Algorithms for constructing society organizations, and also for lives

Shuai Liu
646677064@qq.com

Abstract

In the past, the organization of society, including government and corporations, relied solely on natural experience, lacking a robust mathematical and logical framework for explaining how to structure and optimize these entities. This article draws parallels between the structure of social organizations and neural networks, illustrating that social structures emulate neural network architectures. Social organizations can be seen as neural networks nested within humans.Using the same principles, one can optimize the structure of social organizations. And this article outlines a comparison between neural network algorithms and Darwin's theory of natural selection, highlighting their similarities.

1 Introduction

In the past, the organization of society, including government and corporations, relied solely on natural experience, lacking a robust mathematical and logical framework for explaining how to structure and optimize these entities. This article draws parallels between the structure of social organizations and neural networks, illustrating that social structures emulate neural network architectures. Social organizations can be seen as neural networks nested within humans. Furthermore, the totality of life on Earth, including plants, animals, and humans, forms an extensive neural network. This vast network survives on Earth as described by Darwin's theory of evolution, with life processes following neural network learning algorithms.

The training curve of neural network learning algorithms illustrates Darwin's theory of evolution. The main components of Darwin's theory of natural selection include: over-reproduction, the struggle for survival (also known as survival competition), inheritance and variation, and the survival of the fittest [5]. From neural network algorithms, we can discern certain traces, and this article outlines a comparison between neural network algorithms and Darwin's theory of natural selection, highlighting their similarities. Learning algorithms aim to minimize a target loss function, just as Earth's organizations adapt to fit specific environmental conditions. The higher the degree of adaptation, the stronger the resilience. Hence, it becomes evident that both morphology and knowledge are geared towards fitting specific target loss functions.

2 What is the data?

As shown in the picture 1, this is an environment composed of trees, grass, soil, sky, air, and so on. It represents a limited and directional projection of the real-world environment as captured by a camera. This photograph can only depict a certain perspective of the environment and cannot fully encapsulate the entirety of the world around us.

In another example, let's consider an object like a cup. When viewed from different angles, it can be described in various ways. For instance, you can say it's made of glass or that it's smooth or frosted. You might describe it as cute, rugged, hollow, or impure. You can also mention that it's cold, hot, hard, soft, smells like coffee, or actually has the aroma of milk. It might seem like plain

Figure 1: a picture.

water today. Is it composed of molecules or atoms? Is the object itself colored, or is it the light it reflects? The nature of the cup can vary under different conditions and in different environments. Precise descriptions depend on the specific environmental conditions.

Extending this concept to image data, we can see that it can be generalized to environments. Similarly, language (including the language of various fields) is a means of describing the world's environment for communication. We can also generalize language to environments, as well as sounds in the same way.

Hence, we can extend from data to environments, which can be broadly understood as the input to neural networks being the environment. This perspective highlights how our understanding of objects and concepts can be context-dependent and influenced by the environmental conditions and perceptions.

3 organizations simulate neurons

Why is it said that social organization simulates neural network structure? We can compare their structures. M-P model, relu is an important component of neural network, which needs to be paid more attention to.

3.1 Election vs. M-P neuron model

In the electoral process, if there is a candidate A, and ordinary voters cast their votes for A. Let X_i represent the vote of the i-th person for A (with a vote being 1 or 0). The candidate's vote tally is calculated as

$$Sum(A) = \sum_{i=0}^{K} X_i \tag{1}$$

Throughout human history, there has been a debate regarding the equality of each person's voting rights, as individuals possess varying capabilities, resulting in differing values for X_i. Furthermore, people differ in their professions, environments, knowledge, morals, and more, leading to varying voting weights, denoted as Wi. Consequently, the generalized vote tally for a candidate is expressed as

$$Sum(A) = \sum_{i=0}^{K} W_i \cdot X_i \tag{2}$$

(where W_i represents the weight of each individual's vote). This demonstrates a parallel between the electoral process and the M-P neuron model.The M-P neuron model was introduced by Warren McCulloch and Walter Pitts in 1943 [1]. When elections occur in processes distinguished by geographical regions, they bear resemblance to convolution [2] processes.

3.2 Selection vs. ReLu

In daily life and work, people often need to engage in learning, take exams, and participate in various competitions to secure favorable qualifications through a process of selection. Through successive rounds of selection, individuals exceeding a certain level of competence are chosen for employment.

This process aligns with the operation of ReLU (Rectified Linear Unit) [3, 4]. In mathematical terms, ReLU provides a more suitable and closer approximation than natural selection [5].Natural selection acts as a filter and is just a component of neural network learning algorithms.

3.3 Multilayer

In many social organizations, a multi-layered, alternating process often emerges through a combination of elections and selective preference. This cascading operation aligns with the structure of the popular deep neural networks [6, 7] in use today.

3.4 Organization plan goal vs. Loss function

In social organizations, performance outcomes often deviate from expectations. In such cases, it is necessary to provide feedback to the organization's internal mechanisms based on the difference between performance results and expectations. After internal adjustments, the organization can progress more effectively toward new expectations. This process closely resembles the loss function at the tail end of deep neural networks.

However, real-world organizational planning may not involve performance-expectation discrepancies; some goals lack well-established mechanisms for adjustment, making it challenging to achieve them directly. It's not that these goals are unattainable, but achieving them is more difficult without a step-by-step, error-smoothing adjustment mechanism, making learning more complex.

In reinforcement learning, the accumulation of rewards is similar to achieving goals, as both entail an expectation of eventual gain. However, rewards in the interaction between individuals and the environment are often sparse, with some even delayed, mirroring the nature of goals.

In deep learning for image object detection tasks, mechanisms like anchor proposal boxes [8] enable more rapid and smoother regression.

Organizational planning goals also consider a holistic view of various impacts, such as territorial transfer payments in a nation's policies. Similarly, when designing error functions in deep neural networks, comprehensive considerations are typically taken into account.

3.5 Forward process

In social organizations, it's common for various departments to collect data and report it to higher-level departments. Each level of department analyzes and integrates data information and continually iterates to report to higher-level departments.

The process of analyzing and integrating information is typically carried out by individuals who have been selected and deemed proficient. They receive information, process it through the human brain (the neural network of the brain), and then report the data through the structure of the social organization. Social organizations mimic neural networks, with neural networks nested within one another. We can consider that the structure they collectively form is still a neural network. In social organizations, individuals, due to their high level of intelligence, sometimes halt the forward process at intermediate nodes. Some information is deemed unimportant and cannot stimulate the continuation of reporting to higher levels (of course, there can be errors in judgment), leading to the termination of the forward process. Some information is crucial, but after analysis at an intermediate node in the network, the forward process stops. These individuals have the authority to directly create an expectation deviation and initiate a reverse process.

In current artificial neural networks, intermediate nodes often lack the authority to initiate a direct reverse process. Generally, reverse processes are carried out through the loss function of the final layer. However, in deep learning, there are examples like SSD [9] in object detection, where intermediate nodes can initiate a reverse process but are located at fixed points. In contrast, the authority nodes for the reverse process in social organizations are more flexible.

3.6 Organizational feedback vs. Backpropagation algorithm

In social organizations, it's typically the organization's top-level think tank or analysis team that, upon receiving the performance results and the expectation deviation, feeds this error back to the next level of nodes within the organization. This intermediate layer of nodes adjusts the professional behaviors in their respective positions based on the error, aiming to improve their future actions. This continuous top-down feedback and adjustment process in the organization aligns with the objective of the backpropagation algorithm [10, 11], which is to enable the feedback of parameter information throughout the entire network based on errors.

3.7 I/O of social organization vs. I/O of deep neural networks

The input for social organizations encompasses data and information from various aspects of life and work. For instance, in the case of a company, the input includes information related to its industry or sector, while the output consists of the company's performance. Similarly, in the context of a national economy, the input comprises factors such as people's consumption, income from employment, education, and so on, with the output being the statistical results for the national economy. In terms of relativity,

$$\|organizationinput \longrightarrow organizationoutput\| \sim \|Netinput \longrightarrow Netoutput\| \tag{3}$$

3.8 Underfitting and Overfitting

Each individual within a network may have varying levels of competence or may neglect their responsibilities. They could potentially abuse their power or engage in favoritism. Similarly, corresponding artificial neural networks may suffer from underfitting or overfitting. There's a need to design more optimal architectures to make models converge faster and become more robust. While humans are relatively flexible, they also have limitations. In comparison to the entire group (the larger the group, the more pronounced this is), an individual is relatively insignificant, much like a single node in a deep neural network is minuscule compared to the vast network. When the group is large enough, the insignificance of an individual within the group, in relative terms, is akin to the insignificance of a single node in a massive deep neural network.

3.9 Conclusion

The above description elucidates that throughout human history, the structure of social organizations has emulated neural networks, yielding comparably intelligent outcomes. In the contemporary milieu, advanced network communication technologies facilitate efficient data transmission, enhancing their intelligence and enabling them to fully exploit their potential.

Transferring the superior structures and algorithms of artificial neural networks into social organizational frameworks is imperative. Incorporating exceptional components and finely tuned network designs into the structure of social organizations can enhance their intelligence. It's possible that such integration already exists, but further research and discourse are necessary to explore this concept in depth.

4 Algorithms also for lives

For the convenience of subsequent reading, this article will break down deep learning into two components: neural networks and learning algorithms.

4.1 Neural networks are extremely adaptable

By examining numerous experimental results from the neural network community, it is evident that neural networks can adapt to a wide range of popular tasks. These tasks encompass object detection, segmentation, translation, speech recognition, reinforcement learning, natural language processing, and more. These tasks manifest in different organizational forms of neural networks, incorporating diverse inputs and loss functions. These observations underscore the remarkably robust adaptability (analogous to fitting) of neural networks, akin to the adaptability seen in natural life. Not only can neural networks autonomously adjust to adapt, but humans altering their appropriate configurations can also aid neural networks in fitting tasks. It is essential, however, that changes in input data and loss function values do not occur too rapidly; an appropriate range of adjustments must be provided to the neural network for learning and fitting, or else learning might fail. Similarly, life exhibits formidable adaptability. In an overly rapidly changing environment, life may struggle to adapt and face elimination, just as life, when undergoing changes too rapidly in a stable environment, may also be unable to adapt and face elimination.

Neural networks possess a profound fitting capacity and only require relatively smooth changes in inputs and loss functions (remaining within their adaptability boundaries) for learning and fitting. Neural networks do not become progressively better or worse; they merely fit the true function. Life demonstrates extraordinary adaptability, perpetually adjusting to variations in the environment and feedback.

4.2 Learning algorithms vs. Darwin's evolution

Next, let's delve into the learning process of neural networks and examine whether it aligns with Darwin's theory of evolution. The algorithms of neural networks encompass a substantial portion of Darwin's perspective on evolution. As we explore neural network algorithms, we can indeed discover these traces.

The main elements of Darwin's theory of natural selection include: overbreeding, the struggle for survival (also called the competition for survival), heredity and variation, and the survival of the fittest [5].When we look at the neural network algorithm, we can find these traces.

1. Overreproduction: As individuals increase, the network becomes wider, and the lenght after good organization becomes longer. It alse increases diversity.
2. Survival struggle: let's discuss the right of the equation 2. In the process of network training, W_i is constantly changing and sparse (most of them are close to 0), and large W_i is more likely to win from the competition; In the end, the big one in W_i*X_i can win.
3. Unity and cooperation: The right of the equation 2, the sum, represents the unity of all forces, the strength accumulated on the long tail can not be ignored, and is conducive to maintaining diversity.
4. Survival of the fittest: In the selection process, some are eliminated. Of course, ones in some accidents and natural disasters are eliminated. It's just to fit.
5. Genetic variation: This is missing from current neural network algorithms.

The figure (Fig. 2) above illustrates the trend of training error reduction for the AlexNet neural network, a pattern commonly observed in neural network training tasks after 2012 [6]. Let us consider neural networks indexed by epochs, denoted as A_0, A_5, A_{10}, A_{15}, A_{20}, A_{25}, A_{30}, A_{35}. Initially, these neural networks do not fit the true function well but progressively converge through learning. As different data (broadly referred to as the environment) is continually input, and the loss function is fitted, the neural network gradually approximates the true function. Assuming that in an environment where A_5 to A_{35} coexist, the appearance of A_{10} to A_{35} alters the environment, making it evident that A_5 lags behind. The probability of elimination forA_{35},A_{30}, A_{25}, A_{20}, A_{15}, A_{10}, A_5, A_0 sequentially increases. Therefore, in the selection process, A35 is prioritized.

Similarly, we can view this from the perspective of biological adaptation to the environment. Initially, organisms may not adapt well to the current environment and feedback. Through continuous exposure to different environments and prolonged learning, they eventually adapt to the environment and feedback. Organisms, in the process of adaptation, also change the environment. Assuming that in an environment where versions of organisms from A_5 to A_{35} coexist, it becomes evident that A_5 is significantly less adapted. The probability of elimination for A_{35},A_{30}, A_{25}, A_{20}, A_{15}, A_{10}, A_5, A_0 sequentially increases. Similar processes can be observed in Charles Darwin's "On the Origin of Species".This is a more formulaic explanation than evolution[5].

Although other machine learning algorithms exhibit similar learning curves, they lack the robust adaptability that neural networks demonstrate, resulting in their superior performance.

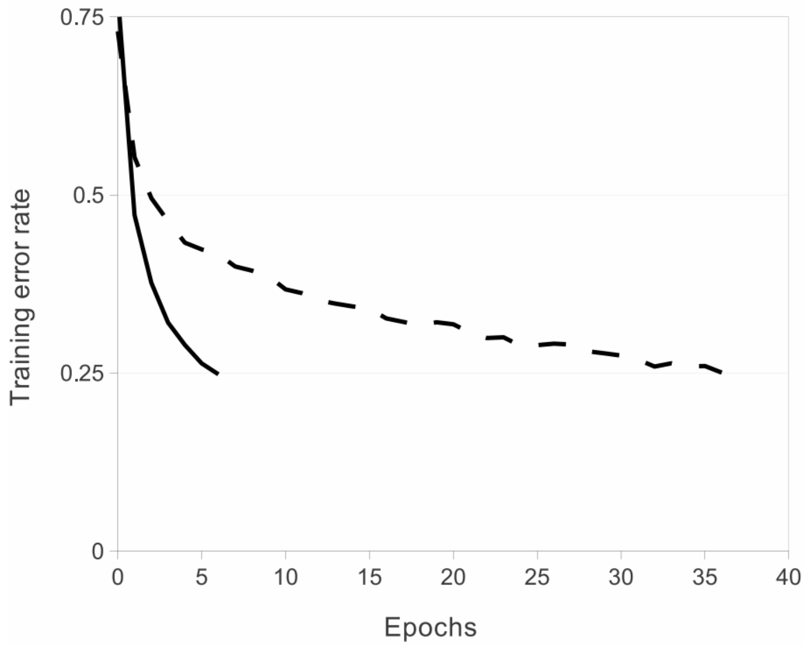

Figure 2: trainloss in learning process shows the downward trend of train error in neural network AlexNet[6] training task.

Simultaneously, it is observed that when examining the train loss curve, the general trend is a decrease with intermittent fluctuations and jumps. From the epoch graph, we can infer the following: initially, in the primitive forms of biological entities, the rate of adaptation-driven changes is the fastest. The survival baseline is low, making survival relatively easy, and these entities exhibit a high degree of plasticity. As the epoch becomes larger, individual changes become smaller and more gradual. However, there is still room for overall improvement in adaptation. The training curve elucidates the process of adaptation and feedback in the biological evolution. The issues of the speed of morphological changes and fluctuations can both be glimpsed through the training curve. Morphological changes are most active at the beginning and slow down in the middle, occasionally exhibiting sudden fluctuations. This process of learning is akin to the human development stages, starting from birth, infancy, childhood, and adulthood, bearing a resemblance to the graph presented above.

4.3 The whole natural system is a huge neural network

Human society is a neural network embedded with brain neurons, and animals similarly possess neural systems, while plants can transmit danger signals through systems akin to animal nervous systems. It can be inferred that the entire natural system comprising humans, animals, plants, microorganisms, and more forms a neural network. In this sense, all individual organisms on Earth harbor neural networks, and the interconnection between all these organisms forms a vast neural network on our planet.

Furthermore, the reproductive system and genetic variations help replenish the population after deaths, maintaining both the population size and diversity. This mechanism prevents a single population from growing to a point where the entire system cannot sustain it, thereby averting a collapse of the entire neural network. Consequently, the overall neural network remains relatively stable. The brain's neural network and this immense natural neural network are fundamentally the same, and they can be unified under this perspective.

4.4 Neural networks are the algorithms of lives

The analysis above indicates that individual life and the biological communities in the natural world exhibit life patterns that adhere to neural network learning algorithms.

4.5 Just to fit

Optimization algorithms are designed to facilitate the fitting of models, including machine learning models and neural network models, to target functions. In contrast, all organisms on Earth strive to fit a specific function within their environment, one that enables them to adapt. The higher the degree of fit, the more successful their adaptation.The Morphology and knowledge of all creatures are just ot fit this function.

So how do organisms adapt?

1.Morphological adaptation. Charles Darwin's "On the Origin of Species"[5] xtensively discusses organisms with morphological adaptations.

2.Discussing the knowledge growth process from birth to adulthood. Observations reveal that when a child is born, they know nothing, yet their plasticity is incredibly high. At birth, due to a lack of oxygen, they have no awareness of concepts like oxygen and air. The environment and feedback from their body guide them. In their instinctive pursuit of adaptation, they cry, receive the breath, and eventually learn to breathe through their nose. Initially, they have no knowledge of what milk is, but their body's hunger signals guide them, and they instinctively learn to drink milk. Gradually, they learn about the world, people, apples, trees, flowers, and more. They come to recognize that they have eyes, skin, ears, a nose, and a central nervous system, adapting through the interplay of their environment, feedback (including natural surroundings, feedback from parents and loved ones, and personal exploration). For instance, concepts like economics are not perceptible through human senses, but a newborn infant remains oblivious, a child has a shallower understanding compared to an adult, while experts have a deeper grasp. These differences represent varying levels of adaptation by neural networks at different stages of development to their environment and feedback.

3. Discussing the process of human understanding of the world's knowledge. Looking at human history, in the beginning, humans only recognized stones. They repeatedly experimented with them, discovering that stones were hard and could be used as weapons to attack animals. Later, after the domestication of plants, stones were used for grinding grains. Subsequently, some stones were found to be ores, and they could be used to extract metals like iron, copper, and more. Eventually, $SiO2$ could be utilized to create silicon wafers. Neural networks accumulate knowledge by continuously receiving feedback from the environment, leading to a wealth of understanding. By integrating this understanding, individuals interact with their surroundings, continually receiving feedback. From a historical perspective, this is an ongoing accumulation through adaptation. What something is at any given moment is influenced by a combination of present experience and historical memory. Humanity's perception of the world is continually advancing. It can also be said that human knowledge is a continuous adaptation to the environment. Fortunately, the rules governing physics, nature, biology, and more remain largely unchanged, but the understanding of living beings in the process of adaptation continues to evolve.

4. Human knowledge constantly fits the real world. Not only from the perspective of individuals, but also from the perspective of human history, every moment is not fully fitted. It is a process of accumulating knowledge and fitting step by step.

4.6 Prospect

It's possible that the oldest learning algorithm related to life is quite rudimentary, continually adapting to the environment and feedback, eventually evolving into the neural network learning algorithms we have today. There might be other life algorithms yet to be discovered, necessitating further discussion and research. In the future, we could witness life algorithms with even greater adaptability than neural networks.

The exact limits of neural network adaptability remain unclear and warrant more discussion and research. It's a personal conjecture that each node within the network needs to adapt, and thus, the overall adaptability is constrained by the adaptability of all nodes. Complete extinction of any population within the network's intermediate layers should be avoided to prevent the entire network from collapsing.

The sensory systems of life, such as vision, hearing, touch, taste, and natural language, have evolved to adapt to the environment and feedback. As a whole, these systems interact with the environment, and their information exchange can accelerate learning. Sensory systems that better adapt to the environment and feedback can facilitate faster adaptation for neural networks, as these sensory systems have also undergone extensive adaptation to the environment and feedback.

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