Car-Car Analogy on Neural Network Science

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Systematic Review

Keywords: Network Neuroscience, Network Dynamics, Car Analogy, Neuroscience Theoretical Framework

Posted Date: August 26th, 2021

DOI: <https://doi.org/10.21203/rs.3.rs-811703/v1>

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Highlight

1. A commonly used conceptual analogy to organise development of current neuroscience.
2. The car-car analogy forms an interdisciplinary framework for different areas, such as physics, biology.
3. The mathematical framework behind the car-car analogy is the combination of the network and the control theory.

Keywords

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Abstract

We present a commonly used conceptual tool which is the "car analogy" to integrate many of the neural network science concepts. The purpose of this article is to show that using this car-car analogy allows us to have a unified framework for the entire discipline. We use this understanding framework to present the phenomena of "emergence" and "self-organization" in complex systems approaches toward neural network science. Meanwhile, we point out the reasons why the nervous system cannot be fully described from the network structure alone, and provide a potential candidate for a well-understood framework. The mathematical description is also discussed as a supplementary material.

1. Introduction

Network theory is currently the main research paradigm in neuroscience.^{1 2 3} Here we combine network theory and control theory to provide a framework for understanding this

¹ Bassett, D., Sporns, O. Network neuroscience. *Nat Neurosci* **20**, 353–364 (2017). <https://doi.org/10.1038/nn.4502>

² van den Heuvel, MP, Sporns, O. A cross-disorder connectome landscape of brain dysconnectivity. *Nat Rev Neurosci* **20**, 435–446 (2019). <https://doi.org/10.1038/s41583-019-0177-6>

³ Fornito, A., Zalesky, A. & Breakspear, M. The connectomics of brain disorders. *Nat Rev Neurosci* **16**, 159–172 (2015). <https://doi.org/10.1038/nrn3901>

discipline.^{4 5 6 7 8} Although nothing new has been discovered, examining this analogy integrating concepts and scientific achievements can still bring some inspiration not only for research work but also for educational purposes. The thinking method by applying analogy promotes the integration of scientific ideas.^{9 10}

The car-car analogy is a generalizable thinking framework. The underlying mathematics structure can also be applied to other situations, such as the hardware facilities of the power grid and the electricity for transportation (in fact, electricity is a kind of energy); the blood circulation system and nutrients for transportation; the nervous system and transportation information. Readers can refer to supplementary materials for practical guidelines on modeling. In the supplementary information we discuss mathematical descriptions. We also realise that not all neuroscientists prefer to adopt an approach containing a high extent of mathematics description.

Although researchers of neuroscience have made a lot of research progress in the past 20 years, there are still some viewpoints that need to be considered. The first is the interaction between several network systems, such as the immune system and neural system. We cannot consider a neural system independently. The nutrient transport network that supports the operation of the nervous system, and the immune system, all have a certain necessity to be taken into consideration during a process of designing research.¹¹ If we only focus on a single neural network system when analyzing a specific problem without specifying whether there is a reasonable consideration in ignoring background, we are likely to be studying a neural network system floating in a vacuum.

Applied control theory has many applications in neuroscience, cognitive science, behavioral science and other fields.¹² However, a main limitation is that there is no dynamics in the hardware structure. For example, we do not have a strong tendency to consider a situation where the factory we study has the possibility of encountering some machines that disappear during work. Although we have fully understood that dissipation of machine parts

⁴ de Vico Fallani, Fabrizio, et al. "Graph analysis of functional brain networks: practical issues in translational neuroscience." *Philosophical Transactions of the Royal Society B: Biological Sciences* 369.1653 (2014): 20130521. <https://doi.org/10.1098/rstb.2013.0521>

⁵ Fleischer, Vinzenz, et al. "Graph theoretical framework of brain networks in multiple sclerosis: a review of concepts." *Neuroscience* 403 (2019): 35-53. <https://doi.org/10.1016/j.neuroscience.2017.10.033>

⁶ Bassett, Danielle S., Cedric Huchuan Xia, and Theodore D. Satterthwaite. "Understanding the emergence of neuropsychiatric disorders with network neuroscience." *Biological Psychiatry: Cognitive Neuroscience and Neuroimaging* 3.9 (2018): 742-753. <https://doi.org/10.1016/j.bpsc.2018.03.015>

⁷ Petri, Carl Adam, and Wolfgang Reisig. "Petri net." *Scholarpedia* 3.4 (2008): 6477.

⁸ Medaglia, John Dominic, et al. "Brain and cognitive reserve: translation via network control theory." *Neuroscience & Biobehavioral Reviews* 75 (2017): 53-64. <https://doi.org/10.1016/j.neubiorev.2017.01.016>

⁹ Wormeli, Rick. *Metaphors & analogies: Power tools for teaching any subject*. Stenhouse Publishers, 2009.

¹⁰ Linsey, Julie S., Kristin L. Wood, and Arthur B. Markman. "Modality and representation in analogy." *Ai Edam* 22.2 (2008): 85-100.

¹¹ Pavlov, Valentin A., Sangeeta S. Chavan, and Kevin J. Tracey. "Molecular and functional neuroscience in immunity." *Annual review of immunology* 36 (2018): 783-812. <https://doi.org/10.1146/annurev-immunol-042617-053158>

¹² Hickok, G. Computational neuroanatomy of speech production. *Nat Rev Neurosci* 13, 135–145 (2012). <https://doi.org/10.1038/nrn3158>

will inevitably occur over time, it is not considered in the theoretical setting. In other words, control theory is concerned with how information (commands or orders) are transmitted within the system, and how the system should respond. Signals and information are transmitted or flowed in a neural network.¹³

Network and transmission content (signal, pulse or something else) may play the corresponding relationship between "hardware" and "software" in the computer science research areas. However, one feature misleading in this analogy is that the software itself needs to be installed. Therefore, it leaves room to introduce some unknown mysterious forces to play a prerequisite role of design in this process. This method of discourse tends to involve philosophy or non-scientific fields in a discussion about this purely scientific question. Due to this reason, we would like to avoid resorting to this hard/software analogy. Behind this type of idea represents a neuromechanical view, that is, human behavior is actually driven by biological machines (many neural circuits or modules in the brain). The status of uncertainty is actually ambiguous in the context and discussion. This view involves many social and moral considerations of determinism and reductionism.^{14 15 16} For scientific purposes, we only consider the insights that the car-car analogy can provide and benefit in boosting understanding.

The correlation between "structural damages" and "disease emergence" is one focus of neural networks. If we only observe the structure, we will ignore the contents actually transported on the network. The disadvantage of this analysis framework is that it is relatively static to observe structural changes. For example, the dynamic properties depend on time.

Structure is a part of a system. The information of network transportation is related to the structure itself. However, there is no certain way to get the full descriptive formalism of the system by describing the structure in detail. For example, it is difficult for us to understand the dynamic state of water power and electricity in a building by observing the structure diagram of the hydropower pipeline and its changes over time (refitting inside the building). We know that lack of structural components will cause a system to lose functions, but these functions need other mechanisms to drive. Under this view, it is likely that we have paid attention to the mechanism that produced the biological structure, and did not pay attention to the mechanism itself.

The necessity of discussing "signals" lies in the fact that the network system may be subject to signal transmission and loss. It is reasonable for the loss to be taken into consideration. The aging of physiological functions that occurs with the increase of age is generally observed. A possible reason behind this is that repeated signal transmission will

¹³ Fox, Michael D., et al. "The human brain is intrinsically organized into dynamic, anticorrelated functional networks." *Proceedings of the National Academy of Sciences* 102.27 (2005): 9673-9678. <https://doi.org/10.1073/pnas.0504136102>

¹⁴ Morse, Stephen J. "Determinism and the death of folk psychology: two challenges to responsibility from neuroscience." *Minn. JL Sci. & Tech.* 9 (2008): 1. <https://doi.org/10.1146/annurev-neuro-060909-153151>

¹⁵ Boone, W., Piccinini, G. The cognitive neuroscience revolution. *Synthese* **193**, 1509–1534 (2016). <https://doi.org/10.1007/s11229-015-0783-4>

¹⁶ Chemero, Anthony, and Michael Silberstein. "After the philosophy of mind: Replacing scholasticism with science." *Philosophy of science* 75.1 (2008): 1-27.

inevitably be accompanied by hardware deterioration, or in simple terms, loss. This loss can be explained by the theory of thermodynamics, especially the second law. As a dissipative system, the nervous system consumes energy all the time to maintain operation and stability. Many studies focus on "neurodegenerative diseases". Although whether it is regarded as a disease or a normal phenomenon still needs further discussion, the deterioration of the neural network system must be foreseeable.

Is a comprehensive explanation theory possible? The answer may be rather vague. We must manually eliminate factors that have less impact on the model, and then only retain the dominant factors when building the model. The purpose of this procedure is to make the "model" work smoothly and gain explanatory power. Some literature refer to this as complexity reduction or simplification of modeling.¹⁷ However, what must be considered is that in many cases it is difficult to rule out deliberate selection of dominant factors to make a model reflect the actual behavior. This kind of research approach probably presupposes a conclusion and then sets up the model according to the conclusion which the researchers expected to observe. In this manner, it is possible to fall into the paradox of inverting the causality.

Making predictions is one of the challenges in analysis of neural networks as a complex system. The long-term prediction is an almost impossible pursuit. While we discuss predicting, we must indicate the system scale and the effective time (some literature in non-linear system analysis refer to this effective time as the Lyapunov Time) of the prediction. The reliability of the behaviour prediction upon a non-linear, many-interaction involving system largely depends on the complexity of the system (of course, this may also be an indicator defined based on research needs). There is still a gap between understanding the nature of the neural network and predicting human behavior even though we have accomplished a huge amount of scientific work. In a short period of time and in a strictly controlled environment, high accuracy prediction is obtained. However when deviating from the appropriate conditions, the prediction becomes a challenge. Calculation is feasible in principle but impossible in practice.

At this stage, seeking an "effective theory" is a compromise. The question will be transformed into the extent of effectiveness and rationality of the effective theory. In other words, what parameters we ignore and what dominating factors we identified. We may get a machine to predict, but we won't be able to get any details revealing the mechanism. In some literature, this is also the main criticism of neural network algorithms. Although the model after data training can solve the problem with high efficiency, it does not reveal much of the physical, chemical, and biological mechanisms behind it. For example, overfitting is a problem. The black box (or gray box) approach is likely to bring progress in practice, but ignoring this limitation will prevent us from further exploration.¹⁸

¹⁷ Bzdok, Danilo, and John PA Ioannidis. "Exploration, inference, and prediction in neuroscience and biomedicine." *Trends in neurosciences* 42.4 (2019): 251-262.
<https://doi.org/10.1016/j.tins.2019.02.001>

¹⁸ Krakauer, John W., et al. "Neuroscience needs behavior: correcting a reductionist bias." *Neuron* 93.3 (2017): 480-490. <https://doi.org/10.1016/j.neuron.2016.12.041>

Network theory describes graph structures.¹⁹ Dynamic network science focuses on the operation of the network components, such as the increase and decrease of nodes and edges; connection and disconnection. Control theory describes the process of information (signal) transmission in the system, and how the system adjusts according to the output (in literature, it is referred to as feedback control for adaptive systems). That is, the system adjusts based on output signal, takes action, and then receives signals (control commands or sensory inputs) from the environment again. The former accords with the observation of neuroanatomy, so there are many literatures described in the mathematical language of graph theory.²⁰ The latter is consistent with the phenomenon that the nervous system is self-regulating.²¹

The gray box model captures the characteristics of complex nonlinear systems, but it is also difficult to put forward a theory from the lowest level unit (neurons) to the highest level phenomenon (consciousness or human behaviours).^{22 23} The reason is that the calculation from the first principle (white box approaches) will consume a lot of calculation resources; while the black box modeling of phenomenology cannot infer the correct mechanism from the function. Convergent evolution is a good example. Although similar in function, the mechanism may be completely different. For instance, the eyes of cephalopods and vertebrates.²⁴ The problem we will encounter when modeling from a single neuron is that comprehensive labeling of nodes and lines consumes computational resources, and the details of each individual network are different. Each model has its own advantages and disadvantages.^{25 26 27}

In this article, we use the car analogy to illustrate that neural networks are actually **two systems**. The first system is a spatial structure system, that is, the spatial structure of a neural network. The second type of system is a transportation system, which discusses how information (or objects) move through the network. In addition, randomness can be reflected in two different time scales. Long-term structural changes (neural plasticity) and short-term information transmission. The car analogy can easily put randomness into the model, and form a model that is extremely simple and easy to understand in explanation. Randomness

¹⁹ Vogels, Tim P., Kanaka Rajan, and Larry F. Abbott. "Neural network dynamics." *Annu. Rev. Neurosci.* 28 (2005): 357-376. <https://doi.org/10.1146/annurev.neuro.28.061604.135637>

²⁰ Bassett, DS, Zurn, P. & Gold, JI On the nature and use of models in network neuroscience. *Nat Rev Neurosci* 19, 566–578 (2018). <https://doi.org/10.1038/s41583-018-0038-8>

²¹ Shikachi, Y., Ishii, S. Decoding the view expectation during learned maze navigation from human fronto-parietal network. *Sci Rep* 5, 17648 (2016). <https://doi.org/10.1038/srep17648>

²² Romijn, Reinout, et al. "A grey-box modeling approach for the reduction of nonlinear systems." *Journal of Process Control* 18.9 (2008) : 906-914. <https://doi.org/10.1016/j.jprocont.2008.06.007>

²³ Molaie, Malihe, et al. "Artificial neural networks: powerful tools for modeling chaotic behavior in the nervous system." *Frontiers in computational neuroscience* 8 (2014): 40. <https://doi.org/10.3389/fncom.2014.00040>

²⁴ Serb, JM, Eernisse, DJ Charting Evolution's Trajectory: Using Molluscan Eye Diversity to Understand Parallel and Convergent Evolution. *Evo Edu Outreach* 1, 439–447 (2008). <https://doi.org/10.1007/s12052-008-0084-1>

²⁵ Herz, Andreas VM, et al. "Modeling single-neuron dynamics and computations: a balance of detail and abstraction." *science* 314.5796 (2006): 80-85.

²⁶ O'Reilly, Randall C. "Biologically based computational models of high- level cognition." *science* 314.5796 (2006): 91-94.

²⁷ Destexhe, Alain, and Diego Contreras. "Neuronal computations with stochastic network states." *Science* 314.5796 (2006): 85-90.

generally considers the phenomenon of noise spreading in the network, but the analogy of vehicles can illustrate the possible sources of noise. Regarding the dynamic model in this respect, it may involve relatively complicated mathematical descriptions.^{28 29}

Using the car analogy, we can discuss the network theory, control theory and information theory aspects of neuroscience under a framework. By thinking about the car-car analogy, readers can integrate all aspects and research discoveries of the brain—this amazing complex system. This provides a helpful manner for reviewing and mastering the knowledge of neuroscience.

2. Car-Car Analogy

The car analogy is a common theoretical tool in elucidating ideas among engineering education as an analogy used to convey abstract concepts. In this article, we use the term car-car analogy as an advanced version inspired by a physics concept which is spin-spin interaction. It is for emphasizing the interaction between cars. The rationality of presenting analogy as explaining manner lies in the similarity of analogy systems, especially discussing abstract concepts and their relationship between each other.

Here we present the detail of our car-to-car analogy and its corresponding neuroscience evidence. The analogy of the term "car" is used because the system does not have only cars and roads, but "many" cars and roads. For readers who are familiar with many-body physics, it will present a high similarity. This process can consider the interaction between cars. The signal that a neuron can transmit at a given time interval is limited. As a path (route) can hold a certain number of cars at a given time interval.

A network composed of neurons can be described by graph theory as the basic principle of neural network science. In the car-car analogy, the network of neurons is the road system. The cars driving on the road are signals transmitted in the neural network.

The system itself will be affected in three causes: (1) The cars crash into the cars. (2) The road is damaged, such as natural disasters and man-made disasters. (3) Vehicles damage the road. The first case corresponds to the interaction between neurotransmitters. It can also be understood that the signal transmission process is affected by other signals. The second situation is damage to brain tissue, such as accidental trauma or degenerative disease. The third situation is the influence of neurotransmitters on nerve structure.³⁰ We already know that the neural connection density (connectivity, or degree distribution in graph theory) of patients with depression will decrease. In the car-car analogy, it can be understood as the lack of maintenance of the road system, which makes many roads

²⁸ Bressloff, PC, Maclaurin, JN Stochastic Hybrid Systems in Cellular Neuroscience. *J. Math. Neurosc.* **8**, 12 (2018). <https://doi.org/10.1186/s13408-018-0067-7>

²⁹ Chow, CC, Buice, MA Path Integral Methods for Stochastic Differential Equations. *J. Math. Neurosc.* **5**, 8 (2015). <https://doi.org/10.1186/s13408-015-0018-5>

³⁰ Pereda, A. Electrical synapses and their functional interactions with chemical synapses. *Nat Rev Neurosci* **15**, 250–263 (2014). <https://doi.org/10.1038/nrn3708>

unusable.³¹ Some literature will prefer to use the robustness to describe the extent of health of a neural network system. In order to prevent readers from getting confused, we do not use robustness as a vague measure of network properties.

Meanwhile, the car-load system will be dynamically adjusted. For example, when traffic congestion occurs on a certain road (path), part of the traffic flow will choose other alternative roads, even though alternative paths will consume much travel time. This is a dynamic adjustment that usually occurs in a short period of time, relative to the time required to grow new synapses. The similarity in this case allows the path integral formalism working on analysis to find out the propagator (or in some literature, the Green's function). Generally speaking, it is a variational problem. The detail of dealing with such kinds of problems and their set-up is beyond the scope of this article.

There will be roads between the two locations due to demand (economic needs and the like). Frequently used roads are easily damaged and therefore require maintenance. There are two mechanisms that form an antagonistic situation, one is for repairing and another is for impairing. Infrequently used roads will be abandoned to save the resource or recycling demands. It takes a relatively long time to build a new road, compared to the time taken to change to other alternative roads on the way from point A to point B. It has been proven that neuroplasticity is the foundation of learning, but it takes time for individuals to learn new skills.³²

The optimization problem of the car-load transportation system in our car-car analogy can be simplified to another version which is minimizing travel time and consumption costs. Some readers from a physics science background will be familiar with the principle of Least Action under this analogy. The more efficient the neural network system has obvious relevance to the individual's behavior.³³ This may involve a mathematical modeling process using variational methods. Basically, this is a possible approach but we will not consider further details in this article. How to apply path integral upon neuroscience is a highly specific problem relating to the necessity of research orientation.

There are different types of cars such as there are many kinds of neurotransmitters that are currently known. Different neurotransmitters transmit different signals. This matter is already widely known in the neuroscience community. Interested readers can find relevant information on Wikipedia as the simplest way to explore this area.³⁴ The point here is to explain that different types of neurotransmitters play different mechanisms in the signal transmission process. These mechanisms can be discussed in depth based on research needs and orientations. The more advanced exploration of roles of each neurotransmitter in

³¹ Holmes, SE, Scheinost, D., Finnema, SJ *et al.* Lower synaptic density is associated with depression severity and network alterations. *Nat Commun* **10**, 1529 (2019).

<https://doi.org/10.1038/s41467-019-09562-7>

³² Galván, Adriana. "Neural plasticity of development and learning." *Human brain mapping* 31.6 (2010): 879-890. <https://doi.org/10.1002/hbm.21029>

³³ Genç, E., Fraenz, C., Schlüter, C. *et al.* Diffusion markers of dendritic density and arborization in gray matter predict differences in intelligence. *Nat Commun* **9**, 1905 (2018). <https://doi.org/10.1038/s41467-018-04268-8>

³⁴ Wikipedia contributors. (2021, August 8). Neurotransmitter. In *Wikipedia, The Free Encyclopedia*. Retrieved 14:21, August 12, 2021, from <https://en.wikipedia.org/w/index.php?title=Neurotransmitter&oldid=1037731590>

the neural network system, the higher the distortion of the car-car analogy may be. However, what readers need to pay attention to is that cars in the road system may have substantial differences and play different roles.

The car system and other systems affect each other, not just only a single system itself. The system here refers to the combination of roads system and the traffic flow contributed by cars and interaction between cars. Cars need fuel or power system support; the rules to maintain smooth transportation also need to consume energy, such as traffic lights. It is a fact that the nervous system consumes a lot of energy. Species equipped with such energy-consuming organs shaped by the process of evolution must be due to the powerful competitive advantage brought by this system. At least human beings are spreaded almost in most corners of this planet by virtue of their intelligence, and cause global warming. One of the last species that can achieve planetary-level climate change is Cyanobacteria.

The car-road system will need the support of the economic system. Just like the nervous system will need blood circulation. The energy supply of neuron cells can be found in related literature. The fuel supply of cars has to be refilled at the gas station. In addition, the interaction between the nervous system and the immune system has become a major research focus. Research in this field has made a lot of progress in recent years, readers can have relative material in references.^{35 36 37 38}

The car-road system in car-car analogy can be recognised partially to special transportation systems such as express roads and highways, or dense systems such as community networks (in terms of graph theory, we are describing high short-range connectivity as a small-world model). Basically, we realize that the brain network system is a short-range intensive processing module, with a long-distance module communication network.^{39 40} This corresponds to specialized neural circuits used to process some high-level functions, such as face and object recognition.^{41 42 43}

Why do we need a car-car analogy? When discussing a complex system, it presents an understanding challenge for us to have a comprehensive theory to describe the process

³⁵ Sternberg, E. Neural regulation of innate immunity: a coordinated nonspecific host response to pathogens. *Nat Rev Immunol* **6**, 318–328 (2006). <https://doi.org/10.1038/nri1810>

³⁶ Rosas-Ballina, Mauricio, and Kevin J. Tracey. "The neurology of the immune system: neural reflexes regulate immunity." *Neuron* **64.1** (2009): 28-32. <https://doi.org/10.1016/j.neuron.2009.09.039>

³⁷ Pavlov, V., Tracey, K. Neural regulation of immunity: molecular mechanisms and clinical translation. *Nat Neurosci* **20**, 156–166 (2017). <https://doi.org/10.1038/nn.4477>

³⁸ Pavlov, VA, Tracey, KJ Neural circuitry and immunity. *Immunol Res* **63**, 38–57 (2015). <https://doi.org/10.1007/s12026-015-8718-1>

³⁹ Coltheart, Max. "Modularity and cognition." *Trends in cognitive sciences* **3.3** (1999): 115-120. [https://doi.org/10.1016/S1364-6613\(99\)01289-9](https://doi.org/10.1016/S1364-6613(99)01289-9)

⁴⁰ Onoda, Keiichi, and Shuhei Yamaguchi. "Small-worldness and modularity of the resting-state functional brain network decrease with aging." *Neuroscience letters* **556** (2013): 104-108. <https://doi.org/10.1016/j.neulet.2013.10.023>

⁴¹ Gauthier, I., Skudlarski, P., Gore, J. *et al.* Expertise for cars and birds recruits brain areas involved in face recognition. *Nat Neurosci* **3**, 191–197 (2000). <https://doi.org/10.1038/72140>

⁴² Haxby, James V., *et al.* "Face encoding and recognition in the human brain." *Proceedings of the National Academy of Sciences* **93.2** (1996): 922-927. <https://doi.org/10.1073/pnas.93.2.922>

⁴³ Suárez, LE, Richards, BA, Lajoie, G. *et al.* Learning function from structure in neuromorphic networks. *Nat Mach Intell* (2021). <https://doi.org/10.1038/s42256-021-00376-1>

from microscopic laws to macroscopic behaviour of systems, as the situation discussed in thermodynamic and statistical mechanics literatures and textbooks. Therefore, the direct establishment of mathematical models may result in "only effective at a single level (scale)." If we want to build a universal model, we may face huge requirements for parameters and computing resources. In physics, it turns out that the impossibility of a predictive model working on quantum mechanics effects to restore the result of classical mechanics in pragmatic consideration is well-known. A corresponding principle-like approach seems to become the final resort of real work. The viewpoint of reductionism cannot provide a clear path from the micro to the macro. It goes back to a notorious situation we have mentioned: in principle, it is possible; in practical, it is impossible.

Dealing with complex systems often brings many wicked problems. The main features of the so-called wicked problems have been discussed and identified for a long time.⁴⁴ Here, we focus on the natural scientific version of the wicked problems instead of the definition used in social science. The challenging question is derived from the concept of social science, and we borrow it to illustrate the complex situation of neuroscience. This means that there is still a lot of work to be done in the future.

The results of the research may largely depend on the goal setting and methodological consideration, such as experimental designs. If we are studying the correlation between IQ and the network structure of the nervous system, we can easily lead to obvious results because of the way we measure IQ. In other words, if we study high IQ subjects (who get high scores on intelligence tests), we will find that their neural network structure is a highly specialized small-world network.⁴⁵ The reason is that in order to get a high score, the logical analysis and causal reasoning will be particularly activated, and then the efficiency of the integrated system will be better than that of the subjects of the low intelligence test. This is equivalent to telling us that running fast has strong thigh muscles.

In order to understand the hierarchical relationship of the neural network system, we continue to work with the car-car analogy. Note that the analogy is used here to illustrate the hierarchy. First of all, we regard cars as a category, but there are many kinds of cars. For example, family cars and trucks. Then if we consider the course of each car after use, we will find that each car is different, such as mileage. This part of consideration is related to the single cell history and the interaction between cell and its environment. Some degenerative discussion is allowed to be included.

Then put these cars into the city's road system. If we only look at the map of the road system (a road leads to another road), such information is of a spatial structure. Similarly, if we encode neurons one by one into nodes of the graph, and then encode synapses into edges, basically this is also a spatial structure. Obviously, the graph will contain all spatial information with difficulty to perform calculation. Complexity reduction therefore is required for the computational neuroscience area.

⁴⁴ Peters, B. Guy. "What is so wicked about wicked problems? A conceptual analysis and a research program." *Policy and Society* 36.3 (2017): 385-396.

⁴⁵ Wang, S., Zhou, M., Chen, T. *et al.* Examining gray matter structure associated with academic performance in a large sample of Chinese high school students. *Sci Rep* 7, 893 (2017).
<https://doi.org/10.1038/s41598-017-00677-9>

The next step is to simplify the work. Going back to the car-car analogy, we realise that it takes a lot of resources to encode all roads. Also note that the road system of each city is different in detail (microscopic extent). Corresponding to neural networks, this means that although the physiological structure of the brain is similar in anatomy, after descending to the level of the synapse, we (1) cannot distinguish which brain is in and (2) cannot distinguish which period one is in. This is a shortcoming of the construction model of the space structure. From the map, we can infer population clusters and desolate places, but it is difficult to know when the traffic is congested.

Put the car into the city! All we need to consider is the complete dynamic network model. The dynamics we mentioned here do not refer to the increase or decrease of the edges of nodes, but also the behavior of information and particles (cars in our car-car analogy) in the network. There are a set of rules for the construction of the road system, and of course there will be a set of rules for the transportation of cars. If we only focus on spatial information, we will lose the actual traffic conditions of cars on the road.

Returning to the car-car analogy, we will need to understand that when a road is driven by a large number of cars, the damage to the road will be faster than that of the small alleys in the community. Therefore, the transportation of vehicles on the road will cause the road system itself to be affected to a certain extent. A maintenance system is needed. Actually, what we can foresee is there are two antagonistic mechanisms. Suppose there is a maintenance system. When this mechanism knows that there are many cars going between A and B, it has at least two options: (1) Maintain this road more (2) Add a few more roads to connect these two locations. In the real situation, both of these schemes may be partially adopted in order to find the most stable scheme. The possible potential force hidden is the evolutionary procedure. If only the first option is adopted, it is very likely that traffic jams will still be encountered. If the second option is adopted, too many useless roads may be created. Therefore, the spatial structure is dynamic and responds to the unit elements (such as cars) that are transported in the network.

Basically, this is the simplest version of the car-car analogy. We believe that readers can expand the car-car analogy into a more applicable thinking framework while supplementing and reading further research in the future. Using analogy is a very challenging way of elaboration, but we should not only resort to mathematics or physical descriptions before we establish a comprehensive understanding. Based on the efficiency at which humans understand concepts that are similar in life, it is more intuitive than doing abstract algebraic thinking. Notice that this is for pedagogical needs, not an absolute fact which is suitable applied to everyone. The car-car analogy may be an instructive research tool.

Regarding network interaction and transmission within the network, we provide a mathematical description in the supplementary document. This can help readers who prefer a mathematical thinking approach have a more feasible reference guide when building models.

3. The limitation of car-car analogy.

The limitation of car-car analogy as a thinking tool is that complexity also bothers after considering network-network interaction and insisting on figuring out corresponding counterparts in analogy framework. The basic reason we present the car-car analogy is upon the similarity of neural and car-road systems. The spatial structure described by graph theory is one point of similarity. The second one the transportation properties can be observed. The third one, the car-road, car-car and other mechanisms supporting the whole car-road system are also existing.

In the process of moving from the real brain to the neural network model, we use a simplification method between the black box and the white box. It is necessary to simplify the model of the complex system in order to fit the orientation driven by research and science curiosities. However an obvious thing is that the neural network is not floating in a vacuum, the nervous system needs other systems to maintain. Therefore, we need to consider the interaction between other networks and neural networks.

The nervous system is different from the transportation system. Therefore, when using analogy, readers should know the gap between the real system researchers focus on and the system described by analogy. If we do not clarify how far the conceptual model using analogy is from the real system, then we are likely to be troubled by analogy. For example, readers may want to find all corresponding objects of the real transportation system from all the results of neuroscience. Basically this matter is impractical, but the use of analogy is still a good choice when considering the understanding of concepts.

No model is perfectly realistic, in general, all models are effective models upon accuracy. In many cases, we have to simplify the details of some real phenomena in order to reach modeling. For example, when we build neural network models (not referring to machine learning), we do not consider the physiological and metabolic processes of a single neuron cell, because we are concerned with information transmission. When we consider the long-term dynamic development of the network, we must consider the cellular mechanism of neurons as a dominating factor or a parameter in the model we construct. Part of this consideration is that other factors other than the main factors are manually excluded from the research needs. Although this procedure has always been very reasonable due to analysis, it is very likely that the model itself will contain results when other factors are excluded. As when using mathematical models, we still have to be clear about the gap between experiment and theory.

The uncertainty phenomenon needs to be explained. When the measurement object of a system and the system itself will have a significant impact, the operation of measurement must be considered. In the car-car analogy, we can send an observation car to observe the traffic flow. Considering the difference between the number of vehicles and the observation car. If there exists large orders of difference, we can ignore the impact of the observation car on the system. What if we send a significant number of observation cars, it may interfere with the system. When the operation of measurement influences the system, we need to consider the measurement itself.

In our discussion, we obviously excluded several parts of the brain that maintain the basic functions of the individual, such as the brain stem. We focus on high-level functions. The high-level functions in this article refer to cognitive abilities, such as the individual processing information or making decisions. There are currently some theories that discuss cognitive abilities from an information point of view.^{46 47} The obvious fact is that the relationship between human behavior and neurons actually has a significant level of difference. Human behavior is a macroscopic phenomenon while the local behavior of neurons is a microscopic phenomenon. Considering the interaction between neurons, there is no way to directly speculate on human behavior. However, when the communication between neurons is affected by external substances, human behavior does have an impact and changes such as behavior after drinking (alcohol molecules spreading among the brain). In the car-car analogy, it is very similar to that we have changed some traffic rules and caused traffic instability or changes in trends.

A black box is a necessary evil, because most complex systems are difficult to have a complete theory to predict long-term future behaviour, such as the difference between weather and climate.^{48 49} Complexity has become a transparent wall-even though we know the control rules and characteristics of unit elements (cars or neurons), taking all the parameters into consideration, we will encounter huge calculation difficulties. This difficulty does not prevent us from conducting scientific research, but we must be clear that local-level theories can only describe some of the characteristics.⁵⁰ Psychological theories describing human behavior have no obvious way to directly understand and predict neurological behavior. In this process, the mechanism between levels (layers or scales, in different areas) still needs to be clarified. The difficulty of prediction caused by complexity is one of the characteristics of complex systems. Although we can make short-term forecasts, long-term forecasts are affected by factors such as environmental or random factors. This is often seen in economic systems.⁵¹

We need to consider the limitations of the agent-based modeling view. It is easy for us to divide a complex system into several nodes using network theory, and then encode some observed phenomena into node functions. The simplest example is a flowchart, followed by the loop structure of the control system, and then a network organized by several functional nodes (in simple terms, it is a graph, and each point and edge has a way

⁴⁶ Tononi, G. An information integration theory of consciousness. *BMC Neurosci* **5**, 42 (2004). <https://doi.org/10.1186/1471-2202-5-42>

⁴⁷ Tononi, Giulio. "Consciousness, information integration, and the brain." *Progress in brain research* **150** (2005): 109-126. [https://doi.org/10.1016/S0079-6123\(05\)50009-8](https://doi.org/10.1016/S0079-6123(05)50009-8)

⁴⁸ Darst, R., Granell, C., Arenas, A. *et al.* Detection of timescales in evolving complex systems. *Sci Rep* **6**, 39713 (2016). <https://doi.org/10.1038/srep39713>

⁴⁹ Liao, Hao, et al. "Ranking in evolving complex networks." *Physics Reports* **689** (2017): 1-54. <https://doi.org/10.1016/j.physrep.2017.05.001>

⁵⁰ Batty, Michael, and Paul M. Torrens. "Modelling and prediction in a complex world." *Futures* **37.7** (2005): 745-766. <https://doi.org/10.1016/j.futures.2004.11.003>

⁵¹ Arthur, W. Brian. "Complexity and the economy." *science* **284.5411** (1999): 107-109.

to define some measurable Amount, or the amount that can be calculated).⁵² But this matter will cause a problem: **how many agents are there?**^{53 54}

The probability of road damage is proportional to the number of times the cars has passed. And the necessity to sustain the stability of a path (route) is dependent on the demand of traffic. In the nervous system, we can assume that there is an error rate in the signal transmission of each synapse, and this error rate is proportional (hypothetical) to the number of times the signal is transmitted. This shows the local random failure is possible to happen such that the prediction is becoming difficult under this picture.

In this framework, it seems to imply that "the less you use your brain, the less there will be "random errors." But what we have actually discovered is that people who are good at using their brains seem to be less likely to have the problem of degeneration of brain function. So how to explain this contradiction? The principle is that the nervous system will not only have a single channel. In the face of random communication errors, other channels will be responsible for bearing this temporary load, and then there is a mechanism to repair this channel. As the number of repairs and errors increases, the network system will inevitably age (not assuming neuron regeneration), and the loss will eventually reach its limit.^{55 56 57} It is suitable to emphasize the impair-repair antagonism.

The question here is, where does the function to perform the repair come from? Obviously, but the most easily overlooked thing is that the nervous system is not suspended and in a vacuum. The nervous system needs energy, blood and immune system support. We can even say that these several systems are **coupled**. Decomposing a coupled system into several subsystems is a way to analyze the problem, but when building it back into the whole, we must be careful about the details that we ignore in the process.⁵⁸

Once a reduction is made, it is difficult not to touch the determinism from a practical point of view. For example, in the car-car analogy, when measures to monitor traffic flow affect car-car transportation.

The measurement will inevitably interfere with the system itself. The impact of this measurement is of scale and mechanism, rather than the mysterious quantum mechanical effects described by some theorists. When we send a large number of scientific exploration

⁵² Harel, David. "Statecharts: A visual formalism for complex systems." *Science of computer programming* 8.3 (1987): 231-274.

⁵³ Goel, Ashok K., Spencer Rugaber, and Swaroop Vattam. "Structure, behavior, and function of complex systems: The structure, behavior, and function modeling language." *Ai Edam* 23.1 (2009): 23-35.

⁵⁴ Grimm, Volker, et al. "Pattern-oriented modeling of agent-based complex systems: lessons from ecology." *science* 310.5750 (2005): 987-991.

⁵⁵ Bossy-Wetzel, E., Schwarzenbacher, R. & Lipton, S. Molecular pathways to neurodegeneration. *Nat Med* 10, S2–S9 (2004). <https://doi.org/10.1038/nm1067>

⁵⁶ Glass, Christopher K., et al. "Mechanisms underlying inflammation in neurodegeneration." *Cell* 140.6 (2010): 918-934. <https://doi.org/10.1016/j.cell.2010.02.016>

⁵⁷ Kostzewa, RM, Segura-Aguilar, J. Novel mechanisms and approaches in the study of neurodegeneration and neuroprotection. A review. *neurotox res* 5, 375–383 (2003). <https://doi.org/10.1007/BF03033166>

⁵⁸ Majdandzic, A., Podobnik, B., Buldyrev, S. et al. Spontaneous recovery in dynamical networks. *Nature Phys* 10, 34–38 (2014). <https://doi.org/10.1038/nphys2819>

teams to investigate the primitive rain forest, if the number of humans entering the forest is too large, it will be difficult not to affect the ecology of the forest. This process is simply that the tools of the detection system interact with the system itself, and from this example, we do not need to resort to the mysterious quantum mechanics mechanism.

When we model the neural network system, it is easy to overlook other systems that interact with the neural network system, such as the immune system. Such negligence can be ignored in research dealing with "information analysis", such as when the experimenter sees a problem and responds, but it must be considered in research involving disease.

It is also difficult to fully reveal the essence of the phenomenon itself. For example, in the car-car analogy, we may be able to determine which areas with dense roads are communities in the road map. However, it is difficult for us to understand the reasons for the formation of communities, such as the impact of hydrology or environmental resources. The determination of correlation and causality is a big challenge. In the nervous system, we can identify specific circuits, but how such circuits are formed and how information is transmitted to each other depends greatly on the interpretation of the results. After all, the current experimental device has its limitations.

Again, "Human behavior" is the macroscopic manifestation of the nervous system, and the neurological configuration is microscopic. The same behavior (or at least similar behavior) may be caused by different microscopic states. Obviously, everyone's brain is different, but humans can have common characteristics.

4. Possible applications of the car-car analogy

The current view of consciousness in the neuroscience community is an "emergence" phenomenon.^{59 60} But this point of view will cause a problem. The similarity of the unit elements (neurons or cars in our car-car analogy) and the similarity of the control rules will lead to the type result of the macro state. From this perspective, we can easily conclude that primates also have consciousness, or that cephalopods (especially octopuses) also have consciousness.⁶¹ This leads to confusing questions: Where is the boundary?

Self-organization is about structure, especially spatial structure. From material and chemical bonds to tissue and network of mold. And emergence is about behaviour. When we use laboratory animals, we must consider the neural network dynamical system's scale of hierarchy. Although there are similar spatial structures, we still have to consider the

⁵⁹ Lagercrantz, H., Changeux, JP. The Emergence of Human Consciousness: From Fetal to Neonatal Life. *Pediatr Res* **65**, 255–260 (2009). <https://doi.org/10.1203/PDR.0b013e3181973b0d>

⁶⁰ Lagercrantz, Hugo. "The emergence of consciousness: Science and ethics." *Seminars in Fetal and Neonatal Medicine*. Vol. 19. No. 5. WB Saunders, 2014. <https://doi.org/10.1016/j.siny.2014.08.003>

⁶¹ Tricarico E., Amodio P., Ponte G., Fiorito G. (2014) Cognition and Recognition in the Cephalopod Mollusc *Octopus vulgaris*: Coordinating Interaction with Environment and Conspecifics. In: Witzany G. (eds) *Biocommunication of Animals*. Springer, Dordrecht. https://doi.org/10.1007/978-94-007-7414-8_19

differences of the system.⁶² This means we would seem the laboratory mice have the same extent of consciousness as humans. However, some discoveries are also based on the experiment animals due to the similarity of mechanism.

Consciousness-intelligence is a coupled problem. If we use black box modeling, you will get a "conscious machine" and an "intelligent machine", for some discipline, the term "agent" is used to replace the machine. Consciousness interferes with the results of intelligence, such as reflection (mind thinking). And intelligence can be reduced to an agent for processing information. Under this framework, what we get is two huge black boxes pulling each other. Under the car-car analogy, this is over-simplify the system to two dominant cities and one branch to communicate. An Observer will infer that all economical and communication behaviour can be reduced to two cities' competition. Then go back to the intelligence and consciousness problem. This will lead to a conclusion that interactive behavior of these two agents determines individuality.⁶³

The explanatory power of this two agent (two cities) framework is very powerful, but it will cause huge problems. One of the problems is that it cannot be proved. We will get stuck: do these agents really exist? The other problem is returning to the theory of opposition between body and mind in traditional philosophy. But this question is a little far away from science, so we won't go into it in depth.

The last point we must mention as a note is that it is very difficult to predict complex systems! It is possible to give effective predictions in a short time. There is a mathematical concept about this time, which is called Lyapunov time. But for practical applications, we must have a nonlinear model first. In the modeling, we will need a reasonable framework to discuss the main dominating factors and scales (level between micro- and macro). There are quite a few textbooks on the prediction and construction of complex systems, and this is basically a long-discussed issue.

5. Conclusion

We have explained the reason why we present the car-car analogy as an understanding framework to organise research achievement and knowledge of neuroscience. And also we emphasize the dynamical property must include the transporting agents inside the network as well as the structure change during the time evolution. We describe some counterparts between our car-car analogy and neuroscience.

Neural network science can be extended by considering the possibility of combination of graph dynamics and control theory. Readers from engineering background will find the similarity between the system we described as the Petri Net. Roughly speaking, we are presenting a combination of structure dynamic of graph and control system based on the

⁶² Goldstone, Robert L., and Todd M. Gureckis. "Collective behavior." *Topics in cognitive science* 1.3 (2009): 412-438. <https://doi.org/10.1111/j.1756-8765.2009.01038.x>

⁶³ Gershenson, Carlos, et al. "Self-organization and artificial life." *Artificial Life* 26.3 (2020): 391-408. <https://doi.org/10.1162/artl.a.00324>

neural transmitters as signal pulse. This work shows the advanced development for theoretical work is required.

Neuroscience has the characteristics of "interdisciplinary", "inter-level", and "inter-species". In terms of disciplines, in addition to the original neuroanatomy, fields such as behavioral neuroscience and cognitive neuroscience began to lay the foundation, and then technology and knowledge in the fields of physics, computer science, mathematics, and engineering began to enter this field. In the visible ten years, this subject will flourish for a while. Especially under the development of machine learning, as the amount of data continues to increase, related technologies have begun to cooperate with this force. The processing of big data will be one of the main challenges of this science. It is likely that in the near future, these technical issues will become a hot topic of discussion in this science. The use of analogies to explain concepts is no more rough than mathematical descriptions. The car-car analogy can reasonably convey the concept of neural network and make up for the original deficiencies. The car-to-vehicle analogy is very useful. We can use the car-to-vehicle analogy to integrate the current neuroscience results.

6. Note

None of the authors can drive. This manuscript, all references are labelled by superscripts index.

The mathematical description of the Car-Car analogy

Suppose a system contains several networks which can be described as graphs $G_i(V_{ij}, E_{ij})$. One network the system can be denoted by index i . Therefore the nodes and edges of i -th network are label by two index. The first index denotes which graph it is belong to. The second index labels a node or an edge's position. If the system contains only single graph. It is the simplest case. $G(V_j, E_j)$. In other notation, people prefer to use a set to present nodes and edges, $G(\mathbf{V}, \mathbf{E})$. And $\mathbf{V} = \{V_1, V_2, \dots V_n\}$ As well as the edge set $\mathbf{E}$. In this presentation, all graph at the initial should be a complete graph. This means if a graph G has N nodes, it has $N(N - 1)/2$ edges. We firstly label all edge and then remove some of them. If we want to have a so-called small world network, we can assign a probability p_i for each eade to be vanished.

There are also a set of operators acting upon a given graph. The operators can be described as add or remove nodes or edges. We use the notation $V_{ij}^{\pm}$ to denote the node V_{ij} add/remove-operation (+ means add, - means remove) in the graph G_i . For example $V_{12}^- G_1 = G_1(V_1, V_3, \dots V_n; E_1, E_2, \dots, E_n)$.

The dynamics of graph can be described as a series of operators. For example, a operator series can be written as $\hat{O} = \{V_{34}^+, V_{25}^-, E_{23}^-\}$. This series is time order, it means we have perform the E_{23}^+ upon the system. The first graph we act is G_2 , and we remove the edge E_3 .

To describe the dynamics, we have to prepare a system containing several graphs and a set of operator. Given an initial configuration of a system, all graphs of system can be encoded by an operator series. In other words, we can create a system by using an operator series acting on a null system containing blank graphs, i.e., the vacuum state of system. Vacuum := $\{G_i = \{0, 0\}\}$.

For a given time interval Δt , we suppose the system is static during this time interval Δt . This means all graphs during this time interval do not changes. This time interval can be long or short upon the situation.

The transmission matters here we call them as particles. There are several species of particles, use notation m_s to denote them. The subscribe s means species. Only m_1 can transmit inside the network G_1 . Meanwhile we have to count all particles inside all nodes and edges in a network. For simplicity, we assume the number of particles is conserved. Therefore, the conservation law must be followed.

Suppose there are two graphs for simplicity. The interaction of two network can be described in the node-node way. There is at least a node $V_{\text{int}} \in G_{1\&2}$. The local rule of V_{int} should be set initially. For example, we have to require V_{int} can only allow 3 m_1 particles and 2 m_2 particles. If the maximum is reached, the particles have to leave this node with a probability p_{int} or another rules. Please note that the local rule refer to the rules for all nodes and edges. It is for convenience to think the nodes is a place and edges is channel. A channel has a maximum limitation to allow particle to pass. This is as well as nodes.

The mechanism of particle flow can be based on observation or artificial set-up. One possible rule for a case is require that once a node contain too much particles m . Some of them must leave to nearest nodes if the channel is pass-allowed.

Another way to describe the multi-network system and the interaction is to reduce other networks $G_2, G_3, \dots, G_n$ to background effect. For example, nutrition landscape. This is similar to put a pipeline network on a mountain and valley. And then using physical laws, such as hydrodynamics to constrain the behavior of water flow. Meanwhile, we also consider the extreme situation. If some channel has extreme high pressure, there has a probability $p_{\text{break}}(\text{parameters}) \in [0, 1]$ to breakdown. Such kind of situation is realistic and readers from engineering areas are equipped relevant knowledge for this case. In physics, to reduce other networks' effect into a non-uniform background is common. A very popular approach is the mean field approach.

In summary, we here perform a simple version of combination of the graph structure dynamics and reduced version of Petri net-like structure. Interested reader can have relevant material from those two area.