

Swarm Learning Based on the Artificially Intelligent Edge

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Abstract

Recently, the practical use of sensor groups, the number of which is growing exponentially, causes problems associated with their simultaneous and at the same time independent operation. The amount of data processed in a group of sensors sometimes becomes so incredibly huge that their effective processing is difficult for high-performance devices, not to mention low-performance processors of small-sized devices such as drones. Therefore, it is extremely necessary to effectively process the data coming from the sensors of such devices located on the edge of the computing system. The purpose of this study is to review and analyze traditional methods of machine learning in a distributed information collection and processing system, as well as the application of a new paradigm for this – artificially intelligent edge computing, as well as ways to implement them in terms of transmitting the collected data and training a model of a swarm of drones performing an independent flight.

Keywords 1

Paper template, paper formatting, CEUR-WS
unmanned aerial vehicle, edge computing, artificial intelligence, blockchain, swarm learning, artificially intelligent edge

1. Introduction

Currently, there are quite a large number of various tasks in which information about the environment is collected by sensors installed on mobile and non-mobile devices. Then this data should be collected into a single information array for further processing of information and making any decision based on the collected and processed data. A fairly common example is a group of unmanned aerial vehicles (UAVs), which are increasingly used to perform some task (for example, a search operation or a monitoring mission) as part of an organized group, which can be called a swarm (or flock) [1]. The control of the UAV swarm can be carried out remotely using a ground station (GS), which allows performing a completely autonomous flight. However, in this case, the operator who is the weakest link in terms of effective management will be included in the control loop of the drone flock. It will be much more advantageous to perform a group of drones without the participation of a person or with his minimal participation. The purpose of this article is to analyze data processing methods at the edge of a computing system, which is a group of drones.

2. Artificially Intelligent Edge

Usually, data processing devices that have sensors for collecting primary information, for the implementation of an artificial intelligence model, send the data collected by the sensors to some central point. The data is used to "train" the model, and then the model is transmitted back to all peripheral devices. The idea of local processing of the collected data, without transferring them to a central server for performing calculations, is natural. This will reduce delays, reduce the energy needs

Proceedings of VI International Scientific and Practical Conference Distance Learning Technologies (DLT–2021), September 20–22, 2021, Yalta, Crimea

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CEUR Workshop Proceedings (CEUR-WS.org)

of devices and, sometimes, heat removal, as well as solve the growing transport and opportunity costs. For this purpose, artificial intelligence algorithms are used. Independent solutions obtained directly on the peripheral device or a server next to the device will be developed in a matter of milliseconds without the need for an Internet connection or the cloud.

Returning to the example of a swarm of drones, we can compare it with a flock of starlings or fish, in which each of the members of the flock is a separately functioning device in terms of collecting, processing and further using the information received about the environment. At the same time, such a flock, as a single object, acts quite synchronously, pulsating and fluttering in the air or water. This behavior of birds or fish is usually called scale-free correlation, noise, or swarming, which allows us to understand the geometric increase in the amount of data collected at the border of the flock.

For such a joint movement of a large set of objects that are elements of a larger object (swarm), according to scientists [2], artificially intelligent boundary calculations are used, which are a combination of nebulous calculations and artificial intelligence that allow the implementation a distributed computing system. Swarm training, which is used for the described systems, is not only a method of placing the model in a protected environment and then training it without moving data anywhere but also eliminates the need to include a certain central leader as a control point: artificial intelligence modeling is performed by boundary devices that are part of the entire system. That is, artificial intelligence is formed at the swarm boundary, which allows reducing the energy and computational load (a fog layer consisting of microprocessors installed on devices of a distributed system and bringing data storage and processing operations closer to the place of their occurrence – sensors installed on devices and included in the described system).

Thus, a set of devices included in a distributed computing system forms a computing node that includes filtering and clustering tools that allow delivering critical information based on importance following the requirements of the application [3].

3. The Method of Teaching the Swarm

To implement machine learning (ML), you initially need sufficiently large data arrays and an appropriate computing infrastructure, which includes a data warehouse for processing and analytics as an integral part. In the case of a distributed system, it is possible to implement several ML techniques, the first of which is local learning ("on edge") – data and computing infrastructure are available locally (Fig. 1).

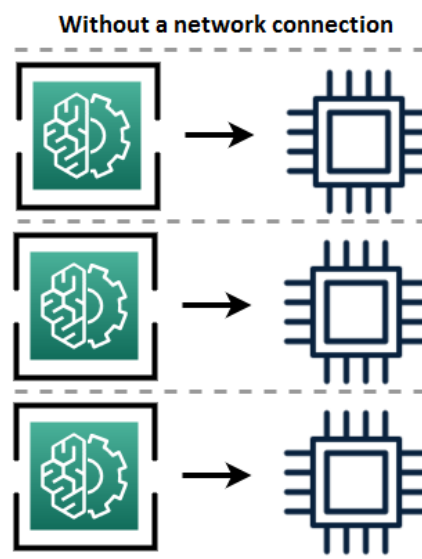


Figure 1: Local machine learning scheme

With a small amount of data at the local level (i.e. insufficient for training), it is possible to combine data obtained from different sources (sensors) and process them centrally, performing

training with ML algorithms in a centralized computing environment (Fig. 2) – using cloud computing, which significantly improves training results [4]. Among the disadvantages of cloud computing is data duplication when transferring from local storage to central storage and an increase in data traffic, problems with locally different data privacy, and security rules [5].

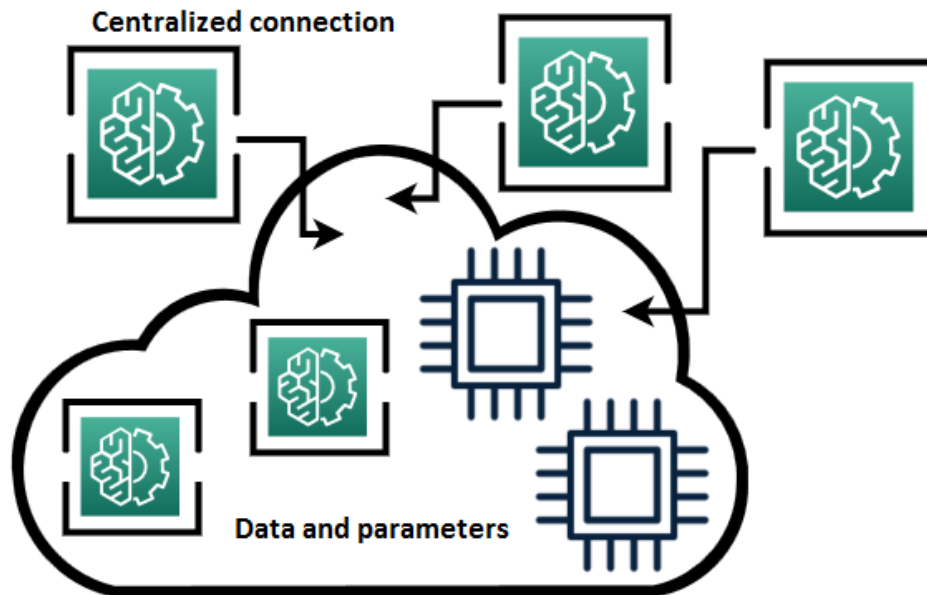


Figure 2: Centralized machine learning scheme

In addition, Google offers an alternative approach called federated learning [6], and Facebook offers Deep learning with Elastic Averaging SGD [7]. In these models, the aggregation and distribution of local learning are carried out due to dedicated parameter servers (Fig. 3). The star-shaped topology gives rise to the disadvantages of these systems associated with the lack of a central structure, and therefore the need to coordinate the transmitted data for their joint use. In addition, the key problem and bottleneck in the federated learning network is the speed of communication, which remains low due to frequent interactions between the central server and clients.

In the considered swarm learning model (SL), there is no dedicated server, and parameters and models are used together only in a local way (Fig. 4). In this case, parameters are transmitted via a network consisting of separate swarm devices (Fig. 5), and training models are built independently based on private data (Model Private Data) on separate nodes called swarm edge nodes.

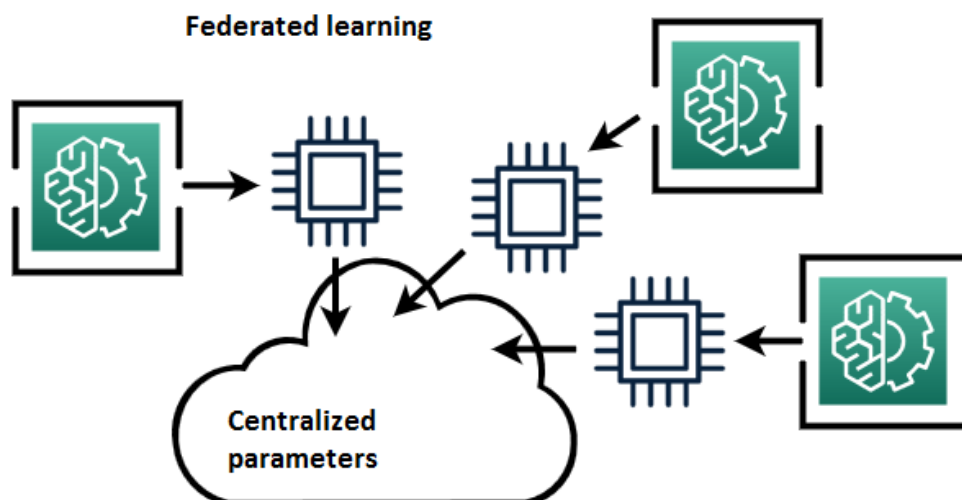


Figure 3: Federated Machine Learning scheme

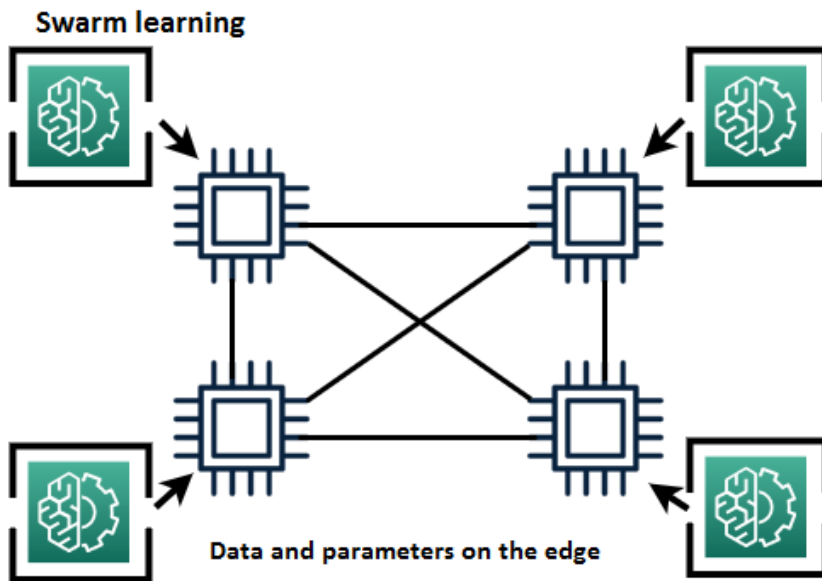


Figure 4: Swarm machine learning scheme

The security and confidentiality of data in the SL model are provided by blockchain technology, which allows various organizations or consortia to cooperate effectively (Fig. 6). Transactions can only be performed by pre-authorized participants since each participant in the blockchain network is clearly defined. Consequently, they use computationally inexpensive consensus algorithms, which largely determine its performance and security and are the most important component of any blockchain system [8]. For continuous scaling of training, new participants or nodes are dynamically included, subject to the appropriate authorization measures of network participants. Registration of a new node is carried out using a smart contract, which is a computer algorithm of the blockchain designed to generate, control, and provide information about the ownership of something and implemented by a set of functions and data located at a certain address in the blockchain [9]. The new node receives the model and performs local training of the model until certain synchronization conditions are met. Then, using the swarm API, the model parameters are exchanged with the rest of the flock members. Thus, the updated model is combined with the updated parameter settings and you can start a new round of training on the nodes.

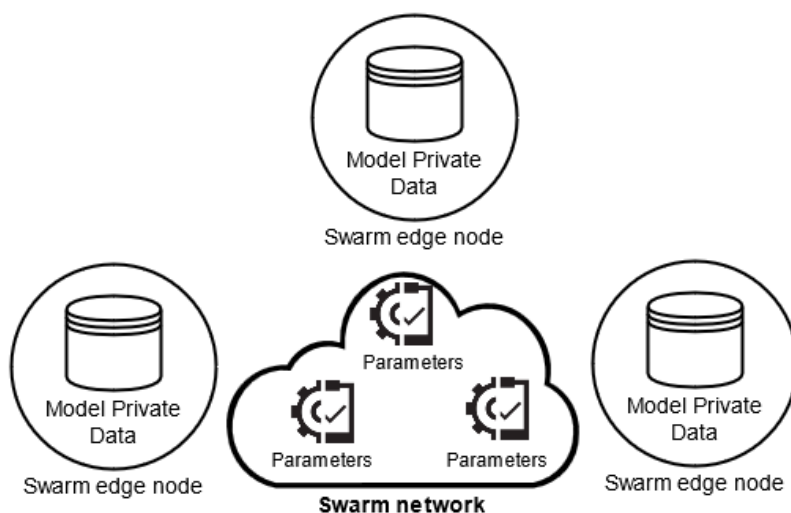


Figure 5: Swarm network diagram

The specified process is repeated until the stopping criteria are reached, which are agreed upon between the swarm participating nodes. To combine the parameters, a dynamic selection of a leader is

used based on a blockchain smart contract, protecting it from semi-honest or dishonest participants. Therefore, there is no need for a central coordinator in such a network (swarm). In the future, the elected leader combines the parameters by applying various functions (including the average, weighted average, minimum, maximum, or median functions). Various merging methods and the frequency of merging allow swarm training to work effectively with unbalanced and unevenly distributed data [10]. Currently, the described algorithms are already used for parametric models with finite sets of parameters, such as linear regression or neural network models.

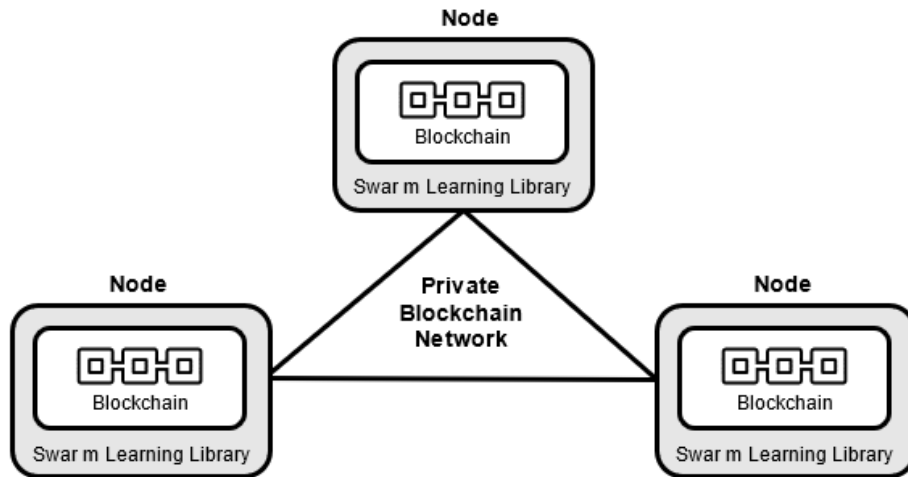


Figure 6: Blockchain in the SL model

At each node of the flock, swarm machine learning can be conceptually divided into an infrastructure layer (hardware layer), which lies at the level of the physical infrastructure, and an application layer (Fig. 7). The ML platform, the blockchain itself, and the swarm learning library (SLL) are included in the application environment of the first of the described sublevels. The layer is designed as a software and hardware swarm interface (Swarm API) in a container deployment, which facilitates the use of swarm training in heterogeneous hardware infrastructures. The application layer consists of data sets and models from the corresponding domain. For a swarm of drones, this can be information about the geographical location, a description of the data sets of assigned missions, and other useful sets.

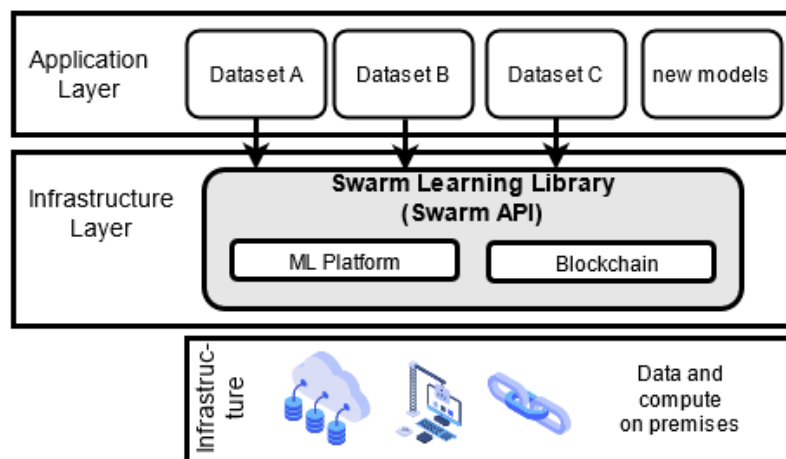


Figure 7: Conceptual levels of swarm machine learning

Thus, swarm learning in the object system under consideration will provide a fully decentralized and, therefore, hardware-independent, confidential, secure, and scalable machine learning environment applicable to many scenarios and areas. The described ML technology is based on

standardized libraries of artificial intelligence classes, with a permitted blockchain chain for securely connecting participants, dynamically selecting a leader among participants, and combining model parameters. The advantage of swarm learning when building a model for a drone swarm is the ability to create a model from an infinitely large data pool without having to move this data across the border of peripheral devices. With the help of swarm machine learning, the configuration process, which requires a lot of computing power, can be carried out on the spot, using a communication channel between the peripheral devices of the flock.

4. Conclusions

Within the framework of this study, issues related to the distributed training of a group of computing objects (using the example of a flock of drones) were considered, i.e. in the study of possible and promising principles for building a decentralized model using data extracted by a large number of drones. The article describes various methods of swarm training, considers the main areas of their application, shows the structure of swarm training at each node, consisting of two layers. Currently, swarm learning is a research project, the development of which technology allows us to recognize several trends that make a new way of thinking vital.

5. References

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