# Experience-Oriented Intelligence for Internet of Things

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**Abstract.** The Internet of Things (IoT) has gained significant attention from industry as well as academia during the past decade. The main reason behind this interest is the capabilities of the IoT for seamlessly integrating classical networks and networked objects, and hence allows people to create an intelligent environment based on this powerful integration. However, how to extract useful information from data produced by IoT and facilitate standard knowledge sharing amongst different IoT systems, are still open issues to be addressed. In this paper, we propose a novel approach, the Experience-Oriented Smart Things (EOST), that utilizes deep learning and knowledge representation concept called Decisional DNA to help IoT systems acquire, represent, and store knowledge, as well as share it amid various domains where it can be required to support decisions. We demonstrate our approach in a set of experiments, in which the IoT systems use knowledge gained from past experience to make decisions and predictions. The presented initial results show that the EOST is a very promising approach for knowledge capture, representation, sharing, and reusing in IoT systems.

**Key words:** Knowledge representation, Decisional DNA, deep learning, Internet of Things.

## INTRODUCTION

During the past decade, the Internet of Things (IoT) [1][2][3] has received significant attention from industry as well as academia. The capabilities of the IoT for seamlessly integrating classical networks and networked objects [4] are the main reasons behind this interest [1][5]. The basic idea of IoT is to connect all things in our surrounding world to the Internet, and the ultimate goal of IoT is to build an intelligent environment around us, where things can communicate with each other in a manner similar to communication between humans, make decisions by themselves, and act accordingly without explicit instructions, and even know what we need, what we want, and what we like [3][5]. Furthermore, the latest great progresses on computer networks and relevant technologies make a number of new smart conceptual applications possible. Therefore, increasingly more governments, academics, researchers, and practitioners are taking part in constructing such an intelligent environment that is composed of various computing systems, such as intelligent transportation, smart health care, global supply chain logistics, smart home, or smart cities [6][7][8]. Consequently, how to extract knowledge from the data captured or generated by IoT becomes these days one of the most important emerging challenges.

The ideas presented in this paper are also relevant for the role the IoT would play in the incoming fourth industrial revolution termed Industry 4.0. Efforts are being made around the world to improve the productivity and efficiency of industries which can be achieved by integrating engineering technologies with information and communication domains. The main objective behind this integration is to reap the benefits of the unprecedented advancement in the field of information and communication technologies one of which is the concept of IoT [3] [9] [10].

This idea leads to the emergence of the new concept of Industry 4.0. It is a powerful concept which promotes the computerization of traditional plants and factories and their eco-systems towards a connected and 24/7 available resources handling scheme. The goal is the intelligent factory, which is characterized by adaptability, resource efficiency and ergonomics as well as the integration of customers and business partners in business and value processes. Industry 4.0 promotes vision of smart factories being part of a broad perception of smart cities, and is based on the technological concepts of Cyber-Physical Systems (CPS) and Internet of Things (IoT) [10][11][12].

CPSs refer to the next generation of engineering systems that require tight integration of computing, communication and control technologies to achieve stability, performance, reliability, robustness and efficiency in dealing with physical systems of many application domains [10] [13] [14]

Knowledge engineering based IoT plays an important role in the Cyber-physical systems as there is a need for a unified framework to represent the myriad types of data and application contexts in different domains and interpret them under the appropriate context [15][16]. These issues are becoming increasingly important not only to physical domains but also to a countless challenges related to social systems and services [17][18][19].

To address some of the above mentioned issues and challenges, we propose in this paper a novel concept supporting sustainable IoT growth and development, the Experience-Oriented Smart Things (EOST). It combines knowledge and experience representation thorough Decisional DNA with deep learning in order to help IoT systems acquire, represent, and share knowledge in a standard way, so that the acquired knowledge can be distributed and reused amongst different IoT systems.

## KNOWLEDGE, EXPERIENCE, AND MACHINE LEARNING

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. The Oxford Dictionary defines Knowledge as "facts, information, and skills acquired through experience or education; the theoretical or practical understanding of a subject"[20]. While 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"[21]. Knowledge is not a real knowledge until the information inside itself has been engaged and used by people [22].

If knowledge is to be used in IoT it must be represented. Consequently, knowledge representation is a fundamental field dedicated to representing information about the world in a form that computer systems can utilize to solve complex tasks [3] [23]. It is the study of thinking as a computational process. Knowledge representation and reasoning, therefore, is the field of Artificial Intelligence (AI) that is mainly focused on how an agent makes decisions based on what it knows.

***Experience, its acquisition, and experience modelling techniques***

Knowledge is most often based on experience. Experience, as a general concept, comprises previous knowledge or a skill obtained through daily life [24][25]. Usually experience is understood as a type of knowledge that one has gained from practice rather than books, research, and studies [26]. In this way, experience or experiential knowledge can be regarded as a specialization of knowledge that includes information and strategies obtained from performing previous tasks. When these tasks involve making decisions, the specific experience that is gained is called decisional experience.

The importance of decisional experience in knowledge engineering, and especially in knowledge sharing, has been recognised for at least last ten years. Studies reported in [27] have established that the primary research aim of knowledge management (KM) should be to use the vast experience that is accumulating each day within organisations and systems, as true knowledge is developed through learning from current and past experiences [25][28][29]. Experience management (EM), its formalization, representation, and experience based systems development is capturing increasingly growing attention of researchers and practitioners. However, the related problems and their solutions do not appear to have progressed too far. The fundamental limitation of current research in this area is that none of the proposed approaches uses experience as ongoing, real time reference during the decisional process in a way similar to what happens naturally when humans make decisions if confronted with a new situation. We challenge the existing techniques used to model experience such as case base reasoning [30][31], decision trees [32], petri nets [33][34] and many others with the proposition that all of them lack the same critical element in assuring progress and useful real life implementations – they don't store and reuse experience in an ongoing, real-time representation system that can provide the following, crucial for useful decision support end user applications, features [25]:

- Adaptability and cross-platform portability,
- Compactness and efficiency,
- Configurability and shareability,
- Security and trust, and
- Being exclusively experience dedicated and oriented.

Artificial bio-inspired intelligent techniques and systems supporting smart, knowledge-based solutions of real world problems which are currently researched very extensively by research teams around the world, have enormous potential to enhance automation of decision making and problem solving for a number of diverse areas, including clinical diagnosis. Bio-inspired ideas and implementations have a long history starting with Chinese effort to develop artificial silk some 3000 years ago, later inspiring Leonardo da Vinci's flying machines, and recently enhancing our everyday lives with Velcro and Gecko tapes, improving drag and friction on Airbus airplane wings by following design principles based on humpback whales flipper and skin of the shark, applying lotus effect to develop self-cleaning surfaces, pine cone effect to manufacture smart fabrics, and amoeba based network design [25][35][36][37]. All these popular real life implementations represent successful biomimetic applications. Nature is full of excellent examples of design and smart organizational/management approaches that produce outstanding results in highly complex situations. The main problem is that most often we simply do not understand how this happens.

The proposed experience acquisition and modelling inspiration stands in the role of deoxyribonucleic acid (DNA) in storing and sharing information and knowledge. In nature DNA contains "...the genetic instructions used in the development and functioning of all known living organisms. The main role of DNA molecules is the long-term storage of information. DNA is often compared to a set of blueprints and the DNA segments that carry this genetic information are called genes." [38]. The idea behind our approach is an artificial system, an architecture that would support discovering, adding, storing, improving and sharing information and knowledge among agents, machines, and organisations through experience. We introduce a novel Knowledge Representation (KR) approach in which experiential knowledge is represented by Set of Experience (SOE), and is carried into the future by Decisional DNA (DDNA) [25][39][40] (see Figure 1).

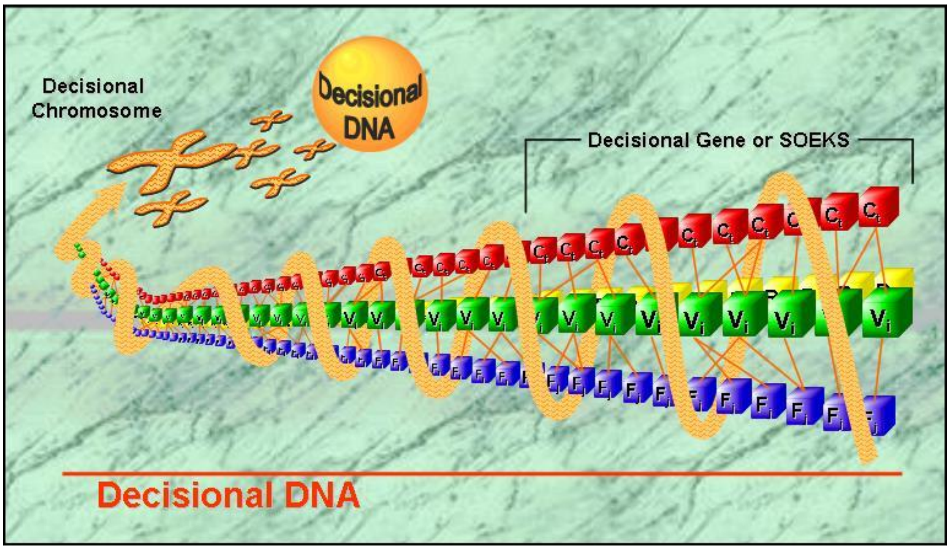


Figure 1. SOE is combination of four components that characterize decision making actions (variables, functions, constraints, and rules) and it comprises a series of mathematical concepts (a logical component), together with a set of rules (a ruled based component), and it is built upon a specific event of decision-making (a frame component); Sets of Experience (Decisional Genes) are grouped according to their phenotype creating Decisional Chromosomes and groups of chromosomes create the Decisional DNA

We initially developed the concept and coined the expressions of "Set of Experience - SOE" and "Decisional DNA - DDNA" in 2006-2007 [41-44], Since then our research efforts resulted in widespread recognition of this innovative KR concept based on DNA metaphor that lately was presented as multi-technology shareable knowledge structure for decisional experience with proven portability, adaptability, shareability, security, and trust in [25] [45].

In our proposed EOST, we use SOEKS to formalize experience. SOEKS, as a flexible, independent, and standard knowledge structure, not only captures and stores formal decision events as experience, but can also be easily applied to various domains to support decision-making and standard knowledge sharing [46]. SOEKS components that are used in EOST most often (variables and rules) are presented next.

Variables formally describe experience-based knowledge structure using an attribute-value language [25][42][46]. This is a well-established measure from the foundation of knowledge representation and is the starting point for SOEKS development and composition. Variables are the center root of the SOE structure and they are the major composition source of the other SOE components.

Rules are used to express logical relationships among variables. They are suitable for representing inferences or for associating actions with conditions under which actions should be performed [46]. Each single rule describes a relationship between a condition and a consequence linked by the statements IF-THEN-ELSE [25][47]. Figure 2 illustrates rules as the compound of multiple classes [25]. A rule is composed of four elements: joints, consequences, confidence, and weight. Joint could be presented more than once and it contains jnt (i.e., AND/OR) and conditions. Each condition comprises factors, sym (≥, ≤, >, =, <), value, and variable. A factor is a composition of parenthesis (lpar, rpar), operator (oper), coefficient (coef), potency (poten) and variables. Figure 3 depicts the structure of a factor with an illustrative and simple example [25]. Consequence (one or many) are comprised by two variables, symbol, and value. If all conditions are satisfied, the first variable of a consequence equals the value; otherwise it is the second variable. The weight provides the level of importance related to the given rule.

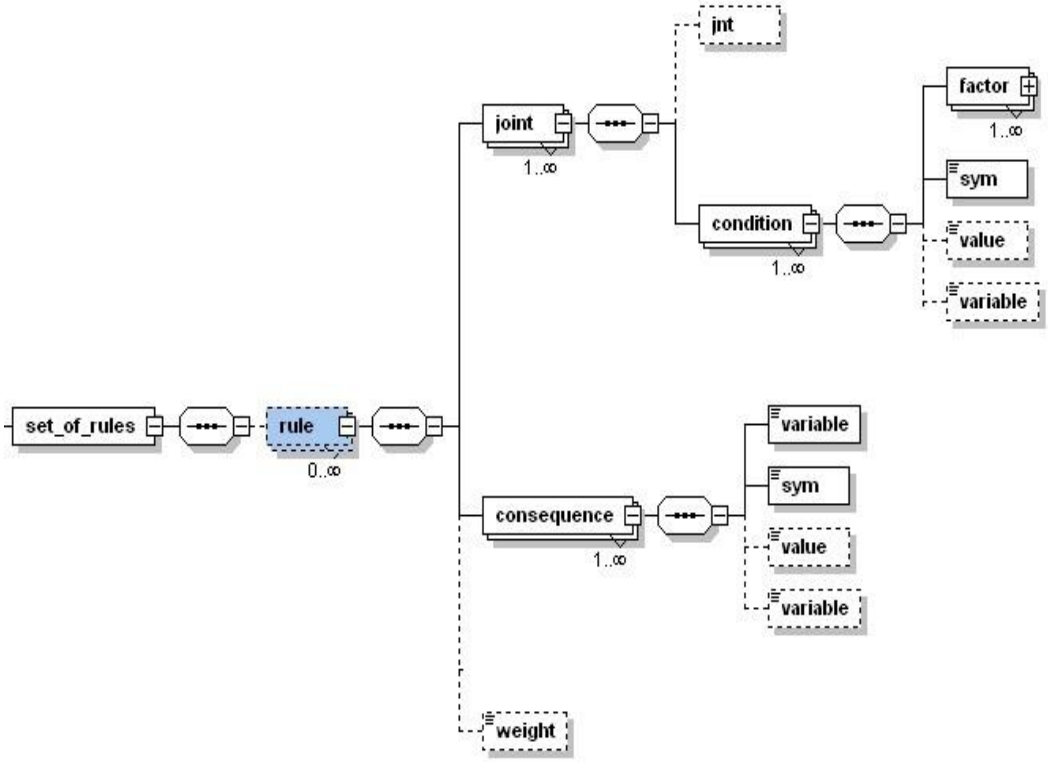


Figure 2. Structure of Rule SOEKS Classes

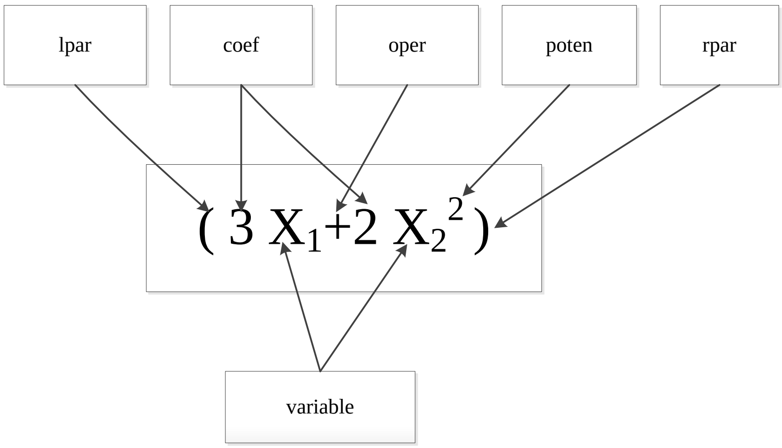


Figure 3. Structure of each factor with example

Functions and constraints are another two elements of standard SOEKS structure that provide further enhancement options of the proposed EOST system. Functions represent relationships between a set of input variables and a dependent variable; besides, functions can be applied for reasoning about optimal states of a studied system. 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.

***Artificial Neural Networks and Deep Learning***

Machine learning, as the core of artificial intelligence, addresses the question of how to build computer systems that can automatically improve themselves through experience [48]. It is one of today's most rapidly growing technical fields. Recent progress in machine learning has been driven by the development of new theories and learning algorithms, such as the Artificial Neural Networks (ANN).

ANN is a biologically-inspired programming paradigm which enables a computer to learn from observational data [49]. 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 [48].

Deep learning is a powerful set of techniques for learning in ANN [49]. It allows computational models that are composed of multiple processing layers to learn representations of data with multiple levels of abstraction [50]. Deep learning learns sophisticated structure in large data sets by using the backpropagation algorithm [51] 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 [48][49][50][52]. 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 [50]. 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 [48] [53].

## KNOWLEDGE DISCOVERY ON IoT

### *Data from IoT*

Basically, every single thing of IoT might produce data containing various kinds of information. According to [54], data produced by IoT can be divided into two classes: the data about things and the data generated by things. The data about things usually contain information that can be used to improve the performance of IoT. The data generated by things carry information on operations and interaction with humans. In recent years, the total amount of data produced worldwide every year has exceeded one zettabyte [3], and the data generated by IoT per day has increased fast beyond the limits of available data processing tools today. Hence the term “big data” was introduced to describe this data-deluge situation [55]. Although a range of traditional tools [56] can be used to solve or ease the issues of handling the big data problem, such as data condensation [57], divide and conquer [58], incremental learning, and random sampling [59], these tools are generally not powerful enough to deal with such amounts of data as produced by IoT [48][60][61].

Consequently, a number of research proposals and attempts to address the big data problem have been made. Among them, a new approach to solve the big data problem is to reduce the complexity of input data [62][63][64]. Distributed computing, feature selection, and cloud computing are some other promising directions for dealing with this issue [6][65][66].

### *Knowledge-based IoT Systems*

Using the powerful features of the IoT, classical networks and networked objects can be integrated. The new challenge related to this integration can be formulated as follows: how do we extract knowledge and valuable information from the data captured and generated by IoT to enhance the intelligence of the fully interconnected world of things? Some attempts to progress in this direction are known from the literature [48]. López et al. [67] proposed an architecture that integrates fundamental technologies for realizing the IoT into a single platform and examined them. The architecture introduces the use of the Smart Object framework [68][69] to encapsulate sensor technologies, radio-frequency identification (RFID), object ad-hoc networking, embedded object logic, and Internet-based information infrastructure. They evaluated the architecture against a number of energy-based performance measures, and showed that their work outperforms existing industry standards in metrics such as delivery ratio, network throughput, or routing distance. Finally, a prototype implementation for the real-time monitoring of goods flowing through a supply chain was presented in detail to demonstrate the feasibility and flexibility of the architecture. Key observations showed that the proposed architecture had good performance in terms of scalability, network lifetime, and overhead, as well as producing low latencies in the various processes of the network operation. Li et al. [70] introduced the Smart Community as a new Internet of Things application, which used wireless communications and networking technologies to enable networked smart homes and various useful and promising services in a local community environment. The Smart Community Architecture (SCA) was defined in their paper, then solutions for robust and secure networking among different homes were presented with two smart community applications, Neighborhood Watch and Pervasive Healthcare. In [71], a cognitive management framework that empowers the Internet of Things to better support sustainable Smart City development was presented. The framework introduced the virtual object (VO) concept as a dynamic virtual representation of objects and proposed the Composite VO (CVO) concept as a means to automatically aggregate VOs in order to meet users' requirements in a resilient way. In addition, it illustrated the envisaged role of service-level functionality needed to achieve the necessary compliance between applications and VOs/CVOs, while hiding complexity from end users. The envisioned cognition at each level and the use of proximity were described in detail, while some of these aspects are instantiated by the means of building blocks. A case study, which presented how the framework could be useful in a Smart City scenario that horizontally spans several application domains, was also described. In [72], Lee et al. applied human learning principles to user-centered IoT systems. This work showed that IoT systems could benefit from a process model based on principles derived from the psychology and neuroscience of human behavior that emulates how humans acquire task knowledge and learn to adapt to changing context.

According to the survey presented in [3][48], after a comprehensive comparison of different data mining technologies and their applications for IoT related data mining, a promising direction was formulated that recommends using knowledge discovery technologies to make IoT smarter and more intelligent. In our approach, we propose to combine deep learning and the Decisional DNA to enhance the intelligence of IoT systems [48][66].

## THE EXPERIENCE ORIENTED SMART THINGS (EOST)

By utilizing deep learning and the Decisional DNA, experiential knowledge can be extracted from practical processes such as problem solving and decision-making, and represented in an explicit and standard way enabling knowledge sharing and reusing for different IoT systems. The Experience-Oriented Smart Things (EOST) approach is proposed as the intelligence engine for IoT systems [66]. This section presents the main features, architecture, and initial experiments of this approach.

### *Main Features of the EOST*

The EOST is proposed and designed to allow experience-oriented knowledge acquisition, representation, reusing, and sharing for IoT systems [48][66]. In order to achieve these aims, the EOST embraces the following features:

*a) Experience-oriented*: one of the ways to deal with the big data issue is to capture only the relevant data instead of all data. Experience, as one kind of knowledge learned from practice, is the ideal source for improving the efficiency of knowledge acquisition. By mimicking natural learning from experience, the EOST abstracts experiences from past data capture and uses this experience to select relevant data.

*b) Cloud-based*: the EOST is designed as an open platform for all things. To allow that, cloud computing and open Application Program Interface (API) are important characteristics of this approach. Besides, cloud computing can also allow universal knowledge sharing and exchange amongst various IoT systems.

*c) Self-learning*: the EOST is designed to learn automatically from data of things so that it can help IoT systems achieve better performance, smarter behavior, and operational efficiency. Early AI systems are based on expert knowledge, which is not universal [73]. Therefore, the EOST uses deep learning to address this matter due to its universality for all learning tasks [50].

*d) Compatible*: the EOST is expected to work with different domains, and process data from various IoT systems. Since most IoT are customized, the hardware and software for each of them could be distinctly different; thus, compatibility is essential for the EOST.

***System Architecture***

The proposed EOST consists of Prognoser, Knowledge Repository, and Deep Learning Engine [48] [66]. The Prognoser is the control center of the EOST. It is in charge of experience capturing, knowledge abstraction, knowledge creating, knowledge retrieval, and knowledge reusing. For experience capturing, the Prognoser catches the scenario information when a decisional event occurres, and sends it to the Knowledge Repository for store. The Prognoser abstracts knowledge based on captured experience by utilizing the Deep Learning Engine. Finally, it creates experience-based knowledge and sends this knowledge to Knowledge Repository for storing. To support decision-making, it retrieves and reuses the knowledge that is stored [48][66].

The Deep Learning Engine runs deep learning algorithms, abstracts knowledge from experience, and reuses abstracted knowledge. Deep learning allows computational models that are composed of multiple processing layers to learn representations of data with multiple levels of abstraction, and it can automatically discover the representations of input data for detection or classification. By using deep learning, knowledge can be abstracted from sets of experience, and stored as Decisional DNA [48][66]. For knowledge reuse, the Deep Learning Engine loads the Decisional DNA, re-construct the deep learning network, and gives predictions according to learnt knowledge.

The Knowledge Repository stores and manages the EOST's experience and knowledge. In the EOST, a single decision event is captured and represented as an experience, stored as one Set of Experience (SOE), and a set of SOE are organized as the Decisional DNA carrying the decisional fingerprint of the EOST. The Knowledge Repository provides functionality of query, store, insertion, editing and deletion of experience and knowledge [48][66].

***Initial Experiments***

In order to initially examine our concept, we tested various elements of the proposed EOST approach in a set of experiments by using different data and different problems. These experiments are presented next.

***The IoT Bike Scenario***

In the first experiment, we designed an application which was a sensor-equipped IoT bicycle [48][66]. By using the Bluetooth wireless communication technology, the bicycle sends sensor data to the smart phone APP; afterwards, these data is sent to the EOST via the Internet for knowledge discovery. Finally, the EOST sends suggestions back to assist the bicycle user in their decision making.

The main hardware components of the bicycle consist of a NXP LPC1769 board, a HC-06 Bluetooth module, and two MD-PS002 pressure sensors. The NXP LPC1769 is an ARM 32-bit Cortex-M3 Microcontroller with MPU, CPU clock up to 120MHz, 64kB RAM, 512kB on-chip Flash ROM with enhanced Flash Memory Accelerator. It supports In-Application Programming (IAP) and In-System Programming (ISP), has eight channel general purpose DMA controller, nested vectored interrupt controller, AHB Matrix, APB, Ethernet 10/100 MAC with RMII interface and dedicated DMA, USB 2.0 full-speed Device controller and Host/OTG controller with DMA, CAN 2.0B with two channels, four UARTs, one with full modem interface, three I2C serial interfaces, three SPI/SSP serial interfaces, I2S interface, General purpose I/O pins, 12-bit ADC with 8 channels, 10-bit DAC, and four 32-bit timers with capture/compare. The NXP LPC1769 board is easy to use, uses low power, and easily handles different peripherals and sensors working together. Through the HC-06 Bluetooth module, the board is able to communicate with other devices, such as a smart phone, so that the captured data can be sent for further processing [48][66].

In terms of the adaptability examination of Decisional DNA in this experiment, we converted the file format of SOEKS from XML to plain text so that the captured data can be organized and stored on the NXP LPC1769 board. Whenever bicycle was in use, pressure sensors collected the two tires' real-time tire pressure. Besides the pressure, date and time are captured as well and they are collected for future use, such as learning the riding routine of a given user [48][66].

By organizing and sending captured data to the APP running on an Android phone via Bluetooth connection, tire pressure information was collected. Then, the APP sends the information to the EOST, and the EOST stores it as experience base on the principals of Decisional DNA. Finally, the EOST analyzes experiences and extracts knowledge from them. In this initial experiment, we introduced the FarthestFirst [74] algorithm to help learn the user's normal weight distribution based on tire pressure information, and eventually to use it to distinguish its current user from other riders (i.e. user clustering). We collected tire pressures when the user was riding in order to train the system. After training we changed the rider, and the bicycle was able to detect the change from the tire pressure differences. Figure 4 shows the result of the user clustering in Weka [75] by using real-time data of tire pressures. The system clusters the riders correctly; the Cluster 1 (marked as cross) stands for the current user, and the other riders are clustered as the Cluster 2 (marked as solid dot) [48][66].

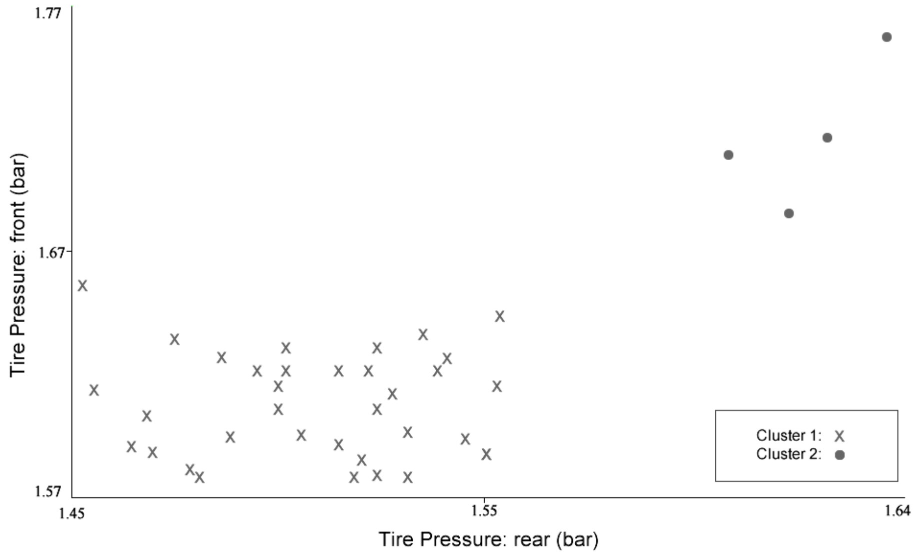


Figure 4. The result of the user clustering on EOST

As we can see from this initial experiment, by using the Decisional DNA and some machine learning algorithms, for example, the FarthestFirst algorithm in this case, we created The EOST knowledge-based platform for IoT. Through its open API, this IoT application connects to EOST platform, and illustrates how smart services of EOST can be accessed.

***Testing Deep Learning ability to predict in various IoT data scenarios***

Data from IoT systems may be isolated from each other and come from different devices, for example, we usually connect body temperature, pulse, daily walking steps, and so on to someone's health condition, but these health-related data might be taken from a thermometer, a smart watch, or a smart phone respectively. So, the question is how can we get the big picture of a set of data that consist of data produced by different things dedicated to a particular purpose? The ideal algorithms should be able to learn the features of problems, find out hidden connections and patterns, and extract knowledge from data automatically. In order to test whether the deep learning meets this requirement, a prediction problem is picked for illustration [48][66].

The prediction is about whether a horse with colic would live or die giving 28 attributes describing the health-related information of the horse, such as rectal temperature, pulse, age, etc. There are 368 instances in this experimental dataset [76]. Apart from deep learning, other two machine learning algorithms, namely logistic regression and AdaBoost [77], are chosen to perform the examination. First, 300 instances were used for training, and the rest 68 instances are used for testing. The results showed that the deep learning outperformes logistic regression and AdaBoost in the experimental settings. In the next step of our test, we changed the sizes of the training dataset and test dataset respectively. After this change the deep learning always predicts better than other techniques, even when the training dataset is small and the test dataset is large. It confirms the adaptability and applicability of deep learning algorithm to work with various data sets as required for IoT. The above experiments are mentioned here for the sake of completeness, for more detailed discussion please refer to [48][66])

***Self-evolving with Experience***

Another important feature of this approach is that the EOST collects previous decisional experience and reuses such experience to expand intelligence and improve future decision making. In this experiment, an agent is asked to learn from its experience of exploring a maze, extract knowledge of the maze solving process, and finally reuse extracted knowledge to make proper decisions to move in the maze. There are eight blocks in the maze as shown in Figure 5. At the beginning, the agent knows nothing about the maze, and it is trying to explore and lean the maze by taking four possible actions: going up, going down, going left, and going right. At each block, the agent can take one of the four possible actions. In the end, the agent is expected to know the maze, and able to show us the shortest way to get to the block 8.

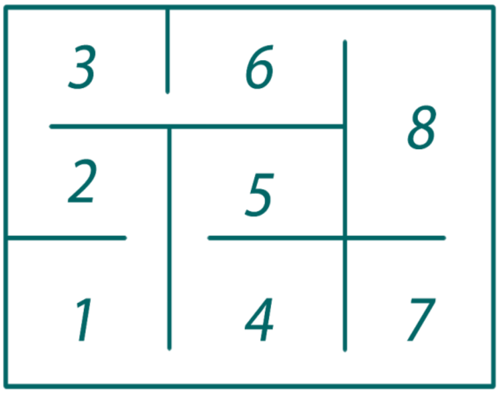


Figure 5. The maze used in the experiment

During the exploration, the agent transitions from one state to another and it makes decisions/actions (i.e. going up/down/left/right) in each state and receives feedback from its operations. These states, actions, feedbacks, and transition make the agent's 'experience'. Inspired by the Markov Processes [78], 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, at 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 next state after the chosen action. The agent starts always from *block 1*, repeats random taking of possible actions until it reaches the *block 8*. Meanwhile, the agent stores every single action taken with feedback from the maze as an SOE during its exploring of the maze. In this experiment, we let the agent randomly take 1000 possible actions for exploration.

The training starts after the exploration. To solve the maze learning problem, i.e. finding shortest way to get to the *block 8*, the agent needs to remember how blocks are connected to each other so that it can make better decisions to reach the final block. In other words, the goal of the agent is to select actions in a fashion that maximizes cumulative future reward. In our case, the deep reinforcement learning [79] is applied to help the agent to learn the maze. More formally, we use a neural network to approximate the optimal action-value function [80]:

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

which is the maximum sum of rewards $r_t$ discounted by $\gamma$ at each time-step *t*, achievable by a behaviour policy $\pi(a|s)$, after making an observation (s) and taking an action (a).

Finally, we examined the agent by sending seven possible states one by one to the agent's neural network, and checked the outputs representing the actions what the agent should choose in certain states respectively. Figure 6 shows the screenshot of the examination results.

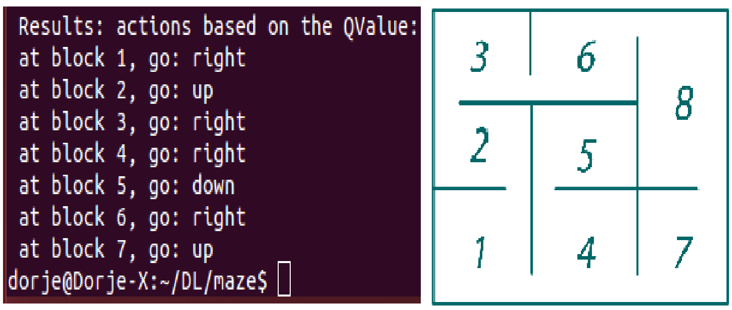


Figure 6. Screenshot of examination results (left) and the experimental maze (right).

As we can see from Figure 6, the experimental agent can not only tell us what is the shortest way to get to block 8 from block 1 (go right at block 1 to get block 4, and then go right again at block 4 to get block 7, then go up to get block 8) but it also knows how to get to block 8 from different blocks, for example, if it is at 'block 2', it knows that it shall 'go up' first.

## CONCLUSIONS AND FUTURE WORK

In this paper, we propose the Experience-Oriented Smart Things (EOST) that utilizes deep learning and Decisional DNA to help IoT systems acquire, represent, store, and share knowledge. We demonstrate our approach in a set of experiments, in which various IoT systems use knowledge gained from past experiences to make decisions and predictions. The results show that the EOST is a very promising approach for knowledge and experience management and engineering within a variety of IoT systems. By seizing advantages of neural networks, reinforcement learning, and the Decisional DNA, the EOST can store knowledge absorbed through its domain's daily operation, and provides an easy way for future knowledge sharing and reusing. .

The future work includes:

1) refinement and further development of the deep learning neural networks engine,

2) further design and development of the EOST framework, especially for supporting a range of third-party deep learning contexts;

3) design and development of the cloud platform dedicated for EOST knowledge management.

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