New Generation Computing
https://doi.org/10.1007/s00354-024-00251-8

EDITORIAL

The Way Forward with AI-Complete Problems

Sven Groppe[1] · Sarika Jain[2]

1 Introduction

In the AI world, we come across the types of intelligence: Artificial Narrow Intelligence (ANI) and Artificial General Intelligence (AGI). ANI is designed and trained to perform specific tasks as programmed and cannot generalize its knowledge beyond what it is programmed for. Examples include self-driving cars, search engines, chatbots, and Virtual Personal Assistants. AGI, on the other hand, aims to perform any intellectual task that a human can. It has the ability to understand, learn, and make decisions. Intelligent agents are "intelligent" software that can work autonomously, seek necessary/present/relevant/authentic information, coordinate with each other, understand the contents, take necessary actions to make life simple for human beings and improve their performance by acquiring knowledge. Consider the simple and straightforward problem of machine translation from language A to language B; it includes tasks such as Natural Language Processing (NLP) in both languages, reasoning, knowledge engineering, contextual understanding, and social intelligence. Task-specific algorithms will not be able to solve the said problem as it involves simultaneous solutions to multiple subproblems. Such problems whose solution is beyond the capabilities of Artificial Narrow Intelligence (ANI) and which require Artificial General Intelligence (AGI) to reach human-level machine performance are termed as "AI-complete."

Before introducing the papers of this special issue, let us have a look at the brief history of AI and the last 10-year timeline toward the efforts made to achieve Artificial General Intelligence (AGI):

S. Groppe and S. Jain have contributed equally to this work.

✉ Sven Groppe
groppe@ifis.uni-luebeck.de

✉ Sarika Jain
jasarika@nitkkr.ac.in

[1] Institute of Information Systems (IFIS), University of Lübeck, Lübeck, Germany

[2] Department of Computer Applications, National Institute of Technology Kurukshetra, Kurukshetra, Haryana 136119, India

Published online: 19 March 2024

- **Symbolic AI:** During the very first generation of AI research, also called the Classical AI or the Rule-based AI, it was believed that AGI would be achieved in just a few decades. Strong claims were made by the then-researchers regarding the human intelligence capability of machines. Several projects, such as Doug Lenat's Cyc project (that began in 1984) [1], and Allen Newell's Soar project [2], are witnesses of these predictions. It was around the 1970s when the funding agencies, as well as the researchers, got skeptical of AGI, with AI being limited to Expert systems.
- **Narrow AI:** By the 1990s, AI researchers stopped mentioning AGI or human-level intelligence for machines, and the focus shifted to performing well in narrow and specific domains. This artificial narrow intelligence (ANI), sometimes called Weak AI, is quite mature today. Many AI systems we encounter today, such as virtual assistants (like Siri or Alexa), recommendation algorithms, chatbots, and specialized image or speech recognition systems, are examples of ANI. These systems are designed for specific functions and do not possess human-like general intelligence.
- **AGI Research:** In its basic form, "artificial general intelligence" was used to characterize the ability to complete tasks with maximum intelligence in various environments. Today's definition of AGI includes the capability of open-ended learning, innovation, and human-like reasoning.
  - In 2012, the ImageNet competition was won by AlexNet [3] with 15.3% top-5 test error rate and 26.3% second best.
  - In 2014 and 2017, the maximum IQ values of roughly 27 and 47, respectively, corresponding to a 6-year-old child in first grade, were found in intelligence tests conducted on publicly available and freely accessible weak AI, such as Google AI, Apple's Siri, and others [4, 5].
  - 2020, GPT-3 by OpenAI [6], which could perform many diverse tasks without training for specific tasks, is far from AGI but too advanced to be classified as Artificial Narrow Intelligence (ANI).
  - 2022, Gato by DeepMind [7], can perform more than 600 different tasks.
  - 2023, GPT-4 by OpenAI [8], is an early/incomplete version of AGI that demands further exploration.
  - 2023, the AI researcher Geoffrey Hinton stated "It was 30 to 50 years or even longer away. I no longer think that." [9]

Only restricted versions of AI-complete problems can be solved by the current AI systems, and that too without any commonsense knowledge. The current solutions cannot recognize uncertain situations. We have seen in the past decade that statistical models have revolutionized the world. Though the statistical models have already proven themselves, they are not a universal solution but a tool like others. Deep learning (DL) is very good at learning in a static world and executing low-level patterns, provided it is fed a lot of data. More deep, more intelligent, and, of course, more black. This is the crux of the problem that this special issue will emphasize. The question is, "Is the AI of today Artificial Super Intelligence (ASI)/Artificial General Intelligence (AGI)/Artificial Narrow Intelligence (ANI)? Is the AI of today the AI that we are craving for?" There are several instances where DL has generated delusional and unrealistic results. Accuracy alone is not sufficient. We require exploring ways of opening the black box of statistical models. When DL researchers are asked to open the black box, this today implies less intelligent models to them (with limited capability). In addition to increased performance, AGI aims to build trust.

2 The Way Forward

There are three information aspects for an intelligent agent: syntax (sentence construction, grammatical correctness), semantics (human-level interaction), and pragmatics (intention behind the communication. An intelligent agent must fuse heterogeneous sources of information, for which it should be equipped with both the data-driven (statistical) and knowledge-driven (symbolic) AI disciplines. We need a representation of our data that not only includes the data itself but also where the interactions in it are first-class citizens.

Symbolic AI and statistical AI have to go together to achieve contextual computing. Nowadays, the symbolic approach is manifested as a knowledge graph that advanced statistics and machine learning can run on top of. The Hybrid Model combines machine intelligence with human intelligence to reach conclusions faster than possible by humans alone, along with the explanations needed for trust in the decisions and results, while requiring far fewer data samples for training and conversing in natural language. The Hybrid Model can generalize and is excellent at perceiving, learning, and reasoning with minimal supervision. In addition, semantics have come a long way in enhancing explainability in AI systems. Complete AGI is speculative of its performance as of 2023. On one hand, many AI researchers believe in achieving AGI, while many also deny this possibility.

3 About this Special Issue

Our call for submissions to this special issue was well received: there have been over 40 submissions showing that many computer scientists are using neuro-symbolic AI techniques to address practical issues. Submissions are still being accepted as of this writing and will be included in later issues of this journal. Eight submissions for the special issue have been accepted thus far; some are still being reviewed. This graph already demonstrates how fiercely competitive computer science research on neuro-symbolic AI is, with the scientific community accepting only the most innovative methods.

The chosen papers cover a wide range of subjects.

- One paper employs multiple convolutional layers with differing kernel sizes to better capture the contextual information from user posts in depression detection from textual social media data [10]. Further, each layer has its attention layer to focus on significant parts, i.e., bigrams, trigrams, and quadgrams.

- A graph-based framework is proposed to match large ontologies by dividing them into small pieces and then matching them using sub-graph mining algorithms [11]. They used the Karger and CP (clique percolation and nearest neighbor) algorithms to divide bigger ontologies. For matching purposes, GraMi and gSpan algorithms are employed.
- Some authors highlighted the needs, challenges, and opportunities in the field of Explainable Artificial Intelligence (XAI) [12]. They explored different evaluation methods and metrics used in the literature for the effective evaluation of Explainable AI models. Application domains where Explainable AI is used are also identified, along with the tools and platforms for its implementation.
- One publication employed a CNN-LSTM-based hybrid architecture to analyze people's sentiment about Monkeypox disease on social media platforms [13]. An open-access dataset of tweets on Monkeypox documented in over 73 countries worldwide is used for this work.
- While the authors in Ref. [14] proposed a neuro-symbolic AI approach for text classification using a deep CNN and the Computer Science Ontology (CSO) as a semantic resource, the proposed system accepts the abstract and keywords of a particular research paper as input to find the relevant research topic of the paper.
- Another publication experimented with different topic modeling methods to categorize legal judgments into extracted topic groups [15]. The proposed approach eliminates time-consuming manual judgment analysis in favor of automated judgment analysis that can quickly examine many judgments in less time.
- Further, an Internationalized Resource Identifier (IRI)-debug tool is provided in Ref. [16] to validate the crafted ontology and gauge how much its concepts or properties comply with the standard ontologies. The tool helps users select an appropriate ontology from the available ontologies and validate the new ontology.
- The work in Ref. [17] studies which dataset classifier combination is optimal for categorizing thunderstorm occurrence in Ranchi, India. For this purpose, the authors deployed multiple soft computing techniques such as KNearest Neighbor (KNN), Decision Tree (DT), Logistic Regression (LR), and Support Vector Machine (SVM) with various kernel functions.

We hope you find the selected papers exciting and informative. Have fun reading the papers!

References

1. Lenat, D.B.: Cyc: a large-scale investment in knowledge infrastructure. Commun. ACM **38**(11), 33–38 (1995)
2. Laird, J.E., Newell, A., Rosenbloom, P.S.: Soar: An architecture for general intelligence. Artif. Intell. **33**(1), 1–64 (1987)
3. Krizhevsky, A., Sutskever, I., Hinton, G.E.: Imagenet classification with deep convolutional neural networks. In: Pereira, F., Burges, C.J., Bottou, L., Wein- berger, K.Q. (eds.) Advances in Neural Information Processing Systems, vol. 25. Curran Associates, Inc. (2012). https://proceedings.neurips.cc/paper_files/paper/2012/file/c399862d3b9d6b76c8436e924a68c45b-Paper.pdf

4. Liu, F., Shi, Y., Liu, Y.: Intelligence quotient and intelligence grade of artificial intelligence. Ann. Data Sci. **4**, 179–191 (2017)
5. Liu, F., Liu, Y., Shi, Y.: Three iqs of ai systems and their testing methods. J. Eng. **2020**(13), 566–571 (2020)
6. Brown, T., Mann, B., Ryder, N., Subbiah, M., Kaplan, J.D., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., et al.: Language models are few-shot learners. Adv. Neural. Inf. Process. Syst. **33**, 1877–1901 (2020)
7. Reed, S., Zolna, K., Parisotto, E., Colmenarejo, S. G., Novikov, A., Gimenez, M., Sulsky, Y., Kay, J., Springenberg, J. T., Eccles, T., Bruce, J., Razavi, A., Edwards, A., Heess, N., Chen, Y., Hadsell, R., Vinyals, O., Bordbar, M., & De Freitas, N.: A Generalist Agent. (2022). https://doi.org/10.48550/arXiv.2205.06175
8. Achiam, J., Adler, S., Agarwal, S., Ahmad, L., Akkaya, I., Aleman, F.L., Almeida, D., Altenschmidt, J., Altman, S., Anadkat, S., et al.: Gpt-4 technical report. (2023)
9. Metz, C.: 'The Godfather of AI' Leaves Google and Warns of Danger Ahead". New York Times. (2023) Retrieved from https://www.nytimes.com/2023/05/01/technology/ai-google-chatbot-engineer-quitshinton.html. Accessed 27 June 2023
10. Dalal, S., Jain, S., & Dave, M.: Convolution neural network having multiple channels with own attention layer for depression detection from social data. New Gener. Comput. 1–21 (2023)
11. Şentürk, F., & Aytac, V.: A graph-based ontology matching framework. New Gener. Comput. 1–19 (2023)
12. Chinu, & Bansal, U.: Explainable AI: to reveal the logic of black-box models. New Gener. Comput. 1–35 (2023)
13. Mohbey, K. K., Meena, G., Kumar, S., & Lokesh, K.: A CNN-LSTM-based hybrid deep learning approach for sentiment analysis on Monkeypox tweets. New Gener. Comput. 1–19 (2023)
14. Malik, S., & Jain, S.: Deep Convolutional neural network for knowledge-infused text classification. New Gener. Comput. 1–20 (2024)
15. Zadgaonkar, A., & Agrawal, A. J.: An Approach for analyzing unstructured text data using topic modeling techniques for efficient information extraction. New Gener. Comput. 1–26 (2023)
16. Lama, V., Patel, A., Debnath, N. C., & Jain, S.: IRI_Debug: An ontology evaluation Tool. New Gener. Comput. 1–21 (2024)
17. Bala, K., Paul, S., Mohanty, S. N., & Mahapatra, S.: Improved prediction analysis with hybrid models for thunderstorm classification over the ranchi region. New Gener. Comput. 1–25 (2022)