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Topic Insights

The Next Breakthroughs of Artificial Intelligence: The Interdisciplinary Nature of AI

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1. Introduction

Artificial intelligence (AI) is committed to the realization of machine-borne intelligence. The technologies underpinning AI have made huge leaps in the past decade, bringing exciting applications such as language understanding, vision recognition, and intelligent digital assistants. However, contemporary AI systems are good at specific predefined tasks and are unable to learn by themselves from data or from experience, intuitive reasoning, and adaptation. From the perspective of overcoming the limitations of existing AI, interdisciplinary scientific efforts are necessary to boost future research on AI. As a result, the next breakthroughs of AI will be interdisciplinary endeavors that draw upon neuroscience, physics, mathematics, electronic engineering, biology, linguistics, and psychology to deliver great theoretical, technological, and applicable innovations, address complex societal issues, reshape the national industrial system, and more.

2. AI and aerospace

AI is becoming an enabling technology for space exploration. As AI-powered solutions are capable of data mining, data fusion, and massive data analysis, they are widely adopted to perform different tasks, such as producing the first picture of a black hole, predicting solar flares, mapping the moon's surface, searching for extraterrestrial communications in the universe, and studying dark matter [1]. Meanwhile, AI is facilitating onboard space missions as well.

AI is empowering spacecraft to be more independent, self-reliant, and autonomous. For example, from its atmospheric entry to its Mars landing, National Aeronautics and Space Administration (NASA)'s lander InSight was beyond the reach of remote control due to weak telemetry signal strength and communication latency. To survive, InSight had to autonomously perform dozens of operations and do them flawlessly. AI is also being used for trajectory and payload optimization, both of which are important preliminary steps in NASA's next rover mission to Mars [2].

AI is helping to accelerate the transition toward an era of smart satellites. Lockheed Martin has developed "SmartSat," a software-defined satellite architecture that allows users to change the mission of a satellite in orbit using a software update. This software-defined solution not only provides the flexibility and ability to reconfigure satellites for different tasks, but could also reduce cost with high reusability, which would be impossible with traditional hardware-defined satellites. Furthermore, a series of formation-flying smart satellites can establish a distributed AI platform, processing data on board and having their functionality changed during the mission. This space-based AI platform is able to train models, deploy applications, and perform online serving. Such onboard processing capability would dramatically improve the operational efficiency of space missions, while reducing communication costs.

Space exploration is full of unknown and unexpected difficulties. Current programming models for spacecraft rely on pre-programming a system for all potential scenarios; however, such a system is unable to react to new, unforeseen circumstances. By introducing new machine learning (ML) mechanisms [3], systems are enabled to learn continuously, adapt to new conditions, and apply previously learned information to novel situations, in order to promote spacecraft autonomy on job scheduling, health monitoring, and onboard data processing. Moreover, with automated program-repair techniques [4], onboard debugging and maintenance activities that are currently executed manually are expected to be reduced by automating the process of analyzing failed executions, identifying the causes of failures, isolating faults, implementing fixes, and validating the fixed system.

3. AI and healthcare

Like a spring breeze that causes thousands of flowering trees to bloom overnight, AI seems to be having a sudden and dramatic "blooming" effect on various fields. ML lies at the core of AI, and has experienced promising advances in its ability to comprehend,

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exploit, and harness massive data. The field of AI has recently advanced through the development of computational power and the explosion of new data. Especially in healthcare and medicine [5], the sheer volume of data that is generated, as well as the proliferation of medical devices and digital record systems, means that human health can benefit immensely from the application of AI. Therefore, the increasing adoption of data-intensive methods can be observed throughout the healthcare system. The associated data flowing through the system thus results in the formulation of distinguishable representations, leading to more evidence-based decisions in regards to health and wellness.

While much attention has been paid to the implications for human health, another area in which AI is significantly evolving is genomics. AI systems can make genetic sequencing and analysis faster, cheaper, and more accurate [6]. Moreover, AI has revolutionized prediction [7] in molecular biology and genetics. With this insight, researchers can make decisions about what an organism might be susceptible to in the future, what mutations might cause different diseases, and how to prepare for the future. Since genetic sequencing and analysis can provide a perspective on the particular genetic blueprint that orchestrates all the activities of a particular organism, they can be ground-breaking in the fields of agriculture, animal husbandry, and genetic disease diagnosis with the support of AI.

As for the next generation of industrial technology, no one can ignore the pivotal roles of both AI and blockchain [8] in boosting healthcare in the wave of the fourth industrial revolution: AI is integrated into the very DNA of the fourth industrial revolution, while blockchain could revolutionize the infrastructure of the economic system. Since the joint force of these two technologies can determine the depth and breadth of the fourth industrial revolution, the synergy or integration of AI and blockchain is necessary in order to allow AI to efficiently assist the implementation of blockchain technology. Based on its deep influence on various fields, AI is destined to inject a self-renewal ability and magnificent vitality into our time.

4. AI and material design

Designing advanced materials with the assistance of AI is also of great significance for the future of human society. Historically, the discovery and industrial applications of new materials often require fairly long periods of time. In 2011, the Obama administration proposed the Materials Genome Initiative (MGI) to enable the discovery, development, manufacturing, and deployment of advanced materials at least twice as fast as was possible at that time. Along with the merging of the MGI and big data in subsequent years, the data-driven model is now treated as the most promising approach in materials research, where AI is the key technology used to process big data and obtain the composition–structure–process–performance relationship.

Due to the potential demonstrated by ML techniques in recent years, it is believed that these techniques could revolutionize materials science. For example, it is well known that the current form of the periodic table of chemical elements was constructed by many eminent scientists over almost one a full century. However, with the aid of AI, it is now possible to reconstruct the periodic table within several hours. An unsupervised machine named Atom2Vec autonomously learns the basic properties of atoms from the extensive database of known compounds and materials, which and then employs them in neural networks to predict the detailed characteristics of new materials with significant accuracy [9]. In drug-candidate synthesis, Segler et al. [10] proposed the use of symbolic AI to discover retrosynthetic routes; this method is 30 times faster and yields almost twice as many molecules in comparison with the traditional computer-aided search method. It is worth pointing out that the neural network must be trained on both successful and failed data, which stands in stark contrast to the conventional assumption that only successful data is useful for training.

In addition to its use in synthesizing materials, AI has the potential to advance the development of artificial materials (termed metamaterials or metasurfaces), which are characterized by effective material parameters determined by geometric dimensions and compositions [11]. Since the structural geometries and basic compositions of artificially structured materials vary far beyond the capabilities of traditional trial-and-error methods, it is necessary to optimize the design with the help of big-data technologies. In turn, the newly developing optical computation technologies enabled by structured materials may help to increase the data-processing speed and reduce the power consumption of deep learning, as the speed of light is much faster than that of electrons, while the passive optical components do not need power [12].

5. AI and marine resources

AI is playing an increasingly important role in the development of marine resources. Developed countries, driven by the era of great navigation, have strong strategic advantages in this regard. As an ocean that accounts for 71% of the Earth's area, AI will be very critical for the deep development of marine resources, but at present we have not done enough in the development of the ocean. For example, AI is utilized to efficiently detect and develop mineral resources in the ocean. Furthermore, "underwater country gates open" is not desired by any technological country with a long coastline. In other words, coastal defense security is undoubtedly the one of the most important national security.

Traditional marine technology is mainly used to detect marine resources from the aspects of acoustics and magnetism. The deep mining and analysis capabilities of AI on marine data can make traditional marine technology more viable for efficient use and effective protection.

As an important channel for obtaining information, optics has a wide range of applications in the field of AI. However, due to the strong absorption and scattering effect of seawater on light, the underwater optical world is chaotic. Data quality and range of application are world-class challenges. As for China, with its vast internal and territorial waters, the use of underwater optics to observe landforms, properties, processes, and other information below the sea surface is an important subject related to national defense security, resource management, and economic development. Therefore, intelligent optics and AI will be indispensable for the development of marine optics.

6. Decentralized AI

We face two major challenges when practicing AI. One is that, in most industries, data exists in the form of isolated islands. The other is the ever-increasing demand for privacy-preserving AI. While conventional AI approaches with centralized data cannot address these challenges, federated learning (FL) is a solution that not only bridges the data islands, but also enables privacy-preserving AI with cross-data, cross-domain, and cross-enterprise applications [13,14].

FL can be considered as privacy-preserving collaborative ML with decentralized data. It is an algorithmic framework with the following features:

- Multiple parties work to jointly build an ML model. Each party holds some training data.
- The data held by each party does not leave that party; only model parameters or gradients are shared.
- The model can be transferred (in part) from one party to another under a security scheme [15,16], so that any party cannot reverse-engineer the data of any other parties.
- The performance of the model obtained from FL is a close approximation of the model built with centralized data collection.

FL can be classified into horizontal federated learning (HFL), vertical federated learning (VFL), and federated transfer learning (FTL), depending on how data is distributed among the parties. HFL refers to a case in which the parties share overlapping data features, but differ in data samples [13,14]. It resembles the situation in which data is horizontally partitioned in a tabular view. VFL applies to a scenario in which the parties share overlapping data samples, but differ in data features [13]. It resembles the situation in which data is vertically partitioned in a tabular view. FTL is applicable for a case in which little overlap occurs, either in data samples or in features among the parties, including instance-based FTL, feature-based FTL, and model-based FTL [13,15].

To facilitate the advance of FL, researchers at WeBank AI have developed the Federated AI Technology Enabler (FATE). FATE is an open-source project and an industrial-grade FL platform that supports HFL, VFL, and FTL. FL is promising for building ML models under data protection. It has potential applications in financing, healthcare, education, smart cities, and edge computing [13,17]. For example, FL can be used to perform local model training inside a bank, a social networking company, and an e-commerce company without sharing data, and can securely aggregate the trained local models to produce a federated model for a recommender system.

7. Conclusion

AI is a highly interdisciplinary field with potential applications in many areas of science, industry, and society [18–21]. We believe that the next breakthroughs of AI will be based on its interdisciplinary nature.

References

[1] Fluri J, Kacprzak T, Lucchi A, Refregier A, Amara A, Hofmann T, et al. Cosmological constraints with deep learning from KiDS-450 weak lensing maps. 2019. arXiv: 1906.03156.
[2] Chien S, Wagstaff KL. Robotic space exploration agents. Sci Robo 2017;2(7): eaan4831.
[3] Anthes G. Lifelong learning in artificial neural networks. Commun ACM 2019;62(6):13–5.
[4] Goues CL, Pradel M, Roychoudhury A. Automated program repair. Commun ACM 2019;62(12):56–65.
[5] Esteva A, Robicquet A, Ramsundar B, Kuleshov V, DePristo M, Chou K, et al. A guide to deep learning in healthcare. Nat Med 2019;25(1):24–9.
[6] Washburn JD, Mejia-Guerra MK, Ramstein G, Kremling KA, Valluru R, Buckler ES, et al. Evolutionarily informed deep learning methods for predicting relative transcript abundance from DNA sequence. Proc Natl Acad Sci 2019;116 (12):5542–9.
[7] Eraslan G, Avsec Ž, Gagneur J, Theis FJ. Deep learning: new computational modelling techniques for genomics. Nat Rev Genet 2019;20(7):389–403.
[8] Corea F. The convergence of AI and blockchain. In: Corea F, editor. Applied artificial intelligence: where AI can be used in business. Cham: Springer; 2018. p. 1–26.
[9] Zhou Q, Tang P, Liu S, Pan J, Yan Q, Zhang SC. Learning atoms for materials discovery. Proc Natl Acad Sci 2018;115(28):E6411–7.
[10] Segler MHS, Preuss M, Waller MP. Planning chemical syntheses with deep neural networks and symbolic AI. Nature 2018;555(7698):604–10.
[11] Luo X. Subwavelength artificial structures: opening a new era for engineering optics. Adv Mater 2019;31(4):1804680.
[12] Lin X, Rivenson Y, Yardimci NT, Veli M, Luo Y, Jarrahi M, et al. All-optical machine learning using diffractive deep neural networks. Science 2018;361 (6406):1004–8.
[13] Yang Q, Liu Y, Chen T, Tong Y. Federated machine learning: concept and applications. ACM Trans Intellt Syst Technol TIST 2019;10(2):12.
[14] McMahan HB, Moore E, Ramage D, Hampson S, Arcas BAy. Communication-efficient learning of deep networks from decentralized data. 2017. arXiv:1602.05629.
[15] Liu Y, Chen T, Yang Q. Secure federated transfer learning. 2019. arXiv:1812.03337.
[16] Bonawitz K, Ivanov V, Kreuter B, Marcedone A, McMahan HB, Patel S, et al. Practical secure aggregation for privacy-preserving machine learning. In: Proceedings of the 2017 ACM SIGSAC Conference on Computer and Communications Security (CCS'17); 2017 Oct 30–Nov 3; Dallas, TX, USA; 2017. p. 1175–91.
[17] Yang Q, Liu Y, Cheng Y, Kang Y, Chen T, Yu H. Federated learning. Williston, VT, USA: Morgan & Claypool; 2019.
[18] Pan Y. Heading toward artificial intelligence 2.0. Engineering 2016;2 (4):409–13.
[19] Pan Y. Special issue on artificial intelligence 2.0. Front Inform Technol Electron Eng 2017;18(1):1–2.
[20] Pan Y. Special issue on artificial intelligence 2.0: theories and applications. Front Inform Technol Electron Eng 2018;19(1):1–2.
[21] Zhuang Y, Wu F, Chen C, Pan Y. Challenges and opportunities: from big data to knowledge in AI 2.0. Front Inform Technol Electron Eng 2017;18(1):3–14.