predictive of complex biological dynamics. Additionally, these findings also have broad implications in understanding beta oscillations in normal motor function as well as their inappropriate expression in other disorders with striatal involvement.

Mühendisler ne yapıyor?

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- About our Work
- Neurogrid
  - The Challenge
  - The Board
  - The Chip
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- People
- Lab Positions
- Contact
- Courses
- Publications
- Downloads
- In the News

On This Page

The Board: Neurogrid

Inspired by **GRAPE-6**, a $60K supercomputer revolutionized astrophysics, Neurogrid provide affordable option for brain simulations. It uses computation to **emulate** ion-channel activity **softwire** synaptic connections. These techn because they operate in parallel and in serial, constrains the number of distinct ion-channel —unlike digital computation, which simply tak Digital communication constrains the number activated per second—unlike analog communi inputs onto the same wire. Working within the its goal of simulating multiple cortical areas in choices.

Recent breakthroughs in neuromorphic engineering make it possible to combine analog's parallel operation with digital's programmability, reaping the best of both worlds.

Neurogrid simulates one million neurons with two subcellular compartments each, a choice motivated by neurophysiological studies. Nonlinear interactions between projections that terminate in distinct cortical layers have been replicated in a pyramidal-cell model with just **two compartments**. Furthermore, varying the compartments' electrical coupling replicates the firing patterns of various pyramidal-cell types. Capturing these behaviors using the smallest number of compartments minimizes the number of distinct ion-channel populations that need to be simulated, thereby maximizing the number of neurons a model can have.

Neurogrid simulates a million neurons connected by billions of synapses in real-time, rivaling a supercomputer while consuming a 100,000 times less energy—five watts instead of a megawatt!

frontiers in NEUROSCIENCE

REVIEW ARTICLE
published: 31 May 2011
doi: 10.3389/fnins.2011.00073

Neuromorphic silicon neuron circuits

Giacomo Indiveri[1], Bernabé Linares-Barranco[2], Tara Julia Hamilton[3], André van Schaik[4], Ralph Etienne-Cummings[5], Tobi Delbruck[1], Shih-Chii Liu[1], Piotr Dudek[6], Philipp Häfliger[7], Sylvie Renaud[8], Johannes Schemmel[9], Gert Cauwenberghs[10], John Arthur[11], Kai Hynna[11], Fopefolu Folowosele[5], Sylvain Saighi[8], Teresa Serrano-Gotarredona[2], Jayawan Wijekoon[6], Yingxue Wang[12] and Kwabena Boahen[11]*

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Hardware implementations of spiking neurons can be extremely useful for a large variety of applications, ranging from high-speed modeling of large-scale neural systems to real-time behaving systems, to bidirectional brain–machine interfaces. The specific circuit solutions used to implement silicon neurons depend on the application requirements. In this paper we describe the most common building blocks and techniques used to implement these circuits, and present an overview of a wide range of neuromorphic silicon neurons, which implement different computational models, ranging from biophysically realistic and conductance-based Hodgkin–Huxley models to bi-dimensional generalized adaptive integrate and fire models. We compare the different design methodologies used for each silicon neuron design described, and demonstrate their features with experimental results, measured from a wide range of fabricated VLSI chips.

Keywords: analog VLSI, subthreshold, spiking, integrate and fire, conductance based, adaptive exponential, log-domain, circuit

https://web.stanford.edu/group/brainsinsilicon/neurogrid.html

frontiers in Neuroscience

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A reconfigurable on-line learnin spiking neuromorphic processo comprising 256 neurons and 12 synapses

*Ning Qiao, Hesham Mostafa, Federico Corradi, Marc Osswald, Fabio Stefan Dora Sumislawska and Giacomo Indiveri **

Institute of Neuroinformatics, University of Zurich and ETH Zurich, Zurich, Switzerland

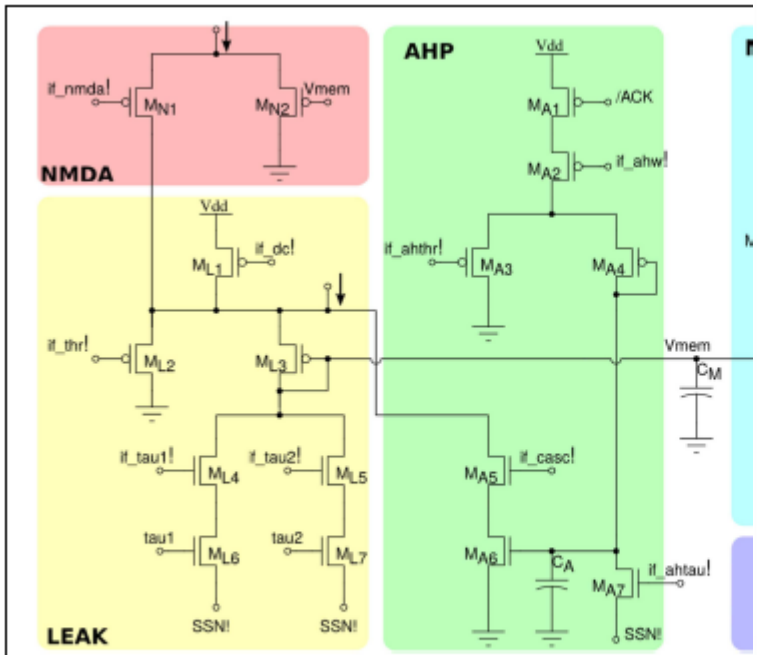


FIGURE 3 | Silicon neuron schematics. The NMDA block implements a voltage gating mechanism; the LEAK block models the neuron's leak conductance; the spike-frequency adaptation block AHP models the after-hyper-pola the effect of the models the Pot

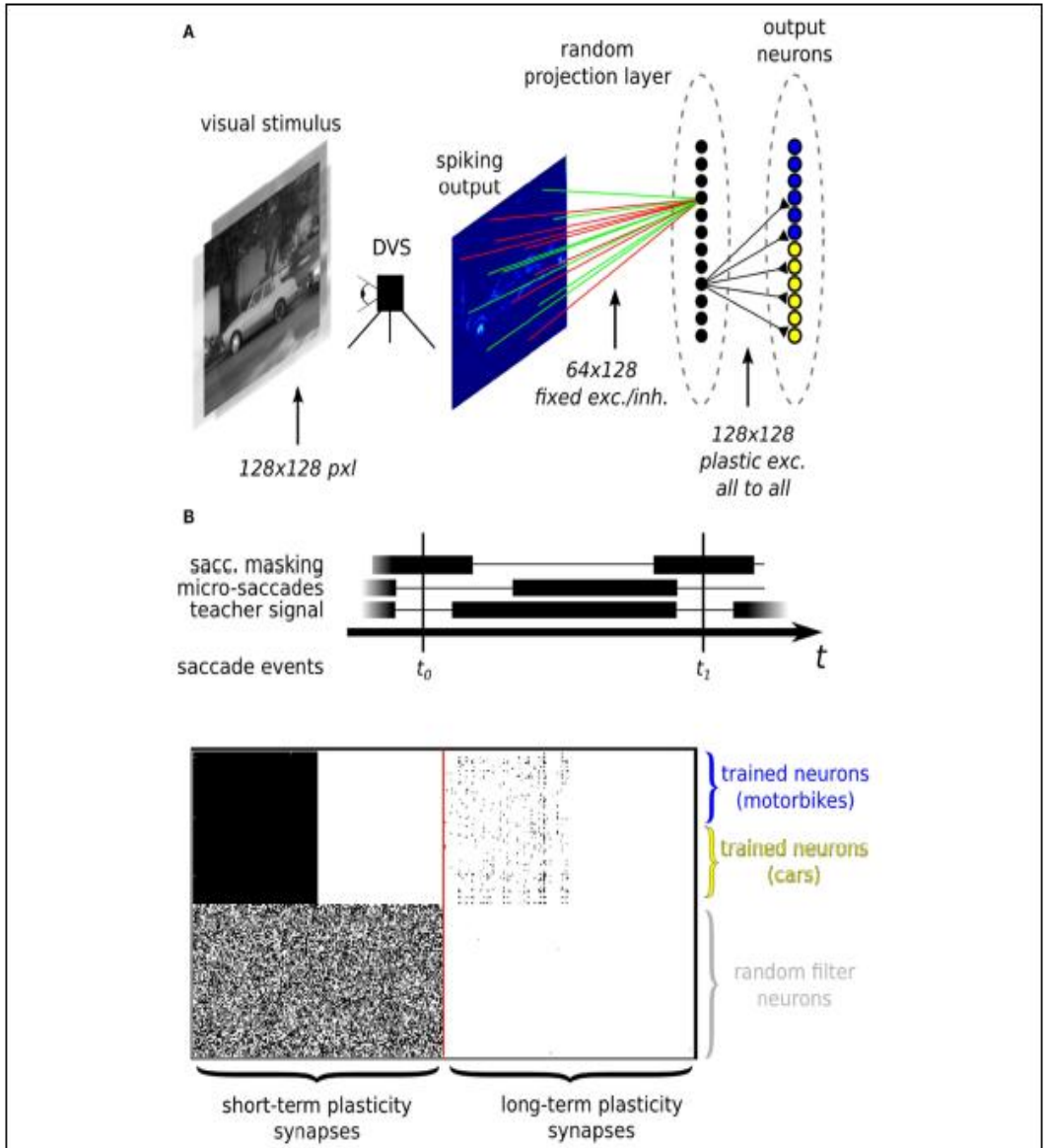
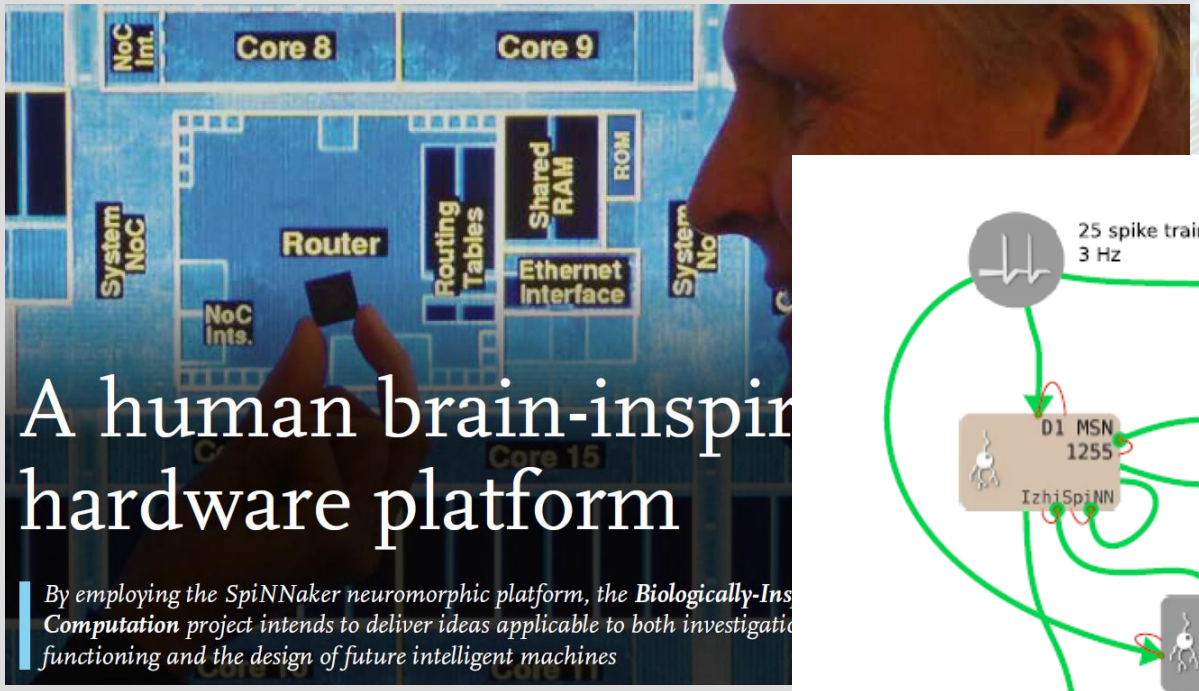


FIGURE 12 | (A) Image classification example using inputs from a DVS. **(A)** Top: neural network architecture. Two different classes of images (here motorbikes or cars) are displayed on a screen with a small jitter applied at 10 Hz. A random subset of the spikes emitted by the DVS are mapped to 128 hidden layer neurons. Specifically, each of the 128 neurons is connected to 64 randomly selected pixels with either positive or negative weights, also set at random. The output neurons in the last layer receive spikes from all the 128 hidden layer neurons, via plastic synapses. The output layer neurons are also driven by an external "teacher" signal which is correlated with one of the image classes. **(A)** Bottom: diagram of the experimental protocol timeline. Notice the presence of a saccade inhibition mechanism which electronically suppresses DVS input during a virtual saccade, i.e., when the displayed image is replaced with the next one. **(B)** Synaptic matrices of the ROLLS neuromorphic processor showing the hardware configuration of the classification neural network. The STP synapses represent the synapses of the hidden layer; the LTP synapses represent the synapses of the output layer.



A human brain-inspir hardware platform

By employing the SpiNNaker neuromorphic platform, the ***Biologically-Ins*** ***Computation*** *project intends to deliver ideas applicable to both investigati functioning and the design of future intelligent machines*

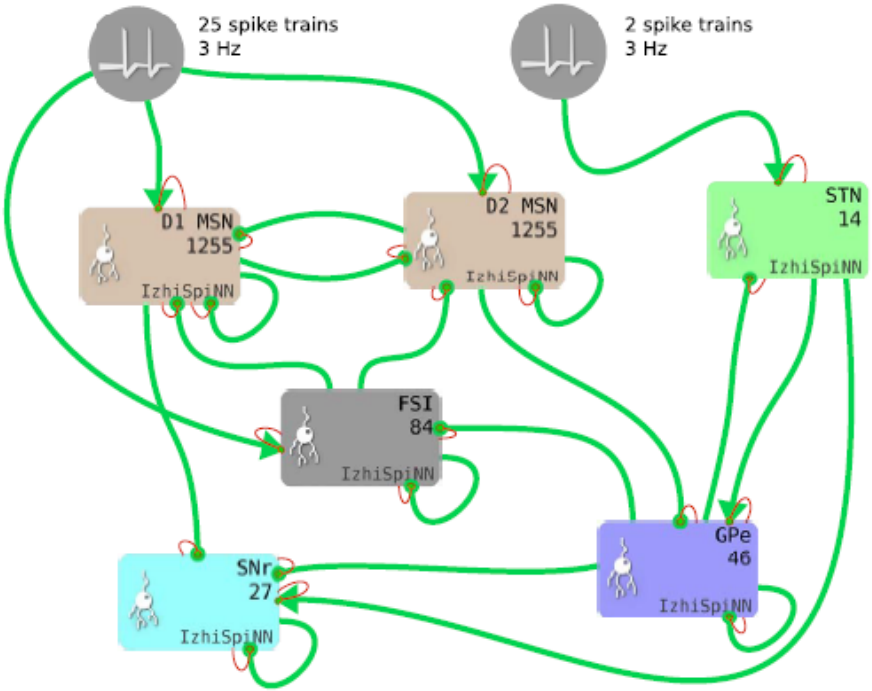
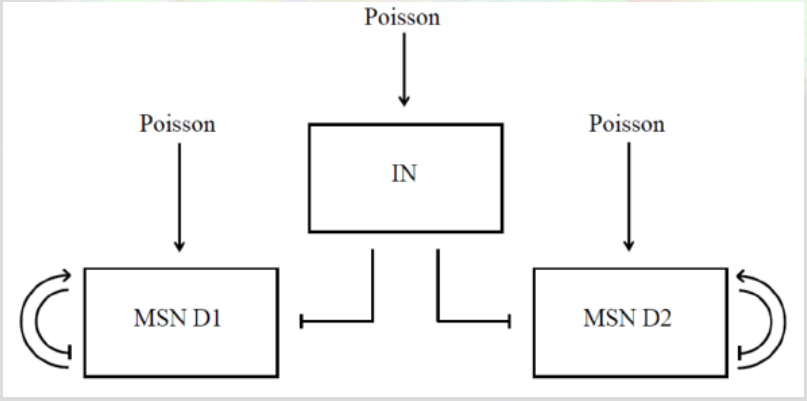


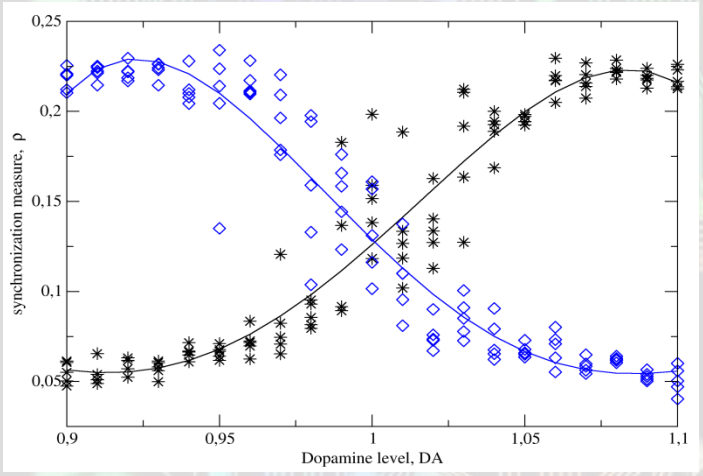
Fig. 3. Single-channel BG network, as exported from SpineCreator. Rectangular boxes are neural populations. The population name, number of elements, and SpineML component are shown in the box. Gray circles represent Poisson spike train sources. Green arrows are projections with element to element connectivities that are parameterized as in the SpiNNaker-based model and reported in Tables I–III. Projections with arrow heads are excitatory, those with circles for heads are inhibitory. The thinner, red lines which connect populations to arrowheads connect the membrane voltage variable $v(t)$ [defined in (1)] in the efferent population to the synapse component in each projection (on a one to one basis), allowing the synaptic current to be computed.

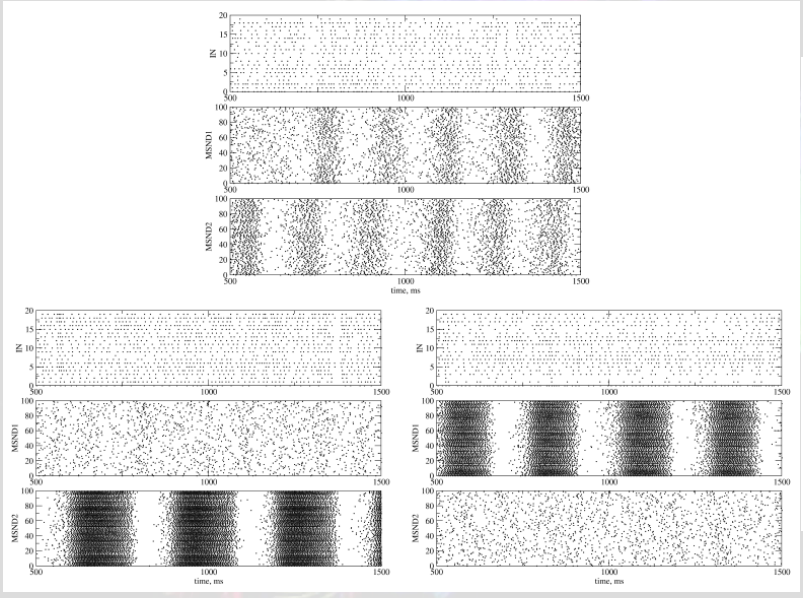
Sen-Bhattacharya, B. et al. "Building a Spiking Neural Network Model of the Basal Ganglia on SpiNNaker." *IEEE Cognitive and Developmental Systems* (2018).

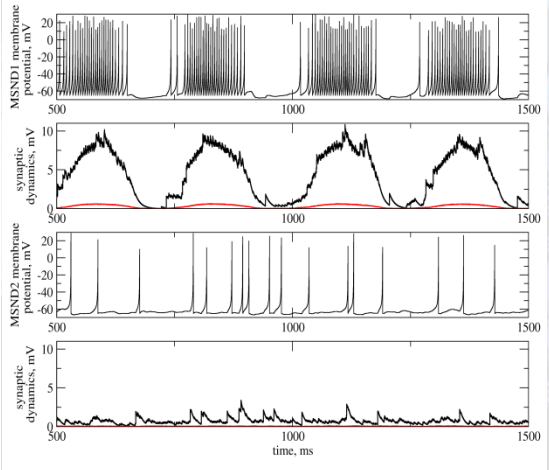
SimAG ’da ne yapılmakta

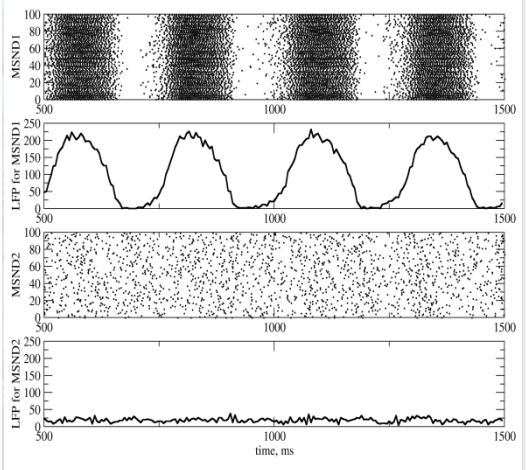
Striatumdaki Senkronizasyona Dopaminin Etkisine Dair Bir Hesaplamalı Model





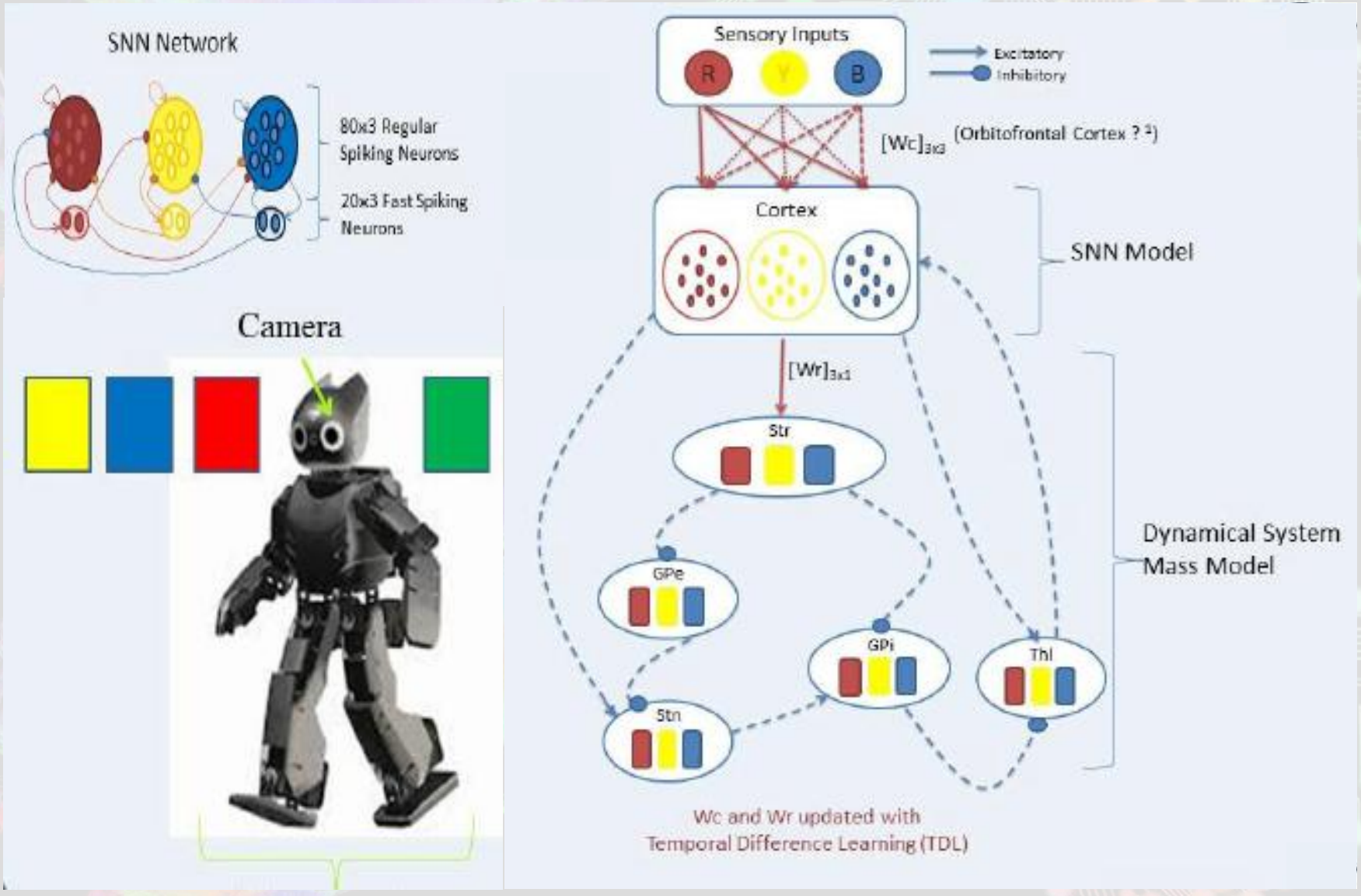






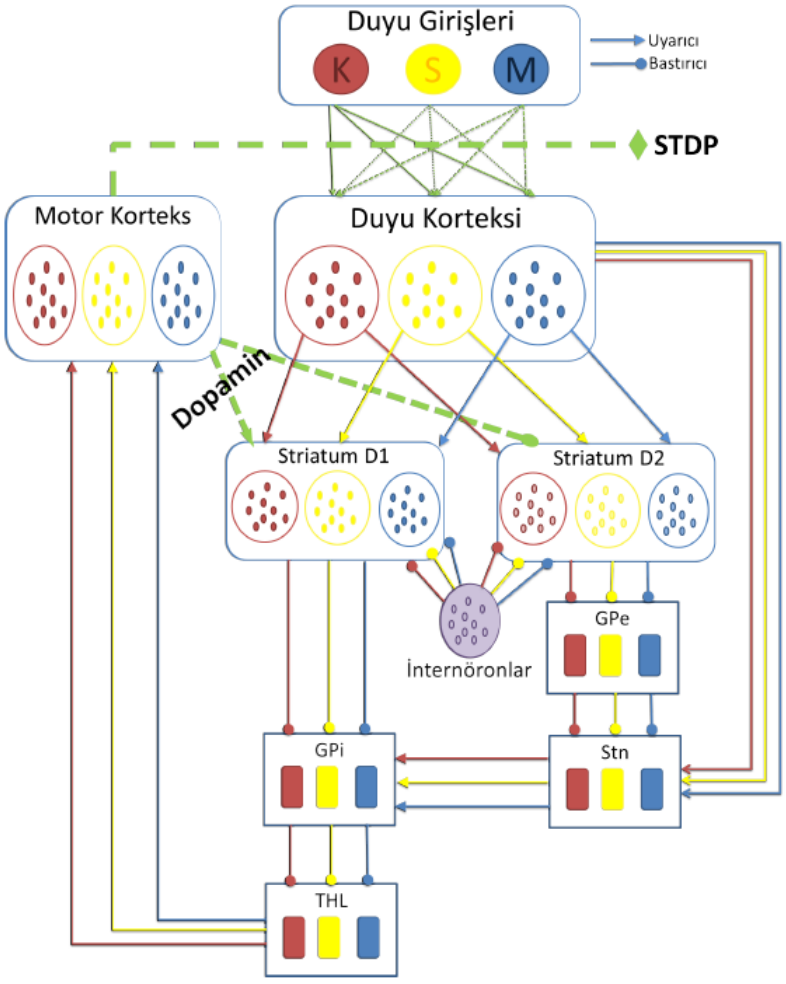
Elibol&Şengör, IJCNN, 2015,

Hareket Seçimini Öğrenme

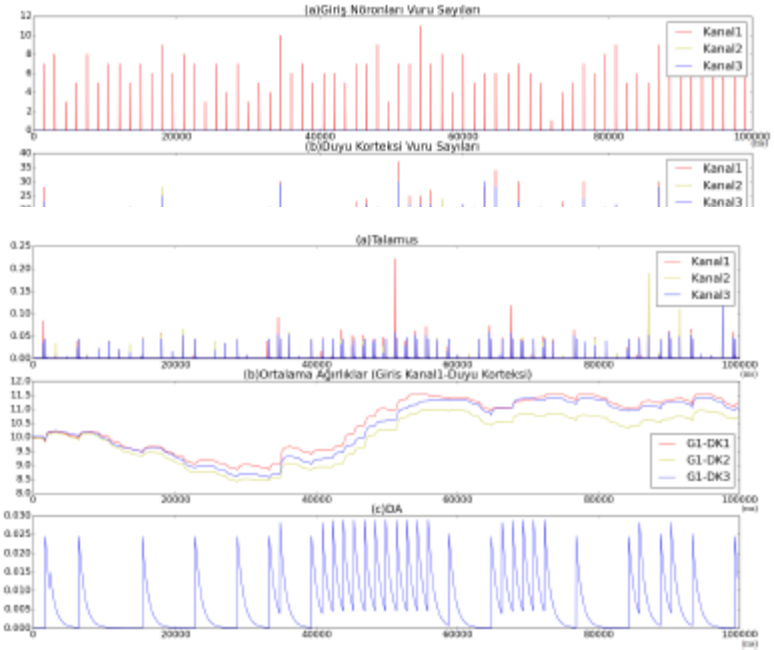


Erçelik &Şengör, IJCNN, 2015,

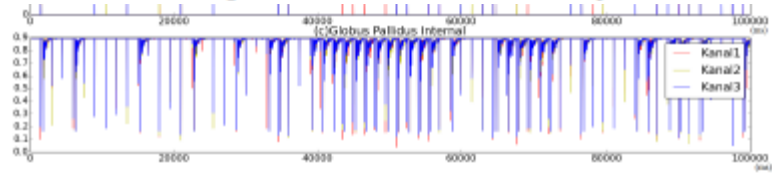
Uyaran Hareket Seçiminin Oluşmasına dair bir Model



Şekil 1: Ödüle dayalı eylem seçimine ilişkin model.



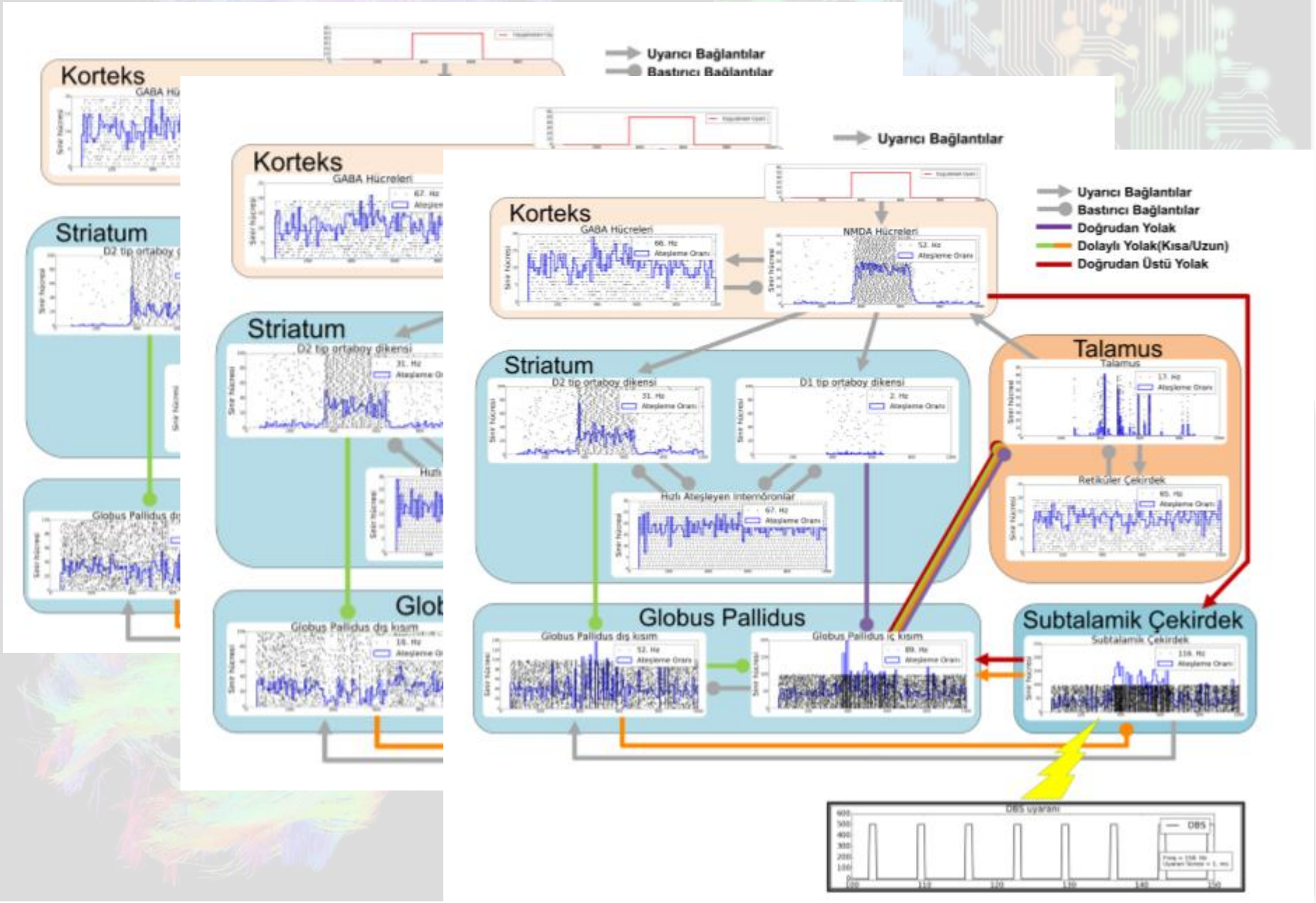
Şekil 4: (a): Talamus yığın modeli değerleri. (b): Duyu girişleri ile duyu korteksi kanalları arasındaki bağlantı ağırlıkları. (c): Verilen ödül ile dopamin (DA) değerindeki değişim.



Şekil 3: (a): Striatum D1, (b): D2 nöronları vuru sayıları. (c): Globus Pallidus İnternal yığın modeli değerleri.

Erçelik ,Elibol &Şengör, SİU, 2015,

Parkinson ve derin beyin uyarımı



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