Summary of the Paper (*Sejnowski, T. J. (2020), The unreasonable effectiveness of deep learning in artificial intelligence. Proceedings of the National Academy of Sciences, 117(48), 30033-30038)*

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***Abstract*—This paper provides a comprehensive summary fpr the paper titled: *"The unreasonable effectiveness of deep learning in artificial intelligence" by Sejnowski (2020*).". The article explores the impact of deep learning in the field of artificial intelligence AI, and provide insights of the interesting findings during the evolution of research in the field of AI since 1940 up today.**

Keywords—AI, Deep Learning, overfitting, perceptron, neuronal network.

I. Introduction

The paper elaborated by Sejnowski, T. J. (2020) explores the evolution on Deep learning research starting from 1940 up recent days. The approach in the paper consists of showing results obtained in various applications where key questions and findings embrace the evolution of deep learning -in artificial intelligence field- understanding.

About Terrence Sejnowski: Neurobiology professor at the Salk Institute. Adjunct professor at the University of California, San Diego. Works in the field of understanding the principles of the brain and applying this results in the development of more advanced machine learning algorithms. Obtained the following recognitions: Swartz Prize for Theoretical Neuroscience Research (2001). Hebb Award from the Neural Society (2005). Paul G. Allen Foundation Science and Technology Prize (2016). Member of the National Academy of Sciences of the United States.

II. Key Findings

A. 1940

Warren McCulloch & Walter Pitss created a computational model for neural networks that generated research not only in the brain but also in its application to artificial intelligence. The proposed model was composed of artificial neurons, in which each of them was characterized as being active or inactive. Activation occurred in response to stimulation produced by a sufficient number of neighboring neurons.

B. 1949

Donald Hebb proposed and demonstrated an updating rule to modify the strengths of connections between neurons. He created Hebbian learning, which is observed from a biological perspective, stating that the synapse between two neurons strengthens if the two neurons are simultaneously active.

C. 1950

As computers became more advanced in the 1950s, it finally became possible to simulate a neural network. The first step towards this was taken by Nathanial Rochester from the IBM Research Labs. Unfortunately for him, the first attempt to do so failed.

D. 1951

Marvin Minsky & Dean Edmonds built the first artificial neural network that simulated a rat finding its way through a maze. They designed the first neurocomputer (40 neurons), called SNARC (Stochastic Analog Reinforcement Computer). It used 3000 vacuum tubes and an autopilot mechanism salvaged from a B-24 bomber aircraft to simulate a network with 40 neurons.

E. 1958

Frank Rosenblatt created the perceptron, a simple neural model that could be used to classify data into two sets. However, this model struggled in that it could not correctly classify an exclusive OR. Perceptrons are considered the first models of artificial neural networks. A perceptron is a simplified model of an artificial neuron that takes multiple inputs and produces a single output.

F. 1959 & 1962

Widrow & Hoff created Adeline, a model to recognize binary patterns and predict the next bit when reading a telephone line.

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Madeline was the first neural network applied to a real-world problem, using an adaptive filter that eliminates echoes on telephone lines. Additionally, they developed a learning procedure that examines the value before adjusting the weight (i.e., 0 or 1) according to the rule: Weight Change = (Value of previous line to weight) * (Error / (Number of inputs)).

They are the authors of the Least Mean Squares (LMS) Filter.

G. 1969

Marvin Minsky & Seymour Papert on their research highlighted the limitations of perceptrons and led to a decline in research and interest in neural networks in the 1970s, which became known as the "AI winter.". They raised interesting questions and challenges that inspired future researchers to seek solutions and develop new techniques and models of neural networks, such as multilayer neural networks and backpropagation.

H. 1974

Paul Werbos introduced the backpropagation error algorithm, which efficiently calculates error gradients and adjusts the weights and connections of neurons to minimize the output error of the network. With this, he established the theoretical foundations of backpropagation and demonstrated its utility for training multilayer neural networks.

I. 1980

Kunihiko Fukushima developed the neural network model called "Neocognitron". This architecture was designed for pattern recognition in images and included learning mechanisms that allowed the network to adjust its weights and connections to improve its pattern recognition capabilities.

J. 1980

John Hopfield´s key contribution was his formulation of an energy function, known as the Hopfield energy function, which allowed the network to reach stable states and solve optimization problems. This helped revitalize interest in neural networks and opened new research directions in the field. The Hopfield network has been successfully applied in various areas, such as pattern recognition, optimization, memory modeling, and information processing.

K. 1986

Rumelhart & MacClelland worked on the feedback learning algorithm that was applied to various learning problems in the fields of computer science and psychology, and the widespread dissemination of the results was achieved through publication in the "Parallel Distributed Processing" collection. Additionally, a "hybrid network" with multiple layers was utilized, with each layer employing a different problem-solving strategy.

L. 1990 up today

Geoffrey Hinton is one of the pioneers and leaders in the field of neural networks and deep learning. His contributions have been instrumental in advancing and popularizing these technologies. Some of his notable contributions include:

1. Training deep neural networks using the technique of "unsupervised pre-training."
2. Convolutional neural networks.
3. Introduction of Restricted Boltzmann Machines.
4. Deep reinforcement learning.

III. NATURE OF DEEP LEARNING

The paper discusses various aspects related to deep learning, artificial intelligence (AI), and the brain functions to inspire the design and understand new models, such as follows:

The third wave of neural network exploration, known as deep learning, has expanded beyond its academic origins and has grounded AI in the real world. Deep learning bridges the gap between the analog and uncertain nature of the real world and the symbolic and rule-based world of traditional AI.

Deep learning has enabled the extraction of both syntactic and semantic information from sentences in natural language processing, moving away from a purely symbolic approach. Word embeddings in deep learning networks are used to represent relationships between words and associations.

The attitude in AI research has shifted from ignoring the brain to recognizing its relevance. Studying the brain can provide insights into how sensory information is processed, decisions are made, and future actions are planned. Deep learning draws inspiration from nature and algorithmic biology, learning from the problem-solving strategies used by biological systems.

Real neurons are complex dynamical systems, while model neurons in neural network models are simplified. Real neurons possess various features, such as diverse cell types optimized for specific functions, short-term synaptic plasticity, biochemical reactions underlying plasticity, sleep states for restructuring, and communication networks between brain areas.

The neocortex, a folded sheet of neurons on the outer surface of the brain, plays a crucial role in cognition. It has a scalable architecture, and its size relative to the central core of the brain has greatly expanded in humans. Specialized regions within the cortex, such as the visual cortex, have evolved circuits that have been utilized in convolutional neural networks.

The cortex contains billions of synapses, providing powerful computing capabilities. Understanding the organization of specialized networks and the flow of information between cortical areas is essential.

Memory management is a challenge for building future AI systems. Maintaining stable lifelong learning and minimizing memory loss and interference between subsystems are crucial. Sleep plays a role in memory consolidation, with oscillatory events called sleep spindles associated with the integration of memories into long-term cortical semantic memory.

In summary, the paper highlights the significance of deep learning, the relationship between AI and the brain, and the potential for synergies between biology and engineering in advancing AI systems.

IV. The Future of Deep Learning

The paper highlights the need for a broader range of neural network architectures beyond deep learning to control movements and vital functions. While deep learning has been inspired by the cerebral cortex, other brain areas such as the basal ganglia and the cerebellum are crucial for reinforcement learning and motor control.

The dopamine neurons in the brainstem play a key role in computing reward prediction error, which is essential in reinforcement learning. The combination of deep learning and reinforcement learning powered AlphaGo to defeat the world champion Go player. Dopamine neurons modulate synaptic plasticity and provide motivation for long-term rewards.

Neuromodulatory systems control global brain states and influence behavior by representing negative rewards, surprise, confidence, and temporal discounting. These systems play a role in economic decision-making and are studied in the field of neuroeconomics.

In the field of motor systems, biologically inspired solutions can offer valuable insights. Animals exhibit exceptional flexibility and coordination in high-dimensional motor planning spaces. Coordinated behavior in such spaces is an active area of research in deep learning networks. Understanding the distributed control and coordination of multiple control layers in the spinal cord, brainstem, and forebrain is also important.

Brains and control systems need to deal with time delays in feedback loops and have mechanisms to optimize open-loop control. The cerebellum's forward model of the body enables the prediction of sensory outcomes of motor commands, which is used to optimize control. Control systems, both in brains and engineered systems, overcome constraints and exhibit diverse speed-accuracy trade-offs to achieve efficient control.

In summary, drawing inspiration from various brain areas and their control mechanisms can contribute to the development of autonomous AI systems, especially in the domains of reinforcement learning, motor control, and coordination.

V. Toward Artificial Intelligence

While deep learning has made significant strides, achieving AI requires advancements in areas such as reasoning, planning, decision making, and unsupervised learning. Drawing inspiration from the brain's architecture and exploring hybrid approaches may pave the way towards artificial general intelligence.

VI. looking Ahead

Looking ahead, we are entering the age of information where data is abundant, and technology allows us to process and derive knowledge from it. Deep learning networks serve as bridges between the digital world and the real world, enabling us to interact with computers more intuitively. We are already witnessing the rise of smart speakers and the obsolescence of keyboards, making deep learning accessible to everyone.

In the universe of mathematics and physics, we have marveled at the effectiveness of mathematical structures in explaining natural phenomena and making empirical predictions. Similarly, deep learning networks possess a wealth of parameters and offer vast potential for exploration in high-dimensional spaces. By analyzing the structure of these networks, we may uncover deep insights into the nature of intelligence and make theoretical predictions.

As we continue to advance, there may be other classes of functions and algorithms yet to be discovered that can capture the complexity of the world in ways beyond our current intuitions. Just as the gentleman square in Flatland and the explorer in the Flammarion engraving ventured into new realms, we too are on the cusp of exploring a world that stretches far beyond our previous horizons.

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