БЪЛГАРСКА АКАДЕМИЯ НА НАУКИТЕ . BULGARIAN ACADEMY OF SCIENCES

ПРОБЛЕМИ НА ТЕХНИЧЕСКАТА КИБЕРНЕТИКА И РОБОТИКАТА, 48
PROBLEMS OF ENGINEERING CYBERNETICS AND ROBOTICS, 48

София . 1999 . Sofia

Artificial Neural Networks – Background, Evolutionary Models and History*

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1. Introduction

The theory of the artificial neural networks (NNs) is an important division of the artificial intelligence (AI) theory. It reflects the key components of the AI-systems [1]: representation, reasoning and learning. On the other hand, according to [2] the artificial NNs differ from the symbolic AI-machines by the level of explanation, by their processing style and by their representational structure. If the symbolic AI is described in a "top-down" fashion, the NNs have a natural learning capability and they operate in a "bottom-up" manner.

If in classical AI the emphasis is on building symbolic representations, which are discrete and arbitrary and the processing is sequential, the NN models are of a parallel distributed processing. In such models the processing takes place through the interaction of a large number of neurons. Each of the neurons sends excitatory or inhibitory signals to other neurons in the network. In addition, NNs place great emphasis on neurobiological explanation of cognitive phenomena.

The role of the artificial NNs as a technical counterpart of their biological prototypes is explained in Section 2.

If in classical AI the processing is sequential, which most probably can be explained by the sequential nature of natural language and logical inference, and also by the von Neumann's machine structure, the parallelism in the NNs makes them more flexible and robust. The false switching of a single neuron is not crucial for the whole system, because each feature is spread in parallel to many neurons. The automatic processing of contextual information is another important corollary of parallelism. Knowledge in NNs is not represented by declarative expressions, but by the very structure and activation state of the network. It is the whole NN that is responsible for the solution of a given problem. Every neuron is potentially affected by the global activity of all other neurons in the network and the result is an automatic context handling.

The texts most closely related to the NN processing style, but encompassing the representativeness of classical AI (in hybrid models) are cited in Section 3.

* The paper was supprted by National Science Foundation, grant I-611/96.

If in classical AI symbolic representations possess a quasi-linguistic structure and if due to the limited stock of symbols the new expressions may be composed in accordance with the compositionality of symbolic expressions, the nature and the structure of representations in NNs is decisive. Most of the network models proposed to date are very closely related to the concrete problem: they solve it for the particular class in a way which cannot be extended easily.

The bibliography for NNs is presented in Section 4; the evolution of ideas in the field is viewed in a special subdivision.

2. Prototypes of the artificial neural networks in biology and their technical counterpart

According to the recently modern evolutionary computation the NNs are one of the basic representatives of the POE (Phylogeny, Ontogeny, Epigenesis) model in the simulated (artificial) evolution [3]. Having reached a certain level of complexity, the living creatures develop highly specialized processes which allow the individual to integrate the vast quantity of interactions with the environment. Such processes are popular as epigenesis covering the learning systems. There are three systems in the living creatures which represent the epigenesis: the nervous system, the immune system and the endocrine system. From the three epigenetic systems, the nervous system has received the most attention. A typical example is the human brain with some 10^{10} neurons and 10^{14} synapses [4] compared to the four-character genome of length approximately 3.10^{9} [3]. The immune system has inspired systems for detecting software errors [5], controllers for mobile robots [6] and immune systems for computers [7]. The endocyne system is made of a large number of glandular tissues and all of them secrete directly in the blood stream hormones regulating and integrating bodily functions such as reproduction. From the functional point of view this system resembles to a certain extent the nervous system in that both help the individual cope with changes in its environment.

The NNs are the artificial counterpart of these three biological systems, with their synaptic weights and possibly topological structure changing with the reactions to the stimuli.

Learning networks exhibit the plasticity necessary to confront complex, dynamical tasks. Such NNs must be able to adapt at two distinct levels, changing the dynamics of interneuron interchanges (usually through changes in the synaptic weights) and also by modifying the network topology itself. The topology modification has proven to be a successful solution to the stability-plasticity dilemma, i.e. how can a learning system preserve the already learned, while continuing to incorporate new knowledge [8].

The NN applicational domains are known as soft computing [9] related to ill-defined problems coupled with the need of a permanent adaptation or evolution; being the artificial realization of the POE model epigenetic axis, the NN paradigm yields impressive results frequently rivaling (if not exceeding) those of the traditional methods. The artificial NNs find application mainly in the software and less in the hardware; their tasks include data analysis, function approximation, association, categorization and within-class categorization, pattern recognition and pattern classification, data compression, predicition and control [10].

The idea of evolutionary artificial NNs including besides the epigenetic axis also the phylogenetic one, has received attention in recent years. The phylogeny in living nature covers the evolution of species by itself [11, 12]. From the NN point of view the technical solution is a population of NNs where evolution proceeds at the global (population) level and learning taking place at the individual (NN) level. Examples are the works of Liu and Yao [13], Nolfi et al. [14] and Yao [15], though they are currently completely off-line. Another interesting (natural) example is that of the Baldwin effect, which ehxibits an intricate interplay between phylogeny and epigenesis. The use of this process in simulated systems has been explored, e.q. by [16] and [17]. The PE (Phylogeny, Epigenesis) plane in nature is related also with the language acquisition in human beings: to what extent this ability is innate (phylogenetic) or acquired (epigenetic). A brief historical perspective one can find in [18] and an exploration of this issue in artifical settings, in [19, 21].

3. System modeling: mathematical equations, neural networks and fuzzy systems

The description (knowledge) of a system may be formulated in three different ways: by mathematical equations, by parameter distribution (NNs) and by linguistic rules [22].

Though their evident simplicity, the mathematical equations are impractical for complex reasons in complex systems: once, to define the exact relationship between the varying parameters (variables), and twice, in the case of time-varient systems.

This disadvantage seems to be overcome in the sets of linguistic rules. Such sets permit easy changes and they even include the ill-defined languages which allow contradictory conclusions from one fact.

The mathematical equations and the crisp/fuzzy If/Then rules formulate the algorithm of the process explicitly. The NNs formulate the algorithm of the process implicitly and they are a typical example for a distributed information processing. The artificial NNs can be viewed as iterative systems in two ways: once, as structurally-iterative, when their architecture is a simple iteration of aggregating elements (directed graph), twice, as algorithmically-iterative; in this case the algorithm tends to find the centroids of the different classes (for self-organizing systems) or to be trained by a supervisor. The disadvantages with the NNs concern the unpredictable behavior at every instant of the network operation and also the unproved convergence for every particular case (therefore instead of total convergence it is a usual approach to prove the asymptotical convergence of the process); even little changes in the input data lead to a new, but similar training of the network. Finally, the NNs have less designability than the fuzzy systems. Still the NNs together with the fuzzy systems are much better for applications for ill-defined problems than the systems of mathematical equations.

The tendency towards fusion of fuzzy logic and NNs producing the so called adaptive fuzzy systems is already in the past [23–27]; fusion of these two has lost much of its novelty now [28–32]. New trends are a fusion of fuzzy logic and chaos as well as NNs. A fuzzy system is a modeling of a human brain summarized from the human expert’s behavior and chaos is a nonlinear dynamical behavior generated by massive NNs of the human brain.

4. Neural networks: history, periods and bibliographical review

The artificial NNs are systems modeling mainly the massive parallel computations in the brain. This approach to system complexity enables their success at complex control and recognition/classification tasks. The biological prototype is mathematically approached by a weighted directed graph of highly interconnected nodes (neurons). The artifical nodes are almost always simple transcendental functions whose arguments are the weighted summation of the inputs to the node; early work on NNs and some current work uses node functions taking on only binary values. After a period of active development in the 1950's and 1960's that slowed due to the limitations of the networks then being explored, NNs experienced a renaissance in the 1980's with the work of Hopfield [33] on the use of networks with feedback (graphs with cycles) as associative memories and that of Rumelhart et al. [34] on backpropagation training and feedforward (acyclic graphs) networks that could learn from input-output examples provided in the training set. Learning in this sense is carried out by a descent-based algorithm that adjusts the network weights so that the network response closely approximates the desired responses specified by the training set. This ability to learn from training data, rather than needing to be explicitly (heuristically) programmed, was important both for an understanding of the functioning of brains and for progress in a great variety of applications in which practitioners had been unable to embed their qualitative understanding in successful programs. The capabilities of NNs were quickly exploited in a great number of applications to pattern classification, control and time-series forecasting [35]. Hopfield's work on associative memories excited the interest of statistical physicists which began to be interested in the NN asymptotic behavior. The information theory distinguished itself with such solid papers as the one of McEliece et al. [36] in providing mathematically sophisticated analyses of network capabilities. The 1990's saw a significant maturation both in application and in theoretical understanding of performance and limitations. In particular, NNs provided a wide spectrum of applied statisticians with a new and powerful class of regression and classification functions, that for the first time allowed them to make successful truly nonlinear models involving hundreds of variables. The problem of setting the type to a "feature" or a "regressor" becomes less critical if it is not necessary to narrow the choices among the input variables.

The initial generation of books on artificial NNs appeared in the late 1980's. These books tended to be either highly simplified overviews with a significant emphasis on neurobiological issues or edited collections of papers, frequently with a physics orientation and focus on Hopfield / recurrent / feedback networks. During the last years several engineering-oriented texts appeared written by capable authors with systems or statistics background. In this new generation of texts perhaps the first was from Hertz et al. [37]. Those of Haykin [38] and Zurada [39] are comparable to the text of Hassoun [35]. Haykin's is the most comprehensive of these books while Hassoun [40] is somewhat more mathematical while attempting to be comprehensive. Unfortunately the attempts by all of these authors to be comprehensive leads to the consequence that their treatment on many important topics is too superficial for advanced professionals and for the readers of the scientific periodics. Typically, mathematical results are quoted from other sources and little or no supporting argument, let alone proofs, provided. An attempt at wider communication that argues for a de-emphasis on rigor becomes corrupted by a de-emphasis on precision and a frequent absence of significant explanation and development. A deeper level of explanation can be found in a newer NN literature represented by Ripley [41], Siu et al. [42] and Vapnik [43]. These authors either make fewer compromises with mathematical theory or explain mathematical issues more soundly. Each of these monographs are more focussed in their treatment of NNs.

Other books that are important for the evolution of the NN paradigm in the course of time are [44–49].

a) More about the NNs during the years (historical notes)

The following historical notes are largely (but not exclusively) based on [50–60].

The idea of neurons as structural constituents of the brain was introduced for the first time by Ramon y Cajal [61]. Still it took about 30 years when the modern era of neural networks began with the work of McCulloch and Pitts [62]. In their paper, McCulloch and Pitts described a logical calculus of NNs. This theory of formal

NNs featured prominently in the second of four lectures delivered by von Neumann at the University of Illinois in 1949; von Neumann used idealized switch-delay elements derived from the idealized neural elements of McCulloch and Pitts in the EDVAC construction that developed out of the ENIAC.

The late 1940's and the beginning of the 1950's marked the theory of the NNs with texts on the organization of behavior, learning and introduced the idea of the adaptive systems [63–66]. The work of Minsky from 1952 was a predecessor of his excellent paper "towards AI" [67] with a large section about the NNs.

Another topic that was investigated in the 1950's is the idea of associative memories. It was started by Taylor [68] followed by the introduction of the learning matrix by Steinbuch [69]. 1969 was the year when a text on nonholographic associative memory appeared [70] concerning two network models: a simple optical system realizing a correlation memory and a closely related NN suggested by the optical memory. 1972 was fertile with the idea of the correlation matrix memory based on the outer product learning rule. It was independently introduced by Anderson [71], Kohonen [72] and Nakano [73].

15 years after the publication of McCulloch and Pitts, a new approach to the pattern-recognition problem was introduced by Rosenblatt in his work on the perceptron [74]. It was this paper where the perceptron convergence theorem was stated and it took two years for its proof, followed by other proofs during the next years. The late 1950's and the beginning of the 1960's was the perceptron epoch for the NNs. Widrow and Hoff [75] introduced the LMS-algorithm and used it to define the Adaline. Soon after that Widrow and his students introduced the Madaline [76]. Both structures differ from the perceptron in their training procedure. Nilsson [77] wrote the best exposition even nowadays of linearly separable patterns in hypersurfaces. It boosted a lot of publications for perceprons. The book by Minsky and Papert [78] cooled down the enthusiasm for perceptrons showing that there are fundamental limits of the single-layered perceptrons.

1970's were eminent with the development of the self-organizing models. Von der Malsburg [79] was the first to demonstrate self-organization with computer simulation. It was followed by the first paper on self-organizing maps [80] motivated by topologically ordered maps in the brain. Still it took some years before the ART model was introduced [81].

1980's were the years of renaissance for the NNs. Perhaps the two publications which influenced the research most of all were [82] and [34]. Hopfield introduced the idea of an energy function as a new understanding the NN operation with symmetric synaptic connections; he established the isomorphism between such a recurrent network and an Ising model in statistical physics. This work started the epoch of neural modeling and the NNs with a feedback became famous as the Hopfield networks. Though its abstraction of the neurobiological systems, the principle of storing information in dynamically stable networks, is profound. The origin of this principle may be traced back to the pioneering works [83] (sigmoid firings), [84–85] (additive model of the neuron), [86] (mathematical dynamical description of the excitatory and inhibitory neurons), [87] (probabilistic model of the neuron) and [88] (brain-state-in-a-box model). Rumelhart and McClelland in their book have greatly influenced the use of back-propagation learning and it emerged as the most popular learning algorithm for the multilayer perceptron training.

Another important texts during the previous decade are [89] establishing the principle of the content-addressable memory, [90] which received more attention than the Willshaw-von der Malsburg model, [91] introducing the principle of the simulated annealing, [92] – the principle of reinforcement learning; [93] – the principle of maximum information preservation, [94] – the radial basis functions as an alternative to multilayer perceptrons, [95–96] – the method of potential functions.

5. Conclusions

This paper is a summary of the eminent publications in the field of the artificial NNs from the point of view of their background, evolutionary models and theoretical history. The analysis starts from the analogy with the biological prototypes and their technical counterpart. Then the review proceeds with the place of the artifical NNs between the systems of mathematical equations and the fuzzy systems. A special place is dedicated to the history in the development of the artificial NN paradigm; the periods and the crucial moments in the theoretical process are viewed with an emphasis. A subject of a peculiar interest is the mathematical formalism and the authors' styles.

References

1. Sage, A. P. Concise Encyclopedia of Information Processing in Systems and Organizations. N.Y., Pergamon, 1990.
2. Memmi, D. Connectionism and artifical intelligence. – In: Neuro-Nimes'89 Int. Workshop on Neural Networks and Their Applications, Nimes, France, 1989, 17-34.
3. Sipper, M., et al. A phylogenetic, ontogenetic, and epigenetic view of bioinspired hardware systems, – In: IEEE Trans. on Evol. Comput., 1997, **1**, April, No1, 83-97.
4. Shepherd, G. M., C. Koch. Introduction to Synaptic Circuits, The Synaptic Organization of the Brain. (G. M. Shepherd, ed.). N.Y., Oxford University Press, 1990, 3-31.
5. Xanthakis, S., et al. Immune system and fault-tolerant computing. – Evolution artificielle 94, 1995, Cepadues, cop.
6. Ishiguro, A., et al. Immunoid: an immunological approach to decentralized behavior arbitration of autonomous mobile robots. – In: Parallel Problem Solving from Nature – PPSN IV (Lecture notes in Computer Science, V. 1141). H.-M. Voigt, W. Ebeling, I. Rechenberg, H.-P. Schwefel, Eds. Heidelberg, Springer-Verlag, 1996, 666-675.
7. Kephart, J. O. A biologically inspired immune system for computers. – In: Artificial Life IV. R. A. Brooks, P. Maes, Eds. Cambridge, MA, MIT Press, 1994, 130-139.
8. Carpenter, G., S. Grossberg. The ART of adaptive pattern recognition by a self-organizing neural network. – In: IEEE Computer, March 1988, 77-88.
9. Yager, R. R., L. A. Zadeh. Fuzzy Sets, Neural Networks, and Soft Computing. N.Y., Van Nostrand Reinhold, 1994.
10. Jain, A. K. Artificial neural networks: a tutorial. – In: IEEE Computer, March 1996, 31-44.
11. Danchin, A. A selective theory for the epigenetic specification of the monospecific antibody production in single cell lines. – In: Ann. Immunol. (Institut Pasteur), Vol. 127C, 1976, 787-804.
12. Danchin, A. Stabilization fonctionelle et epigenese: une approche biologique de la genese de l'identite individuelle. – In: L'identite. J.-M. Benoist, Ed. Paris, Grasset, 1977, 185-221.
13. Liu, Y., X. Yao. Evolutionary design of artificial neural networks with different nodes. – In: Proc. IEEE Int. Conf. Evol. Comput. (ICEC'96), 1996, 670-675.
14. Nolfi, S., et al. Learning and evolution in neural networks. – Adaptive Behavior, **3**, 1994, No1, 5-28.
15. Yao, X. Evolutionary artificial neural networks. – Int. J. Neural Syst., **4**, 1993, No3, 203-222.
16. Hinton, G. E., S. J. Nowlan. How learning can guide evolution. – Complex Syst., **1**, 1987, 495-502.
17. Ackley, D., M. Littman. Interactions between learning and evolution, . – In: Artificial Life II (SFI Studies in the Sciences of Complexity, V. X). C. G. Langton, C. Taylor, J. D. Farmer, S. Rasmussen, Eds. Redwood City, CA, Addison-Wesley, 1992, 487-509.
18. Dennet, D. C. Darwin's Dangerous Idea: Evolution and the Meanings of Life. N.Y. Simon & Schuster, 1995.
19. Werner, G. M., M. G. Dyer. Evolution of communication in artificial organisms. – In: Artificial Life II (SFI Studies in the Sciences of Complexity, V. X). C. G. Langton, C. Taylor, J. D. Farmer, S. Rasmussen, Eds. Redwood City, CA, Addison-Wesley, 1992, 659-687.
20. MacLennon, B. Synthetic ethology: an approach to the study of communication. – In: Artificial Life II (SFI Studies in the Sciences of Complexity, V. X). C. G. Langton, C. Taylor, J. D. Farmer, S. Rasmussen, Eds. Redwood City, CA, Addison-Wesley, 1992, 631-658.

21. Steels, L. A self-organizing spatial vocabulary. – In: Artificial Life, **2**, 1995, No3, 319-332.
22. Yamakawa, T. A fuzzy inference engine in nonlinear analog mode and its application to a fuzzy logic control. – In: IEEE Trans. on Neural Networks, **4,** May 1993, No3, 496-521.
23. Yamakawa, T. Japanese Patent Applications. Tokuganhei, No 1-043600, Feb. 23, 1989, No1-133690, May 26, 1989.
24. Yamakawa, T. A fuzzy neuron and its application to pattern recognition. – In: Proc. Third IFSA Congress, Seattle, WA, Aug. 6-11, 1989, 30-38.
25. Yamakawa, T. Pattern recognition hardware system employing a fuzzy neuron. – In: Proc. Int. Conf. Fuzzy Logic & Neural Networks, Iizuka, Japan, July 20-24, 1990, 943-948.
26. Yamakawa, T. A fuzzy neuron and its application to a hand-written character recognition system. – In: Proc. IEEE Int. Symp. Circuits and Systems, Singapore, June 11-14, 1991, 1369-1372.
27. Proc. Int. Conf. Fuzzy Logic and Neural Networks. Iizuka, Japan, July 20-24, 1990.
28. Yamakawa, T. A design algorithm of membership functions for a fuzzy neuron using example-based learning. – In: Proc. IEEE Int. Conf. Fuzzy Systems, San Diego, CA, Mar. 8-12, 1992, 75-82.
29. Kosko, B. Neural Networks and Fuzzy Systems. Englewood Cliffs. N.J., Prentice Hall, 1992.
30. Kosko, B. Neural Networks for Signal Processing. Englewood Cliffs, N.J., Prentice Hall, 1991.
31. Proc. A Second Int. Conf. Fuzzy Logic and Neural Networks. Iizuka, Japan, July 17-22, 1992.
32. Yamakawa, T., et al. A neo fuzzy neuron and its applications to system identification and prediction of the system behavior. – In: Proc. Second Int. Conf. Fuzzy Logic & Neural Networks, Iizuka, Japan, July 17-22, 1992, 477-484.
33. Hopfield, J. Neural networks and physical systems with emergent collective computational abilities. – In: Proc. Nat. Acad. Sciences, **79**, 1982, 2554-2558.
34. Rumelhart, D. E., J. L. Mc Clelland, Eds. Parallel Distributed Processing. Cambridge, MA, MIT Press, 1986.
35. Hassoun, M. H. Fundamentals of Artificial Neural Networks. Cambridge, MA, MIT Press, 1995.
36. McEliece, R., et al. The capacity of the Hopfield associative memory. – In: IEEE Trans. Inform. Theory, **IT-33**, 1987, 461-482.
37. Hertz, J., et al. Introduction to the Theory of Neural Computation. Redwood City, CA, Addison-Wesley, 1991.
38. Haykin, S. Neural Networks: a Comprehensive Foundation. N.Y., Macmillan, 1994.
39. Zurada, J. Introduction to Artificial Neural Systems. St. Paul, MN, West Publishing, 1992.
40. Hassoun, M. Fundamentals of Artificial Neural Networks. Cambridge, MA, MIT Press, 1995.
41. Ripley, B. Pattern Recognition and Neural Networks. Cambridge, UK, Cambridge Univ. Press, 1996.
42. Siu, K.-Y., et al. Discrete Neural Computation: a Theoretical Foundation. Englewood Cliffs, N.J., Prentice Hall, 1995.
43. Vapnik, V. The Nature of Statistical Learning Theory, N.Y., Springer-Verlag, 1995.
44. Rosenblatt, F. Principles of Neurodynamics: Perceptrons and the Theory of Brain Mechanisms. Washington, DC, Spartan Books, 1962.
45. Cover, T. M. Geometrical and statistical properties of systems of linear inequalities with applications in pattern recognition. – In: IEEE Trans. Electron. Comput., 1965, 326-334.
46. Nilsson, N. The Mathematical Foundations of Learning Machines (1965). San Mateo, CA, Morgan Kaufmann, 1990, reprint.
47. Baum, E., D. Haussler. What size net gives valid generalization? – In: D. Touretzky, Ed. Adv. in Neural Inf. Proc. Syst. I., San Mateo, CA, Morgan Kaufmann, 1989, 81-90.
48. Moeler, M. A scaled conjugate gradient algorithm for fast supervised learning. – In: Neural Networks, **6,** 1993, 525-533.
49. Amaldi, E. From Finding Maximum Feasible Subsystems of Linear Systems to Feedforward Neural Network Design. Sc. D. dissertation, Dept. Math., ETH Lausanne, EPFL, 1994.
50. Saarinen, S., et al. The numerical solution of neural network training problems. – CRSD Report No 1089, Center for Supercomputing Research and Development, 1991, Univ. of Illinois, Urbana.
51. Rall, W. Some historical notes. Comput. Neurosci., E. L. Schwartz, ed., Cambridge, MA, MIT Press, 1990.
52. Widrow, B., M. A. Lehr. 30 years of adaptive neural networks: preceptron, madaline and backpropagation. – In: Proc. of the IEEE, 1990, **78**, 1415-1442.
53. Cowan, J. D. Neural networks: the early days. – In: Adv. in Neural Inf. Proc. Syst. 2 (D. S. Touretzky, ed.), San Mateo, CA, Morgan Kaufmann, 1990, 828-842.
54. Cowan, J. D., D. H. Sharp. Neural nets. – In: Quarterly Review of Biophysics, **21**, 1988, 365-427.
55. Grossberg, S. Nonlinear neural networks: priciples, mechanisms, and architectures. – Neural Networks, **1**, 1988, 17-61.

56. Anderson, J. A., et al. Neurocomputing 2: directions for research. Cambridge, MA, MIT Press, 1990.
57. Anderson, J. A., E. Rosenfeld, eds. Neurocomputing: Foundations of Research. Cambridge, MA, MIT Press, 1988.
58. Selfridge, O. G., et al. Selected bibliography on connectionism. – Evolution, Learning, and Cognition. (Y. C. Lee, ed.), Singapore, World Scientific, 1988.
59. Arbib, M. A. Brains, Machines and Mathematics. 2nd ed. N.Y., Springer-Verlag, 1987.
60. Von Neumann, J. Papers of John von Neumann on Computing and Computer Theory. W. Aspray and A. Burks, eds. Cambridge, MA, MIT Press, 1986.
61. Ramon y Cajal, S. Histologie du systeme nerveux de l'homme et des vertebres. Tome I. Paris, Maloine, Edition Francaise Rebue, 1952.
62. McCulloch, W. S., W. Pitts. A logical calculus of the ideas immanent in nervous activity. – Bulletin of Mathem. Biophysics, **5**, 1943, 115-133.
63. Wiener, N. Cybernetics: or Control and Communication in the Animal and the Machine. N.Y., Wiley, 1949.
64. Hebb, D. O. The Organization of Behavior: a Neuropsychological Theory. N.Y., Wiley, 1949.
65. Ashby, W. R. Design for a Brain. N.Y., Wiley, 1952.
66. Minsky, M. L. Theory of neural-analog reinforcement systems and its application to the brain-mod. problem. Ph. D. Thesis, Princeton University, Princeton, N.J., 1954.
67. Minsky, M. L. Steps towards artificial intelligence, . – In: Proc. of the Inst. of Radio Engineers, **49**, 1961, 8-30.
68. Taylor, W. K., Electrical simulation of some nervous system functional activities. – In: Inf. Theory. E. C. Cherry, ed. V.3. London, Butterworth, 1956, 314-328.
69. Steinbuch, K. Die Lernmatrix. – Kybernetik, **1**, 1961, 36-45.
70. Willshaw, D. J. et al. Non-holographic associative memory. – Nature (London), **222**, 1969, 960-962.
71. Anderson, J. A. A simple neural network generating an interactive memory. – Math. Biosciences, **14**, 1972, 197-220.
72. Kohonen, T. Correlation matrix memories. – In: IEEE Trans. on Computers, **C-21**, 1972, 353-359.
73. Nakano, K. Association – a model of associative memory. – In: IEEE Trans. on Systems, Man and Cybernetics, **SMC-2**, 1972, 380-388.
74. Rosenblatt, F. The perceptron: a probabilistic model for information storage and organization in the brain. – Psych. Review, **65**, 1958, 386-408.
75. Widrow, B., M. E. Hoff, Jr. Adaptive switching circuits. – IRE WESCON Convention Record, 1960, 96-104.
76. Widrow, B. Generalization and information storage in networks of adaline 'neurons'. – Self-Organizing Systems. M. C. Yovitz, G. T. Jacobi, G. D. Goldstein, eds. Washington, D.C., Sparta, 1962, 435-461.
77. Nilsson, N. J. Learning Machines: Foundations of Trainable Pattern-Classifying Systems. N.Y., McGraw-Hill, 1965.
78. Minsky, M. L., S. A. Papert. Perceptrons. Cambridge, MA, MIT Press, 1969.
79. Von der Malsburg, C. Self-organization of orientation sensitive cells in the striate cortex. – Kybernetik, **14**, 1973, 85-100.
80. Willshaw, D. J., C. Von der Malsburg. How patterned neural connections can be set up by self-organization. – In: Proc. of the Royal Soc. of London, Ser. B, **194**, 1976, 431-445.
81. Grossberg, S. How does a brain build a cognitive code? – Psych. Review, **87**, 1980, 1-51.
82. Hopfield, J. J., Neural networks and physical systems with emergent collective computational abilities. – In: Proc. of the Nat. Acad. of Sci. of the U.S.A., **79**, 1982, 2554-2558.
83. Cowan, J. D. A mathematical theory of central nervous activity. Ph. D. Thesis, University of London, UK, 1967.
84. Grossberg, S. Nonlinear difference–differential equations in prediction and learning theory. – In: Proc. of the Nat. Acad. of Sci. of the U.S.A., **58**, 1967, 1329-1334.
85. Grossberg, S. A prediction theory for some nonlinear functional-difference equations. – J. of Math. Anal. and Appl., **21**, 1968, 643-694.
86. Wilson, H. R., J. D. Cowan. Excitatory and inhibitory interactions in localized populations of model neurons. – J. of Biophysics, **12**, 1972, 1-24.
87. Little, W. A., G. L. Shaw. A statistical theory of short and long term memory. – Behavioral Biology, **14**, 1975, 115-133.
88. Anderson, J. A., et al. Distinctive features, categorical perception, and probability learning: some applications of a neural model. – Psych. Review, **84**, 1977, 413-451.

89. Cohen, M. A., S. Grossberg. Absolute stability of global pattern formation and parallel memory storage by competitive neural networks. – In: IEEE Trans. on Syst., Man, and Cybern., **SMC-13**, 1983, 815-826.
90. Kohonen, T. Self-organized formation of topologically correct feature maps. – Biol. Cybern., **43**, 1982, 59-69.
91. Kirkpatrick, S., et al. Optimization by simulated annealing. – Science, **220**, 1983, 671-680.
92. Barto, A. G., et al. Neuronlike adaptive elements that can solve difficult learning control problems, – In: IEEE Trans. on Syst., Man and Cybern., **SMC-13**, 1983, 834-846.
93. Linsker, R. Self-organization in a perceptual network. – Computer, **21**, 1988, 105-117.
94. Broomhead, D. S., D. Lowe. Multivariable functional interpolation and adaptive networks. – Complex Systems, **2**, 1988, 321-355.
95. Aizerman, M. A., et al. Theoretical foundations of the potential function method in pattern recognition learning. – Automation and Remote Control, **25**, 1964, 821-837.
96. Aizerman, M. A., et al. The probability problem of pattern recognition learning and the method of potential functions. – Automation and Remote Control, **25**, 1964, 1175-1193.

Искуственные нейронные сети – происход, эволюционные модели и история

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Представлен обзор искуственных нейронных сетей как средство моделлирования искуственного интеллекта. Он основан на биологических прототипах этих сетей и их соответствие в технике на основе ФОЕ-модели в эволюционном вычислении. Сделан анализ с точки зрения математического формализма. Подробно рассмотрены отдельные периоды развития парадигмы искуственных нейронных сетей.