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Artificial Neural Networks in High Energy Physics Data Processing (Succinct Survey) and Probable Future Developments

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Abstract—The rising the role of artificial neural networks (ANN) as part of machine learning/deep learning (ML/DL) in high energy physics (HEP) and related areas can be seen last decade. Several reasons for rising the role of ANN were observed. It is paid attention to specific topics: learning transfer, distributed learning, ensemble of ANN. A lot of new experimental data will come from existing and new complex data taking systems in coming years, which will require advanced analysis with ANN running on appropriate computing hardware. Finally, the idea of future ANN development directions for HEP and related areas has been supposed.

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THE RISING OF ANN IN HEP

ANN is the specific type of machine learning algorithms that is inspired by the structure and function of the human brain. ANN consists of a number of layers of interconnected nodes (neurons) that process and transfer the data. Each neuron receives input from other neurons in different layer and applies a mathematical function (so called activation function) to that input in order to produce the output. ANN is part of more general approach *machine learning* (*ML*) which in turn is part of Artificial Intelligence[1] (AI) or Artificial General Intelligence[2] (AGI). ANNs are in use in high energy physics many decades [2–4]. Last ten or so years great progress was seen in ANN field due to several reasons:

• Grow of availability of the distributed computing facility and experimental data storages [5–7].

• Many new inventions were introduced thanks to the competitions in between developers [8–10] and presentations in many conferences resulted in the new advanced ANN architectures [11–13].

• General progress with Artificial Intelligence developments [14].

• Creating several ANN specific hardware accelerators and cloud facilities [15].

• Grow the availability of open-source neural network frameworks such as TensorFlow, PyTorch, Keras, etc has lowered the barrier to entry for developers and researchers who want to experiment with and develop neural networks. This has led to a democratization of the technology and contributed to its widespread adoption [16].

• Faster obtain the inferences with appropriately trained ANN in comparison to other methods.

PROBABLE FUTURE OF THE ANN DEVELOPMENTS FOR HEP

Common trend in the data access is becoming more and more open. Known examples are Transform to Open Science (TOPS)[3], Zenodo[4] and similar initiatives [17]. The same can be watched in ANN e.g. FAIR4HEP[5] collaboration. By 2025 USA will introduce common open access rules for all scientific data obtained with government support. Similar movements take place in Europe and China [18]. The importance of open access to the experimental data is deeply discussed in [19] together with physics thoughts of the importance to pay attention for variety of complex datasets, with ongoing and upcoming sources of experimental data such as Gaia [20], Large-aperture Synoptic Survey Telescope [21], Laser Interferometer Gravitational-Wave Observatory [22], and the Square

[1] https://en.wikipedia.org/wiki/Artificial_intelligence.
[2] https://en.wikipedia.org/wiki/Artificial_general_intelligence.

[3] https://science.nasa.gov/open-science/transform-to-open-science.
[4] https://zenodo.org/.
[5] https://fair4hep.github.io/.

Kilometer Array [23] in addition to Large Hadron Collider (LHC)[6]. It is important to share known principles about open datasets: Findable, Accessible, Interoperable, Reusable [24–26]. In this context it is useful to pay attention to distributed ANN (ensemble of ANN) like *federated learning* together with *federated transfer learning* [27–31] which might become attractive for distributed experimental data around the physics laboratories. One of the first attempt to use federated learning in HEP was described in [32]. A number of technical issues (data transfer, security, etc) of distributed ANN might be solved for example with existing WLCG infrastructures and additional tools, e.g. funcX [33].

Until now there are many examples really huge Artificial Intelligence (AI) models/installations, e.g. GPT-3/4 [34–37], LLaMA [38] and the like. Such the models mentioned in as *Foundation Models* are discussed at [39] in light of real advantages and probable risks of wide use. Now may be more interesting to develop special *foundation model* dedicated for physics problems. During the development it must be observed a lot of thoughts like physics itself [40], tradeoffs "precise power-law scalings for performance as a function of training time, context length, dataset size, model size, and compute budget" [41, 42], and rules of ANN explainability [44]. Physics foundation model might be implemented on advanced hardware architectures taking into account known examples like Meta's AI Research SuperCluster (RSC) supercluster [43], Argonne Leadership Computing Facility (ALCF) AI Testbed [45], SambaNova [46], Cerebras [47]. The suggested foundation model dedicated to physics together with open access to the datasets around the scientific world deliver hope to discover new unknown physics phenomena. Total volume of the labor for future proposal for development of physics foundation model may in scale like WLCG or so.

ANN for large systems: a large volume of documentation (technical descriptions, administrative orders, operating manuals, etc), as well as a volume of automatic and semi-automatic log records about the functioning of the entire system. A meaningful analysis (obtaining an answer to a specific question based on all available data) of such a large amount of data (hundreds GB/TB or more) is a non-trivial task, which in many cases turns out to be labor- and time-consuming. As possible solution to mitigate above difficulties is to undertake the development of a special expert system (SES) using ANN technology, which could provide the operator (system administrator) with effective assistance in the described task. Most interesting implementation of such the system would be the kind of interaction in between the operator and the system by natural language [48] where answers from the system might be the recommendations what the operator have to do next.

[6] Large Hadron Collider https://en.wikipedia.org/wiki/Large_Hadron_Collider.

CONCLUSIONS

Several directions of future ANN developments can be expected: distributed ANN ensembles, foundation models dedicated to physics, special expert systems based on ANN technology to help maintain the large installations (computing installations, data taking, etc).

It seems quite possible synergetic effects in several aspects of ANN application in HEP and related areas:

- large scale distributed ANNs which might be used by many physicists around the World to examine scientific assumptions and create new physics theories;
- involving the existing experimental data around the World into analysis and attention of many scientists and may be commercial companies who already have significant experience in ANN and in general machine learning;
- special expert systems based on ANN would be probable part of any large installation (detectors, computing infrastructures, etc).

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CONFLICT OF INTEREST

The author of this work declares that he has no conflicts of interest.

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