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Towards Neural Knowledge DNA

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Abstract. In this paper, we propose the Neural Knowledge DNA, a framework that tailors the ideas underlying the success of neural networks to the scope of knowledge representation. Knowledge representation is a fundamental field that dedicates to representing information about the world in a form that computer systems can utilize to solve complex tasks. The proposed Neural Knowledge DNA is designed to support discovering, storing, reusing, improving, and sharing knowledge among machines and computing devices. It is constructed in a similar fashion of how biological DNA formed: built up by four essential interconnected elements. As the DNA produces phenotypes, the Neural Knowledge DNA carries information and knowledge via its four interdepended rudiments, namely, Networks, Experiences, States, and Actions. These components store the detail of the artificial neural networks for training and knowledge reusing purposes. The novelty of this approach is that it uses previous decisional experience to collect and expand intelligence for future decision making formalized support. The experience based collective computational techniques of Set of Experience Knowledge Structure (SOEKS) and Decisional DNA (DDNA) are used to develop aforesaid decisional sustenance. Together with artificial neural networks and reinforcement learning, the proposed Neural Knowledge DNA is used in an experiment to catch knowledge during the solution of a simple illustrative maze problem. The tryout results show that our Neural Knowledge DNA is a very promising knowledge representation approach for artificial neural network-based intelligent systems.

Keywords: Neural Knowledge DNA, Neural Networks, Deep Learning, Knowledge Representation

1. Introduction

Knowledge representation is a fundamental field that dedicate to representing information about the world in a form that computer systems can utilize to solve complex tasks [4]. It is the study of thinking as a computational process. Then, what is knowledge? This is a question that has been discussed by philosophers since the ancient Greeks, and it is still not totally demystified. Drucker P. F. defines it as "information that changes something or somebody - either by becoming grounds for actions, or by making an individual (or an institution) capable of different or more effective action" [5]. While the Oxford Dictionary defines Knowledge as "facts, information, and skills acquired through experience or education; the theoretical or practical understanding of a subject" [19]. O'Dell and Hubert claim that Knowledge is not knowledge until the information inside itself has been taken and used by people [18]. And for scientists and researchers in the AI field, we can argue it as "knowledge is not knowledge until the information inside itself has been taken and used by computers, machines, and agents".

Consequently, an appropriate knowledge representation shall be easy used by different systems to allow storing, reusing, improving, and sharing knowledge among these systems. A survey [11] carried out by Liao found that there were generally seven categories of knowledge-based technologies and

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applications developed until 2002. Another study presented in [14], after analyzing 30 published articles between 2003 and 2010 from high quality journals, found nine core theories in the knowledge-based area. However, there are following limitations to these technologies:

1. most of them are designed for one specific kind of a product/system/implementation,
2. they don't have standard knowledge presentation,
3. most systems lack the capability for information sharing and exchange, and
4. most of these systems focus only on supporting a particular stage of a product lifecycle [10].

Recent studies [6] [8] [9] in artificial neural networks (ANN) and psychology have found that the image representations in ANN are very similar to those in biological brains. This was our initial inspiration leading to the question: why shouldn't we try to organize and store knowledge in a way similar to the way it exists in the human brain?

In this paper, we propose and introduce the initial concept the Neural Knowledge DNA (NK-DNA), a framework adapting ideas underlying the success of neural networks to the scope of knowledge representation for neural network-based knowledge discovering, storing, reusing, improving, and sharing.

2. Neural Networks and Deep Learning

Machine learning is one of today's most rapidly growing technical/cybernetic fields. It is the corner stone of artificial intelligence that addresses the question of how to build computer systems improving themselves automatically through experience [13]. The recent progress of new theories and learning algorithms, especially in the filed of artificial neural networks (ANN), has become the new driving force in machine learning.

ANN is a biologically-inspired programming paradigm which enables a computer to learn from observational/exemplar data [15]. It consists of a network where the information can be passed from one node to another, and these nodes in the network are called artificial neurons. The network typically is structured hierarchically, and its neurons are usually organized into layers such that each neuron in layer l connects to every neuron in layer l+1. Any layers in between the input layer and output layer are called hidden layers. The forward pass of an ANN is where information flows from the input layer, through any hidden layers, to the output. ANN learns during the backwards pass, which updates the connection's weights of the network [13].

Deep learning is a powerful set of techniques for learning in the ANN domain [15]. It allows computational models that are composed of multiple processing layers to learn representations of data with multiple levels of abstraction [8].

Deep learning learns sophisticated structures and patterns in large data sets by using the backpropagation algorithm to reveal how a neural network should change its internal parameters that are used to compute the representation in each layer from the representation in the previous layer [7] [15]. The essential aspect of deep learning is that these layers of features are not human-designed; they are learned from data using a general-purpose learning procedure. Deep learning has dramatically improved the state-of-the-art in image recognition, natural language process, object detection and many other domains such as drug discovery and genomics [8] [26].

3. Deep Reinforcement Learning

Reinforcement learning is a branch of machine learning concentrated upon using experience obtained via interacting with the world and evaluative feedback to improve a system's capability to make decisions [12] [17]. Reinforcement-learning algorithms [29] are inspired mainly by our perception of human's decision making in which learning is happening through the use of reward signals in response to the observed results of actions. It has been called the artificial intelligence problem in a microcosm because learning algorithms must operate autonomously to perform well and to achieve their objectives. Partly driven by the increasing availability of rich data, recent years have seen exciting advances in the theory and practice of reinforcement learning, including developments in fundamental technical areas such as empirical methodology, exploration, planning, and generalization, leading to increasing applicability to real-life problems [16].

Reinforcement learning can be represented as an interaction between a learner (i.e. the decision making agent) and an environment that gives evaluative outcomes to the learner. The environment in this case is often seen and defined from the perspective of a Markov decision process [1] [20].

A Markov decision process is composed by a set of actions A (the decisions the decision maker can

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choose), and states S (situations in which a decision can be made). These quantities of actions and states can be limited, but spaces with continuous actions and states are often more valuable for capturing interactions in important reinforcement learning applications, such as for example performing physics tasks. Function P (s′| s, a) defines the probability of the state transforming from s to s' by taking the action a [1] [16].

A reward function R(s, a) and discount factor $\gamma \in [0, 1]$ are used to describe the decision making agent's performance: for each time-step, the agent chooses an action, and the environment returns a reward and transitions into the next state. The goal behind this process is to maximize the cumulative discounted expected reward. More specifically, the agent is looking for a behavior policy $\pi^*(a_t|s_t;\theta)$ mapping states to action creating a reward sequence $r_0, r_1, r_2, r_3, \ldots$ such that $E_{r0,\ r1,\ \ldots}$ $[r_0 + \gamma r_1 + \gamma^2{}_{r2} + \gamma^3{}_{r3} + \ldots]$ is as large as possible [16]. The relation between the cumulative discounted expected reward and the environmental interaction (state, action, reward, state, action, reward, …) is captured by the Bellman equation [1] for the optimal state–action value function Q*. The solution to the Bellman equation can be used to optimize the agent's behavior by calculating $\pi^*(s) = \arg\max_a Q^*(s, a)$. The expected cumulative discounted reward for the policy that takes action a from state s and then behaving optimally thenceforth is the immediate reward received, and the expected discounted value of the cumulative discounted expected reward from the resulting state s′ given that the best action is chosen [16][20].

Deep reinforcement learning is the method that uses deep neural networks (DNN) in combination with reinforcement learning to address learning about the environment and gaining the best control policy. DNNs can be used to directly approximate a control policy, a = π(s) from example data points (s_i, a_i) as generated by some other control process. Control policies based on DNNs have been trained and learned to control agents in many ways as reported in [8][12][17].

Deep learning can be further enhanced by supporting its process with learning experience. The tools needed for this enhancement are presented next.

4. Set of Experience Knowledge Structure and Decisional DNA

The presented approach towards constructing Neural Knowledge DNA is a vision that aims to address complex issues and challenges that arise from the pervasive nature of digital technologies as witnessed in recent years in our everyday life. One of such major challenges is the need for nature-like cognitive blueprints for man-made systems as required by the incoming semantic-focused society and the "Internet of Things" [3] [27] [30]. Our past research delivers the cutting-edge component of the above challenge and at the same time the fundamental notion behind the proposed Neural Knowledge DNA – the Decisional DNA (DDNA) technology.

In a broader sense, the above research direction plays an important role in our effort to bridge the gap between current society and the one fully embedded in semantic networks. The fully linked Semantic Web concept offers a future vision of the Web where both humans and machines are able to communicate and exchange information and knowledge [2].

The Decisional DNA is a novel knowledge representation theory that carries, organizes, and manages experiential knowledge stored in the Set of Experience Knowledge Structure (SOEKS or SOE for short) as illustrated in Figure 1 [21] [22] [25].

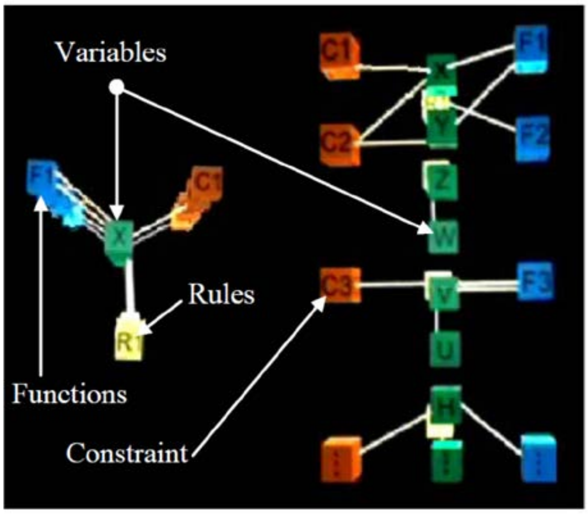

Fig. 1. SOE is the combination of 4 components that characterize decision making actions (variables V, functions F, constraints C, and rules R) and it comprises a series of mathematical concepts (logical element), together with a set of rules (ruled based element), and it is built upon a specific event of decision-making (frame element).

The SOE has been developed to capture and store formal decision events in an explicit way [23]. It is a flexible, standard, and domain-independent

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knowledge representation structure [24]. And it is a model based upon available and existing knowledge, which must adapt to the decision event it was built from (i.e. it is a dynamic structure that depends on the information provided by a formal decision event); moreover, SOEKS can be stored in XML or OWL files as ontology in order to make it transportable and shareable [21].

SOEKS consists of variables, functions, constraints and rules associated in a DNA shape enabling the integration of the Decisional DNA of an organization/system. Variables normally implicate representing knowledge using an attribute-value language (i.e. by a vector of variables and values), and they are the centre root and the starting point of SOEKS. Functions represent relationships between a set of input variables and a dependent variable; besides, functions can be applied for reasoning optimal states. Constraints are another way of associations among the variables. They are restrictions of the feasible solutions, limitations of possibilities in a decision event, and factors that restrict the performance of a system. Finally, rules are relationships between a consequence and a condition linked by the statements IF-THEN-ELSE. They are conditional relationships that control the universe of variables [21].

Additionally, SOEKS is designed similarly to biological DNA at some important features. First, the combination of the four components of the SOE gives uniqueness, just as the combination of four nucleotides of DNA does. Secondly, the elements of SOEKS are connected with each other in order to imitate a gene, and each SOE can be classified, and acts like a gene in DNA. As the gene produces phenotypes, the SOE brings values of decisions according to the combined elements. Then, a decisional chromosome storing decisional "strategies" for a category is formed by a group of SOE of the same category. Finally, a diverse group of SOE chromosomes comprise what is called the Decisional DNA (DDNA) as illustrated in Figure 2 [21].

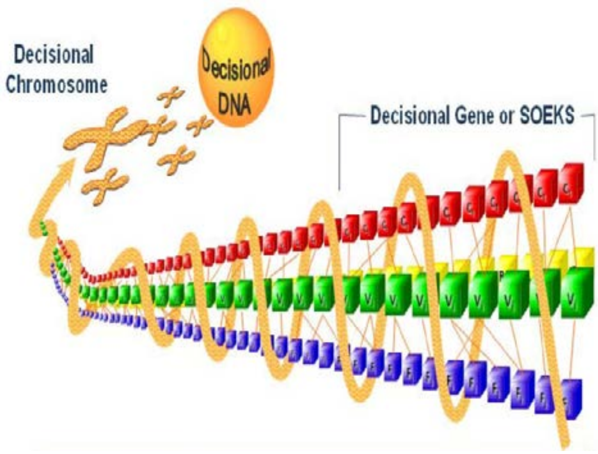

Fig. 2. Sets of Experience (Decisional Genes) are grouped according to their phenotype, creating Decisional Chromosomes, and groups of chromosomes create the Decisional DNA.

SOEKS-Decisional DNA is a general technique to capture, store and reuse the experience and the formal decisions taken in day to day activities. It can be implemented on various platforms (e.g. ontology, reflexive ontology, software based, fuzzy logic etc.) in multi domains, which makes it a universal approach. A DDNA based knowledge system will always have following advantages after its implementation:

(1) Versatility and dynamicity of the knowledge structure, which provides flexibility to change according to the situation.
(2) Storage of day-to-day explicit experience in a single structure, which makes it ever evolving.
(3) Transportability, adaptability and shareability of the knowledge.
(4) Predicting and decision making capabilities based on the collected past experience.
(5) Achieving decisional balance; having right quality and quantity of knowledge at the right time

Human experience, as a form of knowledge, is commonly suggested as a possible way to improve decision-making processes. Our extensive DDNA-based computational experiments described in [23] [24] and [25] provide strong support for similarities between this artificial system and human experience and its role in enhancing decision making processes, clarifying that DDNA model actually acts in a similar

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way as the natural human decisional making experience-based support does.

Our proposed DDNA empowers the vision of the Neural Knowledge DNA by providing smart technology for experience-based storage of information and knowledge in intelligent systems.

The concept of the neural knowledge DNA is presented next.

5. The Neural Knowledge DNA

Recent progress in deep learning has been notably improving the performance of artificial intelligence systems in the continuous control domain and high-dimensional space decision making. However, knowledge acquired in these systems is still isolated, and hard to be accessed, reused, and shared as an experience among different systems. Therefore, we propose the Neural Knowledge DNA (NK-DNA) in order to address this problem.

5.1. Concept and Features

The Neural Knowledge DNA is proposed as a framework that tailors the ideas underlying the success of neural networks to the scope of knowledge representation based on past experience. It is designed to store and represent knowledge captured in intelligent systems that uses artificial neural network as the central power of its intelligence. There are five distinctive features of this novel idea and they are presented next.

1) *Neural Network-based*:

Generally, knowledge is acquired after training in deep learning systems, which is often called the model. The model usually stores information about the hierarchy of the neural network plus weights and biases of the connections between neurons of the neural network in detail. Once the neural network is trained, giving input, the network will send back a result via the computation from the input layer to the output layer.

Similarly, our NK-DNA stores knowledge of an agent using the same idea. Figure 3 shows the concept of knowledge carried by the NK-DNA architecture.

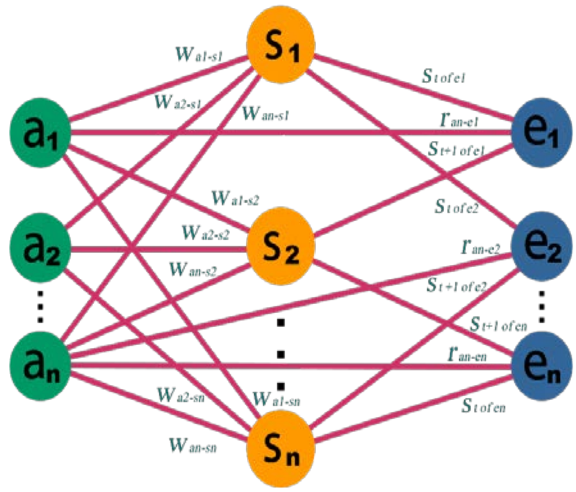

Fig. 3. Concept of the NK-DNA-carried knowledge.

In the NK-DNA, a neural network is used to carry the relation between actions and states. As illustrated in the Figure 3, each state (represented as S_1, $S_2 \ldots S_n$) can have connections with a set of actions (represented as a_1, a_2, … a_n). If an action is connected with a state, it means the connected action is an available action in that state; in other words, the agent can choose the action to perform if it is in that state.

The trained neural network provides the knowledge of which action is the best choice to a specific state. The states here are the inputs, which can be the raw sensory data, or data describing the current situation of the agent.

2) *Experience Oriented*:

Another important feature of this approach is that the NK-DNA uses previous decisional experience to collect and expand intelligence for future decision making formalized support.

Experience, as a certain form of information and knowledge gained from current and past practice, is the supreme knowledge source for learning and improving performance of agents. Usually, the agent transitions from one state to another during its operation, and it makes decisions (picks actions) in each state and receives feedbacks from its operation. These states, actions, feedbacks, and transitions make up what we call 'experience'. Inspired by the Markov Decision Processes [20], the experience of an agent is stored as $e_t = (s_t, a_t, r_t, s_{t+1})$ at each time-step t: where s_t is the current state at the time-step, a_t is the action the agent chooses at that time-step, r_t is the reward (feedback) for undertaking the action, and s_{t+1} is the transition state after the chosen action. This experi-

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ence is represented in the form of SOEKS introduced in Section 4 of this paper.

As the result, experience is collected as the main source for learning support in our NK-DNA. Basically, the experience is treated as samples for doing supervised learning. Additionally, experience in the form of SOEKS is also possible to be shared between different NK-DNA systems, which allows much larger scale of learning in the cloud (discussed in the following third feature).

3) *Sharable*:

Very similar to human society, the NK-DNA is designed to allow agents to share knowledge and experience among each other so that the knowledge and experience can be accessed and reused in a much larger scope.

Figure 4 shows the overview of the envisaged NK-DNA cloud platform. The platform integrates different agents and their tasks as illustrated in two major levels: local and global.

At the bottom of the platform (see Figure 4), there is the local level storing an agent's knowledge, while the global level is at the top storing knowledge from all NK-DNA based systems. Agents can share, download, and evolve their knowledge via this cloud platform. For more details about this concept of knowledge sharing, please refer to our previous work introducing DDNA as a knowledge sharing platform [25].

4) *Flexible*:

As stated before, machine learning is the core of artificial intelligence, which addresses the question of how to build computer systems that can automatically improve themselves through experience. However, there are many different machine learning methods and they are used for different problems. Therefore, the NK-DNA must be flexible to enable itself being used by different systems. It needs to be easily and efficiently tailored for various domain applications.

Because the NK-DNA is neural network-based, all varieties of machine learning method based on neural networks would be suitable to use it, such as normal neural networks, convolutional neural networks, recurrent neural networks, etc. To allow for this flexibility, we designed the DNA like structure holding details of the neural network in which an agent's knowledge was acquired.

Consequently, any agent can reuse another agent's knowledge as long as it has the information about another agent's neural networks.

5) *DNA like Structure*:

The NK-DNA is constructed in a similar fashion of how biological DNA is formed [28]: built up by four essential interconnected elements. As the DNA produces phenotypes, the Neural Knowledge DNA carries information and knowledge via its four fundamental elements, namely, States, Actions, Experiences, and Networks (Figure 5).

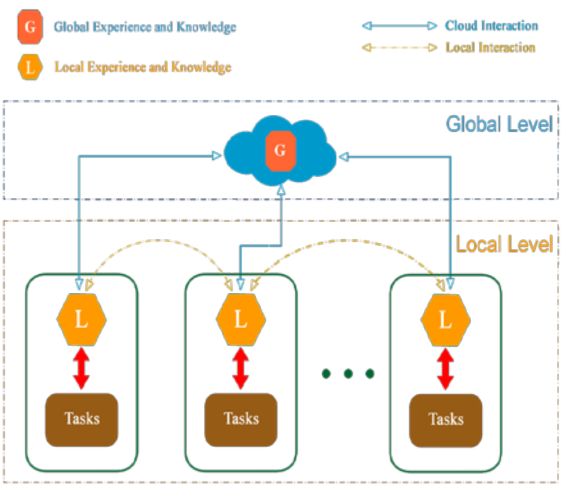

Fig. 4. Overview of the NK-DNA cloud platform.

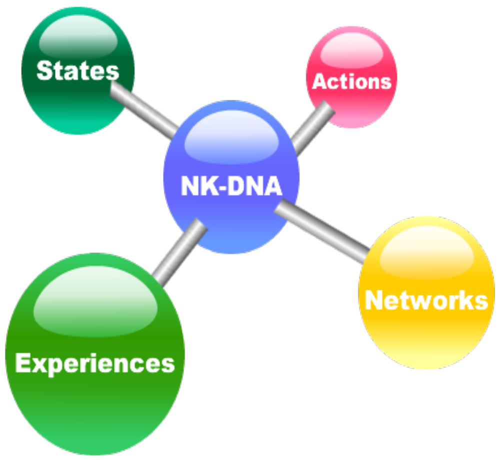

Fig. 5. Structure of the NK-DNA.

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The NK-DNA's four-element combination is able to carry detailed information of reinforcement learning and Markov Decision Processes:

1. ***States*** are situations in which a decision or a motion can be made or performed,
2. ***Actions*** are used to store the decisions or motions the domain can select,
3. ***Experiences*** are domain's historical operation segments with feedbacks from outcomes, and
4. ***Networks*** store the detail of neural networks for training and using such knowledge, like network structure, connections, weights, bias, and deep learning framework used (if a third-party deep learning framework is used, such as MxNet, Caffe, etc.).

5.2. Initial Experiment

5.2.1. Experiment Overview

We examined our NK-DNA proposed framework for solving a simple illustrative maze problem. In this initial experiment, the agent is asked to explore, learn and store the knowledge about the maze (Figure 6) by using NK-DNA. After the training, the agent is expected to find the shortest path from the initial block 1 to the final block 8 (Figure 6).

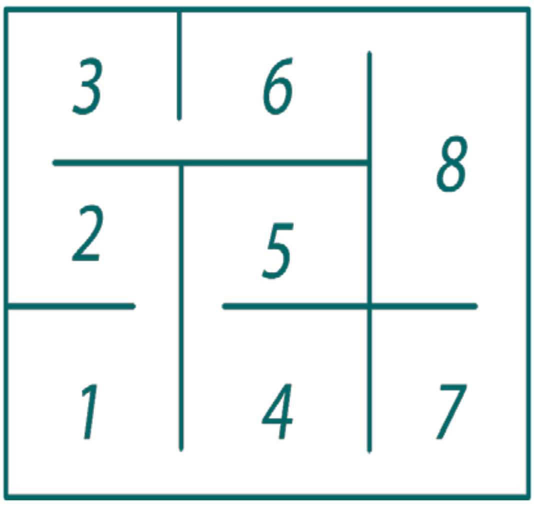

Fig. 6. The maze case study for initial experiments.

5.2.2. Methods

We consider tasks in which the agent interacts with an environment through a sequence of states, actions, and rewards.

First, the states and actions are pre-defined, for example, there are 8 states (8 blocks in Figure 6), and for state 1, the agent can either "go to block 2" or "go to block 4" (i.e. these are the actions of state 1). Then, the agent starts from state 1, and randomly picks an action of its current state to explore the maze as long as it reaches the state 8, and the agent gets a reward for reaching state 8. Meanwhile, the agent stores every single movement (i.e. from one state to another state) with reward from it as an experience (s_t, a_t, r_t, s_{t+1}) during the whole exploration process of the maze.

The goal of the agent is to select actions in a fashion that maximizes cumulative future reward. More formally, we use a neural network to approximate the optimal action-value function [17] given as

$$Q^*(s,a)= \max_{\pi} E[r_t + \gamma\, r_{t+1} + \gamma^2\, r_{t+2} + \ldots \mid s_t =s,\ a_t =a,\ \pi],$$

which is the maximum sum of rewards r_t discounted by γ at each time-step t, achievable by a behaviour policy $\pi(a|s)$, after making an observation (s) and taking an action (a). For more details about the algorithms and methods (these are well established and verified tools) that are used in this initial experiment, please refer to reference positions [12] [17].

5.2.3. Results

After exploring the maze and training the agent via the methods and approaches described above, the agent gained knowledge about the maze, and stored it in the NK-DNA as Actions, States, Experiences, and Networks.

When reusing the knowledge, the agent just sends current state to its neural network, and the neural network gives the output representing the action which the agent shall choose. In this initial case study, after training, the agent put into the current state as 'block 1', is directed by the proposed NK-DNA to go to 'block 4' as the best choice, then to choose to go to 'block 7', and finally, to go to 'block 8' (the destination) which represents the optimal (the shortest) step sequence from start to finish.

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6. Conclusions and Future Work

In this paper, we proposed the Neural Knowledge DNA, a framework adapting ideas underlying the success of neural networks to knowledge representation for neural network-based knowledge discovering, storing, reusing, improving, and sharing. By taking advantages of neural networks, set of experience knowledge structure, and reinforcement learning, the NK-DNA stores the knowledge gained through domain's daily operation, and provides an easy way for future accessing, reusing, and sharing such knowledge. After introducing the proposed concept and architecture, we tested our proposal idea in an initial experiment, and the results show that the NK-DNA remains a very promising novel approach to knowledge representation, reuse, and sharing among neural network-based AI systems.

For further work, we will continue our research as follows:

1) Refinement and further development of the neural networks engine;
2) Further design and development of the NK-DNA framework, especially, for supporting a range of third-party deep learning outlines;
3) Conceptual design and development of the cloud server for NK-DNA knowledge management.

Acknowledgement

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