# Adding Intelligence to Cars using the Neural Knowledge DNA

Haoxi Zhang [1], Fei Li [1], Juan Wang [1], Zuli Wang [1], Lei Shi [1], Jun Zhao [1], Cesar Sanin [2], Edward Szczerbicki [3],

[1] Chengdu University of Information Technology, Chengdu, China

[2] The University of Newcastle, NSW, Australia

[3] Gdansk University of Technology, Gdansk, Poland

**Abstract.** In this paper we propose a Neural Knowledge DNA based framework that is capable of learning from the car's daily operation. The Neural Knowledge DNA is a novel knowledge representation and reasoning approach designed to support discovering, storing, reusing, improving, and sharing knowledge among machines and computing devices. We examine our framework for drivers' classification based on their driving behaviour. The experimental data is collected via smart-phone sensors. The initial results are presented and the direction for our future research is defined.

**Keywords:** Neural Networks, Decisional DNA, Set of Experience Knowledge Structure, Knowledge Representation, Deep Learning.

---

Address correspondence to Haoxi Zhang, Chengdu University of Information Technology, No. 24 Block 1, Xuefu Road, Chengdu, China. E-mail: haoxi@cuit.edu.cn

## INTRODUCTION

Thanks to the advances in sensors, controls, communications, and chip technologies, the perception of cars has been changed dramatically: cars now are engaging with powerful computing units that gather information about cars themselves and the environment, and feed the information back to cars and the drivers. The cars are becoming the indispensable extension of people's daily life, not only providing mobility to the people, but also enabling new smart and convenient services, such as safe navigation, traffic management, entertainment, and Internet connection.

Consequently, the Internet of Autonomous Vehicles shall be the next step in this evolution. Pioneered by the Google Car, the Internet of Vehicles will be a distributed transport fabric capable of making its own decisions about driving passengers to their destinations (Gerla et al. 2014). Like other important applications of the Internet of Things (e.g. the smart building or smart city), the Internet of Vehicles will have communications, storage, and most importantly, intelligence, and learning capabilities to anticipate intentions of the drivers and even making decisions for the drivers (Amadeo et al. 2016). Our proposed Neural Knowledge DNA will help with transition to the Internet of Autonomous Vehicles, especially in knowledge extraction, representation, sharing, and reusing, as well as smart decision making. In this paper, we offer the Neu-Car framework based on the Neural Knowledge DNA in order to enable intelligent functionalities for modern cars.

## THE NEURAL KNOWLEDGE DNA

The Neural Knowledge DNA (NK-DNA) is proposed to store and represent knowledge captured in intelligent systems that uses artificial neural networks (Michael 2015) as the central power of its intelligence. It utilises the ideas underlying the success of deep learning (LeCun et al. 2015) to the scope of knowledge representation (Zhang et al. 2016).

The NK-DNA is constructed in a similar fashion of how DNA is formed (Sinden 1994): built up by four essential elements. As the DNA produces phenotypes, the Neural Knowledge DNA carries information and knowledge via its four essential elements, namely, States, Actions, Experiences, and Networks (see Figure 1).

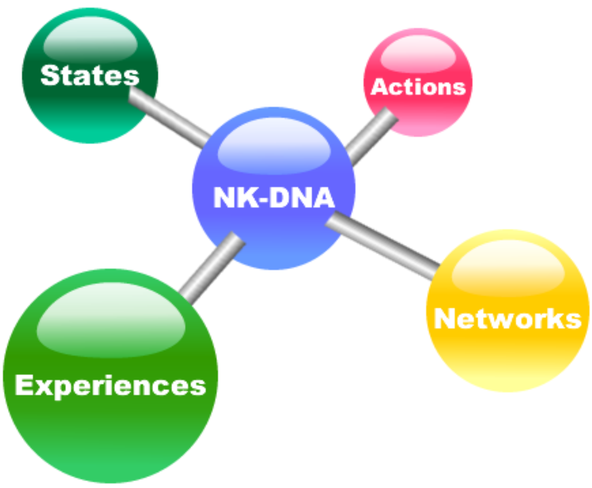


Fig. 1. Conceptual structure of the NK-DNA.

The NK-DNA's four-element combination is designed to carry detailed information related to particular decisions. In Figure 1 *States* are situations in which a decision or a motion can be made or performed; *Actions* are used to store the decisions or motions the domain can select; *Experiences* are domain’s historical operation segments with feedbacks from the outcomes; nd *Networks* store the class of neural networks used for training, such as the network structure, weights, bias, and deep learning framework employed (e.g. TensorFlow).

Generally, knowledge is acquired as models developed after training in deep learning systems. The model usually stores information about weights and biases of the connections between neurons of the neural network, and the hierarchy of the neural network in detail. Once the neural network has been trained, the network will provide results straightforward through the computation of its network layers after feeding it with inputs. Similarly, our NK-DNA stores knowledge using the same idea. Figure 2 illustrates the concept of knowledge carried by the NK-DNA.

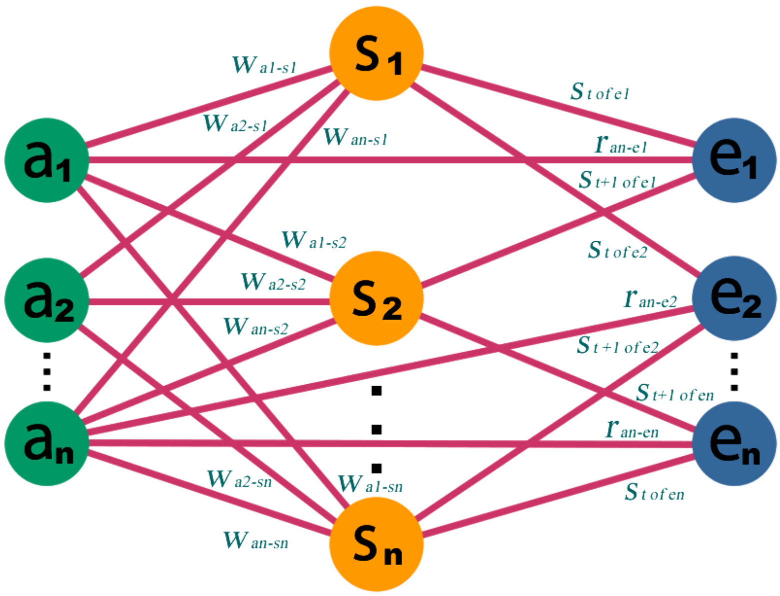


Fig. 2. Concept of the NK-DNA-carried knowledge.

In the NK-DNA, a neural network is used to carry the relation between actions and states: as it can be seen in the Figure 2, each state (represented as $S_1$, $S_2$ … $S_n$) 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.

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 one kind of information gained from practice, is the ideal source for learning and improving performance of agents. Usually, the agent transitions from one state to another during its operation, and it makes decisions (selects actions) in each state and receives feedbacks from its operation; these states, actions, feedbacks, and transitions makes up the called 'experience'. Inspired by the Markov Decision Processes (Puterman 1994), 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.

Most importantly, the *Experiences* are collected as the main source for learning in our NK-DNA. And the *Experiences* are treated as samples for doing supervised learning. The *Experiences* are organized as the Set of Experience Knowledge Structure (SOEKS) (Sanin & Szczerbicki 2006, 2007, Sanin et al 2012, ) in our NK-DNA.

## THE NEU-CAR FRAMEWORK

Modern vehicles contain hundreds or even thousands of sensors (Sheen et al. 1995), measuring everything from fuel level to the current slope of the road. These sensors are often used to help cars adapt to the current driving environment (i.e. intervening the brake system to prevent the wheels from locking up and avoiding uncontrolled skidding, or turning on the lights when it is dark). However, cars can be made much smarter based on these sensors. In this section, we introduce the Neu-Car Framework designed to enable knowledge acquiring, representation, reusing, sharing, and smart decision making of vehicles. The Neural Knowledge DNA (NK-DNA) framework is composed of four main components, namely: Prognoser, Neural Knowledge DNA Manager, Knowledge Repository, and Neural Network Engine (see Figure 3).

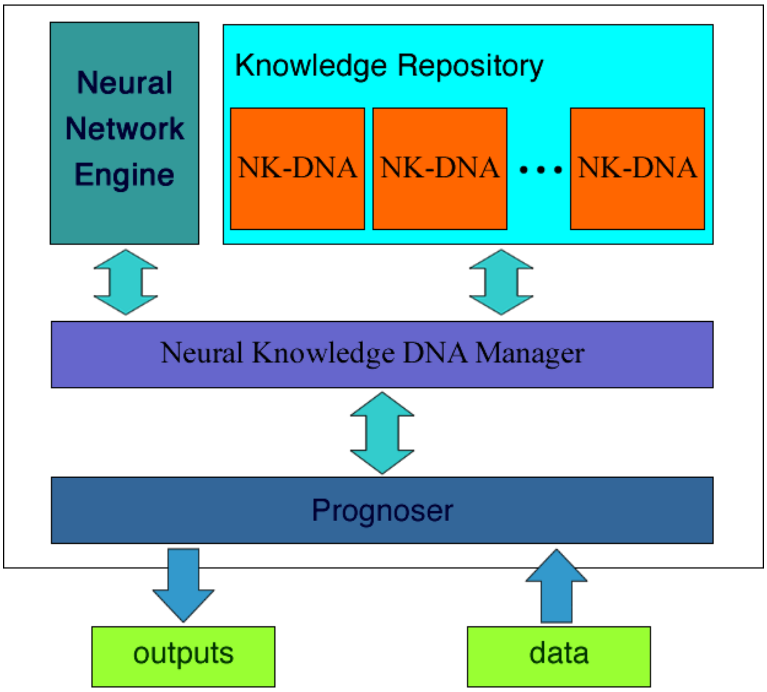


Fig. 3. Architecture of the NK-Car framework.

The Prognoser is in charge of analysing the input data, and cooperate with the Neural Knowledge DNA Manager. There are two kinds of input data: commands and car operation data. The commands are sent orders so that the Neu-Car knows what outputs the car expects, while the car operation data are collected information for generating NK-DNA.

The Neural Knowledge DNA Manager operates according to data received from the Prognoser and some configurations of the system, for example, how often it updates the Knowledge Repository. If the data are commands, the Neural Knowledge DNA Manager will search for matched NK-DNA, and launch neural networks via Neural Network Engine according to information stored in the NK-DNA, and send results of the neural network as outputs. However, if the data are not commands, the Neural Knowledge DNA Manager saves them as the Experiences, and starts learning process based on pre-set schedule. The new obtained knowledge will be stored as NK-DNA in the Knowledge Repository for future use.

The Knowledge Repository is where the NK-DNA knowledge is generated, stored, and managed. And the Neural Network Engine is the central power of knowledge processing: it is where knowledge discovery is happening and where knowledge is reused. The Neural Network Engine is a set of neural network software and libraries; it creates neural networks according to different tasks, and saves acquired knowledge and information of the neural networks used in feeding such knowledge into NK-DNA so that it can re-launch the neural networks to use the acquired knowledge in the future.

## INITIAL CASE STUDY

As automotive electronics continue to advance, cars can potentially have more cutting-edge capabilities, like intelligence: uncover patterns (Sathyanarayana et al. 2012), understand different driving styles (Vaitkus et al. 2014; Ly et al. 2013), and even detect distracted or impaired drivers (Jo et al. 2014). To help with these applications and develop the Internet of Autonomous Vehicles, it is crucial to be able to discover who is currently behind the wheel. In this case study, we model such driving behaviours as pedal and turning operation patterns.

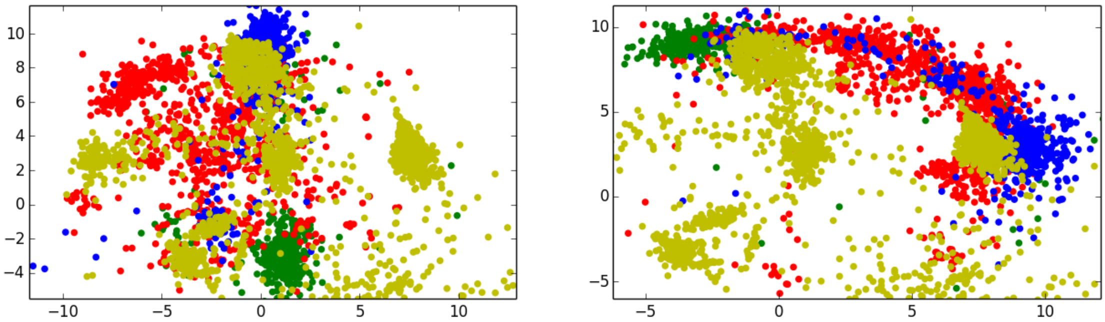


Fig. 4 Driver's pedal and turning operation data collected through smart phone's three-axis accelerometer. Four drivers' data are marked in four different colours: the data from x-axis and y-axis (left), and the data from y-axis and z-axis (right).

Everyone drives differently, and the aim is to leverage these differences to find a unique "signature" for each driver, which can be anything from how hard the driver hits pedals to small micro-adjustments in the steering wheel angle when turning. In this initial case study, we use the smart phone's three-axis accelerometer to collect driver's pedal and turning operation. There are four volunteers who take part in our initial case study as drivers. We developed an APP particularly for collecting the accelerometer data, which reads the accelerometer every 5 seconds. The drivers use the APP to help collect their drive operation data whenever they want in their daily driving. The Figure 4 illustrates the three-axis accelerometer data collected from four drivers.

The driver models are evaluated in driver identification experiments using the collected data. First, a 4-layer fully-connected neural network is created to learn the driver pattern with 1000 data points that are half from the driver and half from the others (randomly picked). Then, the evaluation dataset with 100 data points are used to examine our approach. The evaluation dataset also consists in half from the driver and another half from the others (randomly picked). In evaluation of the experimental data , the Neu-Car approach achieves the accuracy of 0.92 in driver identification tasks. The Experimental results show that our Neu-Car approach can learn driver pattern efficiently even if based on small amount of three-axis accelerometer data and provides a high accuracy in driver identification process.

## CONCLUSIONS AND FUTURE WORK

In this paper we introduced the Neu-Car, a framework utilising the Neural Knowledge DNA and the SOEKS for providing intelligence to modern cars. By taking advantages of NK-DNA, deep learning, and the SOEKS technologies, the Neu-Car enables vehicles of experiential knowledge discovery, representation, reuse, and sharing. We examine our approach in driver identification tasks, and the results show that the Neu-Car approach is a very promising approach that can enhance intelligence in modern cars.

As the Neu-Car is at its early research stage, there are further research steps and refinements remaining to be done, some of them are:

- expand design and development of the Neu-Car framework,
- expand design and development of the Knowledge Repository,
- refinement and further develop of the Neural Network Engine, and
- further design and development of the proposed Prognoser.

**ACKNOWLEDGEMENT**

The authors would like to thank the editors and anonymous reviewer for their valuable comments and suggestions on this paper. This work was supported as part of the Project KYTZ201422 by the Scientific Research Foundation of CUIT.

**REFERENCES**

Amadeo, M., Campolo, C., & Molinaro, A. (2016). Information-centric networking for connected vehicles: a survey and future perspectives. IEEE Communications Magazine, 54(2), 98-104.

Gerla, M., Lee, E. K., Pau, G., & Lee, U. (2014). Internet of vehicles: From intelligent grid to autonomous cars and vehicular clouds. IEEE World Forum on Internet of Things Vol.16, pp.241-246.

Jo, J., Lee, S. J., Park, K. R., Kim, I. J., & Kim, J. (2014). Detecting driver drowsiness using feature-level fusion and user-specific classification. Expert Systems with Applications, 41(4), 1139-1152.

LeCun, Yann, Yoshua Bengio, and Geoffrey Hinton. "Deep learning." Nature 521.7553 (2015): 436-444.

Ly, M. V., Martin, S., & Trivedi, M. M. (2013). Driver classification and driving style recognition using inertial sensors. Intelligent Vehicles Symposium (IV), 2013 IEEE, Vol.36, pp.1040-1045.

Michael A. Nielsen. (2015) "Neural Networks and Deep Learning", Determination Press.

Puterman, M. (1994). Markov Decison Processes: Discrete Stochastic Dynamic Programming. Technometrics, 37(3):353.

Sanin C., Szczerbicki E., (2006) Using Set of Experience in the Process of Transforming Information into knowledge, International Journal of Enterprise Information Systems, 2(2), pp. 40-55.

Sanin C, Leonardo Mancilla-Amaya, Zhang H., E Szczerbicki, Decisional DNA: the Concept and its Implementation Platforms, *Cybernetics and Systems: An International Journal* 2012 Vol 43, No 2, pp 67-80.

Sanin, C., and E. Szczerbicki. “Towards the Construction of Decisional DNA: A Set of Experience Knowledge Structure Java Class within an Ontology System.” *Cybernetics and Systems* 38(2007): 859-78.

Sathyanarayana, A., Sadjadi, S. O., & Hansen, J. H. L. (2012). Leveraging sensor information from portable devices towards automatic driving maneuver recognition. Conference Record - IEEE Conference on Intelligent Transportation Systems, Vol. 116, pp.660-665.

Sheen, S. H., Raptis, A. C., & Moscynski, M. J. (1995). Automotive vehicle sensors. Office of Scientific & Technical Information Technical Reports.

Sinden, R.R. (1994). DNA Structure and Function. Academic Press: San Diego.

Vaitkus, V., Lengvenis, P., & Zylius, G. (2014). Driving style classification using long-term accelerometer information. International Conference on Methods and MODELS in Automation and Robotics.

Zhang, H., Sanin, C., & Szczerbicki, E. (2016). When neural networks meet decisional dna: a promising new perspective for knowledge representation and sharing. Cybernetics & Systems, 47(1-2), 140-148.