Frontiers of Information Technology & Electronic Engineering
www.jzus.zju.edu.cn; engineering.cae.cn; www.springerlink.com
ISSN 2095-9184 (print); ISSN 2095-9230 (online)
E-mail: jzus@zju.edu.cn

Comment:

New directions for artificial intelligence: human, machine, biological, and quantum intelligence*

Li WEIGANG‡1, Liriam Michi ENAMOTO[1], Denise Leyi LI[2], Geraldo Pereira ROCHA FILHO[1]

[1]*Department of Computer Science, University of Brasilia, Brasilia-DF 70910-900, Brazil*

[2]*Faculty of Economics, Administration, Accounting and Actuaries, University of Sao Paulo, Sao Paulo 05508-010, Brazil*

E-mail: weigang@unb.br; liriam.enamoto@gmail.com; denise.leyi@gmail.com; geraldof@unb.br

Received May 4, 2021; Revision accepted Aug. 11, 2021; Crosschecked Sept. 3, 2021; Published online Nov. 3, 2021

https://doi.org/10.1631/FITEE.2100227

1 Introduction

This comment reviews the "once learning" mechanism (OLM) that was proposed by Weigang (1998), the subsequent success of "one-shot learning" in object categories (Li FF et al., 2003), and "you only look once" (YOLO) in objective detection (Redmon et al., 2016). Upon analyzing the current state of research in artificial intelligence (AI), we propose to divide AI into the following basic theory categories: artificial human intelligence (AHI), artificial machine intelligence (AMI), artificial biological intelligence (ABI), and artificial quantum intelligence (AQI). These can also be considered as the main directions of research and development (R&D) within AI, and distinguished by the following classification standards and methods: (1) human-, machine-, biological-, and quantum-oriented AI R&D; (2) information input processed by dimensionality increase or reduction; (3) the use of one/a few or a large number of samples for knowledge learning.

AI has gone through more than 60 years of evolution since its conception to its establishment as a scientific field (Russell and Norvig, 2003; Luger, 2005; Wu, 2020). Whether it is knowledge engineering based on logical symbols or machine learning (ML) proficient in numerical computing, the rapid and continuous development of AI has led to outstanding achievements (Pan, 2017, 2018; Zhuang et al., 2017). In particular, the extraordinary success of deep learning (DL) in natural language processing (NLP) and signal/image/video processing has catapulted human civilization into the era of AI (Goodfellow et al., 2016; Silva and Zhao, 2016).

Previous landmark achievements are undoubtedly important in AI R&D and will impact the subsequent development of this field. IBM's Deep Blue, Google DeepMind's AlphaGo and AlphaFold, and other projects that challenge human intelligence have significant developments in the history of AI (Campbell et al., 2002; Silver et al., 2017; Jumper et al., 2021). This article does not intend to review all processes comprehensively, but will instead focus on several relevant points. For example, "once learning" is a parallel learning mechanism that aims to simulate the phenomenon of "once seen, never forgotten" (in Chinese: 过目不忘) with neural networks (NNs) (Weigang, 1998). The "one-shot learning" method (Li FF et al., 2003) in object categorization tries to reproduce human meta-learning mechanism with one or a few examples (Miller et al., 2000). YOLO and "single shot detector" (SSD) were proposed as novel

‡ Corresponding author
* Project supported by the Brazilian National Council for Scientific and Technological Development (No. 311441/2017-3)
ORCID: Li WEIGANG, https://orcid.org/0000-0003-1826-1850; Liriam Michi ENAMOTO, https://orcid.org/0000-0003-0188-5966; Denise Leyi LI, https://orcid.org/0000-0003-0664-3149; Geraldo Pereira ROCHA FILHO, https://orcid.org/0000-0001-6795-2768

learning models for object detection (Liu et al., 2016; Redmon et al., 2016).

Industrial and business magnates lead R&D in the AI area. For instance, Google Brain proposed the transformer method (Vaswani et al., 2017). Subsequently, the Bidirectional Encoder Representations from Transformers (BERT) was introduced to achieve specific downstream applications such as text generation, translation, and analysis, which led to high precision NLP (Devlin et al., 2018). In addition, a large-scale Chinese corpora for pre-training language models, WuDaoCorpora, was developed by the Beijing Academy of AI (Yuan et al., 2021). Backed by extensive funding, talent, equipment, and data, large corporations propel scientific and technological breakthroughs, setting a new trend in AI R&D. Consequently, this leads to confusion and challenges among researchers (both practitioners and students) of AI theory.

ML and DL occupy the main focus of AI R&D. On Apr. 11, 2021, we used several keywords to search on Google. Google showed 13.64 billion searches for "Twitter." Although "AI" as a keyword of a subject term should have considerable influence, the number of matching searches was only about 680 million, far fewer than the 2.38 billion hits on "ML" and 2.17 billion on "DL." Similarly, on Google Scholar, there were about 3.19 million documents pertaining to AI, only 41% of the number related to "Twitter." There were more than 5.36 million documents related to ML and 4.90 million related to DL. From Table 1, compared to AI basic research, it was notable that intensive ML/DL research is significant for promoting the development of AI, but excessive and repeated research may cause a waste of human and other resources in the whole AI field.

Despite the great progress made in theoretical research of AI in recent decades, there is a need to outline a theoretical system and scientific classification to guide R&D in AI (Pan, 2016; Evans and Grefenstette, 2018; Li JZ and Tang, 2019). There is an opportunity to develop a framework to complement the theoretical system to guide the direction of R&D, while avoiding uneven development. Financial and human resources are limited, and many researchers are working on ML, whereas only a few focus on basic AI theory. The theoretical framework of AI still needs to be strengthened, and programmatic guiding ideologies are necessary.

Quantum computing and communications are areas that are developing rapidly. Putting them into practical use is just around the corner, and this is bound to elevate AI into a new age (Arute et al., 2020; Yang et al., 2020). Although quantum computing and AI have been developed in parallel and each has achieved significant results, these two fields should be able to be combined to complement each other in both theory and applications (Weigang, 1998; Sgarbas, 2007; Dunjko and Briegel, 2018).

In this comment, we review the evolution and challenges of the OLM and analyze the current status of AI. Considering the existing problems and prospective solutions, our proposal is to classify AI into four basic categories. The first is AHI, which focuses on the development of human-like learning, human-like robots, and other human-oriented AI. Next, AMI focuses on the development of ML, machine-like robots, and other machine-oriented AI. Third, there is ABI, which focuses on the realization of bio-inspired learning, bio-robots, and other biological-oriented AI. Lastly, AQI focuses on the quantum generalizations of AI and the development of new methods of quantum AI. These new concepts can be considered the basic branches and main macro directions for future AI R&D.

2 Once learning, one-shot learning, and you only look once

Humans can acquire most of the information directly and indirectly related to them from the natural environment, perform knowledge processing, and

Table 1 Keyword search results from Google on Apr. 11, 2021

Site	Number of searches/documents ($\times 10^6$)			
	Twitter	ML	DL	AI
Google	13 640 (100%)	2380 (17%)	2170 (16%)	680 (5%)
Google Scholar	7.75 (100%)	5.36 (69%)	4.90 (63%)	3.19 (41%)

ML: machine learning; DL: deep learning; AI: artificial intelligence optimize decision-making. The phenomenon of "once seen, never forgotten" means visually perceiving the real world with a glance, and then learning, memorizing, and reasoning the observed scenes to make decisions and even express emotion.

To describe this phenomenon and thinking process, the "once learning" approach was proposed by Weigang (1998) and Weigang and Da Silva (1999). The idea was based on self-organizing mapping (SOM) with an unsupervised learning model (Kohonen, 1990). Regarding human behavior following visual knowledge acquisition, three characteristics are modeled: (1) full-screen information input of two-dimensional (2D) images/texts is processed once; (2) an unsupervised learning mechanism is established using a few parameters; (3) parallel and synchronous memory processing and knowledge learning for full-screen information are implemented.

The "one-shot learning" method was proposed in regard to object categories of computer vision (Li FF et al., 2003). As the basic learning mechanism of meta-learning, the current "few-shot learning" technique has become a standard learning paradigm in AI (Miller et al., 2000; Li FF et al., 2006). Extended methods such as "zero-, one-, and few-shot learning" have been successfully used in NLP (Brown et al., 2020).

Some computer vision developers proposed the YOLO and SSD models (Liu et al., 2016; Redmon et al., 2016) for object detection. Unlike the previous region-based method, these methods demonstrate the practicality of region-free skill and have achieved successful applications.

Although the motivations and purposes differ, the first step of the information input process of these three approaches follows the OLM. "Once learning" is not limited only to the planar graph and text learning of 2D information, but can also be extended to multi-dimensional information (Valova et al., 2005). The parallel learning mechanism of "once learning" has also been proposed for quantum computing (Weigang, 1998). Some scholars have made promising progress in this topic (Li F et al., 2004; Bhattacharyya et al., 2014; Konar et al., 2016; Wiśniewska et al., 2020).

Considering the potential of OLM for further development of human-like learning, it is imperative to propose a new classification of AI research.

3 Perspectives: AHI, AMI, ABI, and AQI

As the R&D of AI continues to progress rapidly, it is generally accepted that AI is currently classified by its applications, such as expert systems, image processes, NLP, and robotics. In this case, if AI is regarded as a discipline, classification of its secondary disciplines is neither clear nor reasonable. In this section, we discuss the classification of AI using the method of ontology. Table 2 shows the acronyms and the meanings of some new or uncommon terminologies used in this paper.

Table 2 Acronym and its meaning

Acronym	Meaning
ABI	Artificial biological intelligence
AGI	Artificial general intelligence
AHI	Artificial human intelligence
AMI	Artificial machine intelligence
ANI	Artificial narrow intelligence
AQI	Artificial quantum intelligence
ASI	Artificial super intelligence
GHLR	General human-like robots
HEP	Human emotion processing
HLL	Human-like learning
MML	Multimodal learning
OLM	Once learning mechanism
SHLR	Super human-like robots

AHI focuses on the development of human-oriented AI, such as human-like robots and human-like learning. Human-like robots will be the mainstream of AHI. It is proposed to include the following sub-branches:

1. Human-like robots, which are robots with human bodies and even human emotions. They include super human-like robots (SHLR) that live with humans as partners, as well as general human-like robots (GHLR) that assist humans as domestic workers, security guards, and drivers, and provide other related services.

2. Human-like learning (HLL), which is a theoretical and technical subject related to human-like robots and includes meta-learning, "once learning," and other new learning approaches.

3. New and upcoming human brain science and engineering subjects including human emotion processing (HEP).

4. Knowledge engineering, which includes the combination of symbolical knowledge processing and numerical computing.

5. Research on the theory and application of AHI, such as wearable smart devices.

AMI focuses on the development of machine computing capabilities that can strengthen ML/DL, machine-like robots, and other machine-oriented AI. AMI is proposed to include the following sub-branches:

1. ML, which includes NNs, DL, and other numerical computing.

2. Machine-like robots, such as humanoid robots, machine arms, unmanned aerial vehicles (UAVs), automated driving systems, and remote surgery systems.

3. Engineering related to the implementation of AMI, such as electronics, machinery, materials, equipment, and computers.

4. Research on the applications of AMI related to, for example, smart cities and intelligent transport systems.

ABI focuses on the realization of bio-inspired learning, bio-robots, and other biological-oriented AI under the guidance of AI ethical principles. ABI is proposed to include the following sub-branches:

1. Bio-inspired learning and others.

2. Bio-robots, such as RoboSwift, Spider, biomedical engineering, and cybernetics.

3. Genetic programming, swarm intelligence, and other traditional topics.

4. Research on the theory and application of ABI, including protein structure prediction.

AQI focuses on the quantum generalizations of AI problems and the development of new methods of AI using quantum computing. AQI is proposed to include the following sub-branches:

1. Quantum enhancements for AI, such as quantum perceptron, learning, and emotion.

2. Quantum generalizations of AI problems.

3. New quantum methods in AI problem solving.

4. Related research and applications of quantum computing for AHI, AMI, and ABI.

4 AI classification: research object, sample size, and dimensionality

4.1 Traditional AI classification

Several classifications of AI have been proposed (Russell and Norvig, 2003; Luger, 2005; Floreano and Mattiussi, 2008; Wu, 2020). Russell and Norvig (2003) designed a combination of thinking/action and human/rational, demonstrating four fields related to AI. This classification is an effective guide for AI studies, but it is necessary to complement the theoretical architecture of AI.

Another popular scheme categorizes AI into artificial narrow intelligence (ANI), artificial general intelligence (AGI), and artificial super intelligence (ASI) (Gottfredson, 1997; Bostrom, 2006). This classification is based on the characteristics of intelligence, but it does not have obvious boundaries or classification methods.

The traditional classification of AI branches is based mainly on the following aspects:

1. The research fields of AI, which include mainly: robots and unmanned machines; NLP; image, audio, and other signal processing; Internet of Things; automatic driving.

2. AI technology, which includes mainly the following: search; knowledge expression and reasoning; expert systems; NNs and ML/DL; data mining; pattern recognition.

3. The application fields of AI, which include mainly the following: intelligent transportation systems; smart cities; e-commerce; smart recommendations; social networks; data science; others.

The concepts and classifications mentioned above play a positive role in the development of AI. However, with the progress of AI R&D, new concepts and classification methods need to be explored.

4.2 Classification standards and methods

1. Divided by object of research: human-oriented vs. machine-oriented vs. biological-oriented vs. quantum-oriented

This classification method is relatively intuitive and is based on the object of research. Human-oriented intelligence research methods and technologies are classified as AHI. Examples include human brain studies, emotion processing, knowledge-based reasoning systems, and human-like robots. AI research that incorporates machines as the main subject is classified as AMI, and includes ML, DL, and machine-like robots. AI research with biology as the main object is classified as ABI, which is exemplified by bio-robots. As an important up and coming topic, AI research with quantum computing and communication as the main object is classified as AQI and includes quantum learning, quantum NNs, and etc.

2. Divided by the manner of input samples: few samples vs. more samples

"Once learning" as well as "few-shot learning" uses a system with prior knowledge from a small number of samples, which allows for the identification of new objects. This process embodies the human learning model and can be considered as human-like intelligence. Most ML methods require learning a large or even a vast amount of data/knowledge. These supervised learning methods can be classified as machine intelligence.

3. Divided by the knowledge processing mode: dimensionality increase vs. dimensionality reduction

Humans and most animals have five senses: touch, sound, sight, smell, and taste. If an intelligence system is able to accept multiple senses and process the information comprehensively, it is called multimodal learning (MML) (Baltrušaitis et al., 2019; Ramesh et al., 2021). At present, research on MML among images, videos, audios, and semantics is one of the most popular fields of study. Traditional intelligence systems generally accept only one type of sense and perform information processing. This is known as monomodal learning. To enhance the high-level intelligence of a system, the dimensionality of information input, called the ascending dimensionality for short, must be increased. This type of research can be summarized as a branch of AHI.

On the other hand, because NNs and even computers are good at processing low-dimensional information in ML, data dimensionality reduction on data is widespread, such as One-Hot encoding and various embedding methods. Embedding operations are used to reduce information dimensionality for the convenience of machine calculations. Related research can be classified as machine intelligence.

Table 3 summarizes several essential aspects of AI classification, including intelligent objects, input dimensionality, sample collection, knowledge expression, learning mechanisms, and various robots. The definitions and categorizations are initial proposals, which need to be discussed further and studied in the AI community.

5 Final considerations

We started this comment with a review of three specific learning methods that appear in the literature: "once learning," "one-shot learning," and YOLO. These methods can be summarized as OLM because both the information input processing and learning paradigm use the same approach. Additionally, "one-shot learning" is widely accepted by the academic community, and has been extended to include "few-shot learning," which has become a typical method of NLP, meta-learning, and other AI applications.

To strengthen the theoretical study of AI, we propose to categorize AI into four branches: ABI, AHI, AMI, and AQI. This classification can be considered a new framework of sub-disciplines that will promote AI study. With the highlighting of new concepts in AHI, HLL and HEP will advance quickly and reflect the state-of-the-art AI R&D. Taking robotics, which is an essential part of AHI, as an example, human-like robots including SHLR and GHLR will become more important in the near future. On the other hand, the combination of quantum computing and AI has become important for R&D in both fields. The proposal of AQI is an initiative based on previous studies and will form the next AI wave together with AHI. There will be many challenges and opportunities for AQI if the quantum computer becomes a practical computing tool for human beings.

Some standards and classification methods are also discussed here, including the object of research, scale of input samples, and dimensionality increase or reduction. In future research, it is imperative to discuss the following topics: (1) classification

Table 3 Summary of the classifiers of AI

Topic	ABI	AHI	AMI	AQI
AI object	Biological-oriented	Human-oriented	Machine-oriented	Quantum-oriented
Learning	Heuristic	Human-like	ML/DL	Quantum learning
Robotics	Bio-robots	Human-like	Machine-like	Quantum-like
Input	Dimensionality increase		Dimensionality reduction	
Sample	Few data		Big data	
Knowledge	+Symbolic		+Numeric	

standards; (2) classification methods; (3) development plans for each branch of AI; (4) AI concepts and sub-branch extensions.

Contributors

Li WEIGANG designed the research and drafted the manuscript. Liriam Michi ENAMOTO processed the data using the machine learning algorithms. Denise Leyi LI helped with the search results from Google. Geraldo Pereira ROCHA FILHO helped organize the manuscript. All of the authors revised and finalized the paper.

Acknowledgements

The authors would like to thank the valuable suggestions from Marcos DIB, Peng WEI, and Wu XING. Also, thanks Sophia CHENG for English proofreading.

Compliance with ethics guidelines

Li WEIGANG, Liriam Michi ENAMOTO, Denise Leyi LI, and Geraldo Pereira ROCHA FILHO declare that they have no conflict of interest.

References

Arute F, Arya K, Babbush R, et al., 2020. Hartree-fock on a superconducting qubit quantum computer. *Science*, 369(6507):1084-1089. https://doi.org/10.1126/science.abb9811

Baltrušaitis T, Ahuja C, Morency LP, 2019. Multimodal machine learning: a survey and taxonomy. *IEEE Trans Patt Anal Mach Intell*, 41(2):423-443. https://doi.org/10.1109/TPAMI.2018.2798607

Bhattacharyya S, Pal P, Bhowmick S, 2014. Binary image denoising using a quantum multilayer self organizing neural network. *Appl Soft Comput*, 24:717-729. https://doi.org/10.1016/j.asoc.2014.08.027

Bostrom N, 2006. How long before superintelligence? *Linguist Philos Investig*, 5(1):11-30.

Brown TB, Mann B, Ryder N, et al., 2020. Language models are few-shot learners. https://arxiv.org/abs/2005.14165

Campbell M, Hoane AJJr, Hsu FH, 2002. Deep blue. *Artif Intell*, 134(1-2):57-83. https://doi.org/10.1016/S0004-3702(01)00129-1

Devlin J, Chang MW, Lee K, et al., 2018. BERT: pre-training of deep bidirectional transformers for language understanding. https://arxiv.org/abs/1810.04805

Dunjko V, Briegel HJ, 2018. Machine learning & artificial intelligence in the quantum domain: a review of recent progress. *Rep Prog Phys*, 81(7):074001. https://doi.org/10.1088/1361-6633/aab406

Evans R, Grefenstette E, 2018. Learning explanatory rules from noisy data. *J Artif Intell Res*, 61:1-64. https://doi.org/10.1613/jair.5714

Floreano D, Mattiussi C, 2008. Bio-inspired Artificial Intelligence: Theories, Methods, and Technologies. MIT Press, Cambridge, UK.

Goodfellow I, Bengio Y, Courville A. 2016. Deep Learning. MIT press, Cambridge, MA, USA.

Gottfredson LS, 1997. Mainstream science on intelligence: an editorial with 52 signatories, history, and bibliography. *Intelligence*, 24(1):13-23. https://doi.org/10.1016/S0160-2896(97)90011-8

Jumper J, Evans R, Pritzel A, et al., 2021. Highly accurate protein structure prediction with AlphaFold. *Nature*, 596(7873):583-589. https://doi.org/10.1038/s41586-021-03819-2

Kohonen T, 1990. The self-organizing map. *Proc IEEE*, 78(9):1464-1480. https://doi.org/10.1109/5.58325

Konar D, Bhattacharyya S, Panigrahi BK, et al., 2016. A quantum bi-directional self-organizing neural network (QBDSONN) architecture for binary object extraction from a noisy perspective. *Appl Soft Comput*, 46:731-752. https://doi.org/10.1016/j.asoc.2015.12.040

Li F, Zhao SM, Zheng BY, 2004. Research on the characteristics of quantum neurons. *J Circ Syst*, 9(4):76-80 (in Chinese).

Li FF, Fergus R, Perona P, 2003. A Bayesian approach to unsupervised one-shot learning of object categories. Proc 9th IEEE Int Conf on Computer Vision, p.1134-1141. https://doi.org/10.1109/ICCV.2003.1238476

Li FF, Fergus R, Perona P, 2006. One-shot learning of object categories. *IEEE Trans Patt Anal Mach Intell*, 28(4):594-611. https://doi.org/10.1109/TPAMI.2006.79

Li JZ, Tang J, 2019. Report of Artificial Intelligence Development. Tsinghua University, Beijing, China (in Chinese).

Liu W, Anguelov D, Erhan D, et al., 2016. SSD: single shot multibox detector. 14th European Conf on Computer Vision, p.21-37. https://doi.org/10.1007/978-3-319-46448-0_2

Luger GF, 2005. Artificial Intelligence: Structures and Strategies for Complex Problem Solving (5th Ed.). Addison-Wesley, Harlow, USA.

Miller EG, Matsakis NE, Viola PA, 2000. Learning from one example through shared densities on transforms. Proc IEEE Conf on Computer Vision and Pattern Recognition, p.464-471. https://doi.org/10.1109/CVPR.2000.855856

Pan YH, 2016. Heading toward artificial intelligence 2.0. *Engineering*, 2(4):409-413. https://doi.org/10.1016/J.ENG.2016.04.018

Pan YH, 2017. Special issue on artificial intelligence 2.0. *Front Inform Technol Electron Eng*, 18(1):1-2. https://doi.org/10.1631/FITEE.1710000

Pan YH, 2018. 2018 special issue on artificial intelligence 2.0: theories and applications. *Front Inform Technol Electron Eng*, 19(1):1-2. https://doi.org/10.1631/FITEE.1810000

Ramesh A, Pavlov M, Goh G, et al., 2021. DALL·E: Creating Images from Text. OpenAI Blog. https://openai.com/blog/dall-e/

Redmon J, Divvala S, Girshick R, et al., 2016. You only look once: unified, real-time object detection. Proc IEEE Conf on Computer Vision and Pattern Recognition, p.779-788. https://doi.org/10.1109/CVPR.2016.91

Russell S, Norvig P, 2003. Artificial Intelligence: a Modern Approach (2nd Ed.). Prentice Hall, Upper Saddle River, USA.

Sgarbas KN, 2007. The road to quantum artificial intelligence. https://arxiv.org/abs/0705.3360

Silva TC, Zhao L, 2016. Machine Learning in Complex Networks. Springer International Publishing, Springer Nature, Switzerland.

Silver D, Schrittwieser J, Simonyan K, et al., 2017. Mastering the game of Go without human knowledge. *Nature*, 550(7676):354-359. https://doi.org/10.1038/nature24270

Valova I, Gueorguieva N, Kempka M, 2005. ParaGro: a learning algorithm for growing parallel self-organizing maps with any input/output dimensions. *Int J Gen Syst*, 34(6):735-757. https://doi.org/10.1080/03081070500422919

Vaswani A, Shazeer N, Parmar N, et al., 2017. Attention is all you need. Proc 31st Conf on Neural Information Processing Systems, p.6000-6010. https://doi.org/10.5555/3295222.3295349

Wiśniewska J, Sawerwain M, Obuchowicz A, 2020. Basic quantum circuits for classification and approximation tasks. *Int J Appl Math Comput Sci*, 30(4):733-744. https://doi.org/10.34768/amcs-2020-0054

Weigang L, 1998. A study of parallel self-organizing map. https://arxiv.org/abs/quant-ph/9808025v2

Weigang L, Da Silva NC, 1999. A study of parallel neural networks. Int Joint Conf on Neural Networks, p.1113-1116. https://doi.org/10.1109/IJCNN.1999.831112

Wu F, 2020. Introduction to Artificial Intelligence: Models and Algorithms. Higher Education Press, Beijing, China (in Chinese).

Yang B, Sun H, Huang CJ, et al., 2020. Cooling and entangling ultracold atoms in optical lattices. *Science*, 369(6503):550-553. https://doi.org/10.1126/science.aaz6801

Yuan S, Zhao HY, Du ZX, et al., 2021. WuDaoCorpora: a super large-scale Chinese corpora for pre-training language models. *AI Open*, 2:65-68. https://doi.org/10.1016/j.aiopen.2021.06.001

Zhuang YT, Wu F, Chen C, et al., 2017. Challenges and opportunities: from big data to knowledge in AI 2.0. *Front Inform Technol Electron Eng*, 18(1):3-14. https://doi.org/10.1631/FITEE.1601883