Fog Computing
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Machine Learning

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Introduction (1/4)

It is not about IoT but about data

- Given the number of **physical objects on Earth**, if only a **tiny fraction of them are in fact sensors/actuators**:
  - IoT will certainly have the potential to be the largest **source of Big Data** on the planet and as such,
  - brings numerous research **challenges** to be solved to enjoy all the possible benefits of this paradigm
- Although the **IoT paradigm** is focused on the connection of objects:
  - its real potential lies not in the objects themselves, but in **the ability to generate valuable knowledge from the data extracted from these objects**
- It can be said that IoT actually is **not about things but about data**:
  - thus, the process of transforming the raw data collected through the perception of the physical environment in value-added information and, ultimately, in high-level knowledge capable of optimizing decision making, is **crucial to obtaining the real benefit of IoT**
- At the **heart of this transformation process is computational intelligence (CI)**:
  - in particular, **machine learning (ML) techniques are promising** to process the data generated in order to transform them into **information, knowledge, to predict trends, produce valuable insights, and guide automated decision-making processes**
  - however, **the use of machine learning (ML) techniques in IoT brings up several challenges**, especially regarding the computational requirements demanded by them

Introduction (2/4)

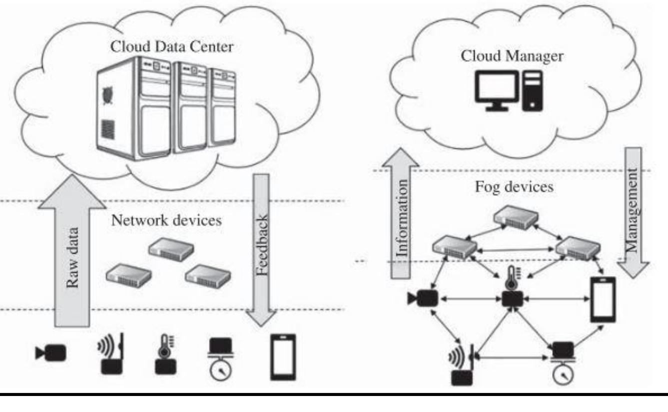
IoT devices can not perform complex processing

- The **IoT devices themselves may be part of this data transformation process:**
  - however, **with their limited resources, they generally cannot perform very complex processing**
- With their vast computing capabilities, **cloud platforms are the natural candidates as backend of IoT systems** and perform computationally intensive analysis and long-term data storage:
  - however, with the increasing growth in data generated by sensors and IoT devices, **their discriminated transmission to the cloud began to generate a set of problems**
- Among them:
  - the **excessive use of network bandwidth** has brought congestions and **poor performance** in the communication infrastructure
  - several IoT applications have **critical response time requirements**, and the **high and unpredictable latency of the Internet** for accessing remote data centers in the cloud is not acceptable in this context

Introduction (3/4)

minimizing network latency and improving computational performance

- The challenge of **minimizing network latency** and **improving computational performance** in the context of IoT environments has been recognized among the **main concerns of the IoT research community**
- In this context, the concept of **fog computing** was suggested by the industry and further extended by academic researchers



Introduction (4/4)

Where processing can happen

- It enables that **computations be executed on small datacenters close to the edge device**
- In this way, some **advanced data analytics and processing can be performed near the devices**, thus **reducing system response time and network traffic**
- The data produced by the IoT devices can then be **processed**:
  1. **in the data source itself** (also called the Things tier/layer),
  2. **in cloud platforms**, and
  3. **in the intermediate layer of fog/edge**
- Depending on the **application requirements** (such as response time) and the **complexity of the required processing technique**:
  - **each tier will be more suitable for performing the computation**

Big Data, Big Data Stream, and Data Stream Processing

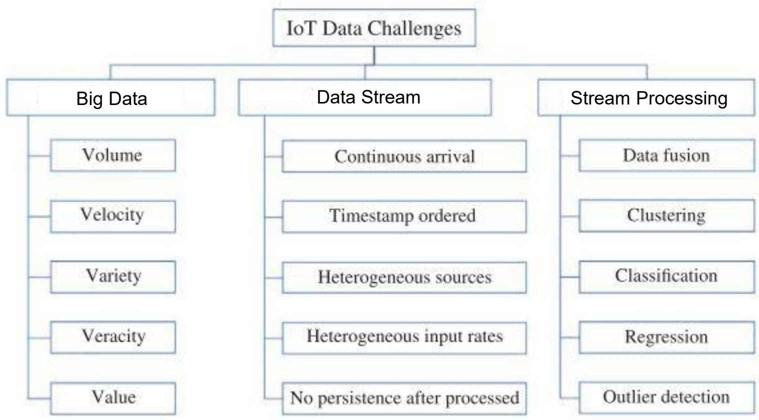
Challenges in Data Processing for IoT

- The **number of IoT devices/sensors has increased exponentially**
- A **plethora of applications can emerge**, exploiting the diversity of real-time monitored data, and combining them in different ways to provide value-added information to users
- **Examples** of advanced and intelligent applications are **smart home**, **smart building**, and **smart city**
- We discuss the challenges introduced by IoT systems in three **different dimensions**:
  - **generation**, **transmission**, and **processing of data**
- Such dimensions are typically related to and addressed by three well-known research fields:
  - **Big Data**,
  - **Big Data Stream**, and
  - **Data Stream Processing**

Big Data in IoT (1/5)

Big Data

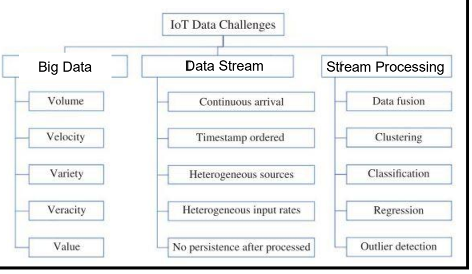
- **Big Data refers to voluminous and complex data sets** that require **advanced data processing** application software:
  - it involves **capturing, storing, sharing, searching, transferring, analyzing, visualizing, updating, and protecting** data



Big Data in IoT (2/5)

Big Data volume, velocity, …

- Data scientists have defined six **features** to address all the issues related to Big Data:
  1. **Volume** - key aspect to consider a data set to be "big," as the **size of the data** is measured as volume
  2. **Velocity** - related to the rate of data generation and transmission; the **huge amount and speed of IoT Big Data** coming from several sources demands the support for big data in real-time
  3. **Variety** - with increasing volume and velocity comes increasing variety, which describes the **huge diversity of data types** any IoT system can produce
  4. **Variability** - **different rates of data flow**, which may vary from time to time or place to place; e.g., in an IoT application for traffic management using sensors, the speed at which data is loaded in a database can have expressive variations depending on the heavy traffic hours
  5. **Veracity** - how accurate and how truthful is the data set; it is more than reliability of the data source, it also involves the **degree of confidence in the analysis of the data**; this feature is quite important in IoT system that uses crowd-sensing data
  6. **Value -** data must have value, i.e., all the infrastructure required to collect and interpret data on an IoT system must be justified by the **insights you can gather** to improve the user experience and services



Big Data in IoT (3/5)

Big Data freshness

- Another important aspect for the value of data is its **temporariness**:
  - the potential value of data depends on **data freshness** that needs to be processed
  - otherwise, **the processing results and actions become less valuable or even worthless**

- Three **categories for IoT data** (regarding different characteristics):
  - **data generation**,
  - **data quality**, and
  - **data interoperability**

- **Data generation**:
  - related to the Big Data features aforementioned such as **velocity, scalability, dynamics, and heterogeneity**

Big Data in IoT (4/5)

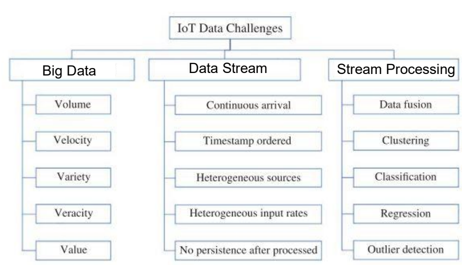
- **Data quality**:
  - **Uncertainty** - in IoT data, uncertainty can refer to **variance from the expected states of the data**, due to several reasons such as transmission errors or sensing precision
  - **Redundancy** - **errors in sensor reading logic can produce multiple data that can interfere in the semantic of sensor data**; e.g., in radio-frequency identification (RFID) data, the same tag can be read multiple times at the same location when there are multiple RFID readers at the same spot to improve the sensing
  - **Ambiguity** - refers to **different ways of interpreting data** from diverse things to distinct data consumers; this misunderstanding may interfere with the overall inference about the sensed environment
  - **Inconsistency** - **such as ambiguity, inconsistency may occur** in the interpretation of data that may produce misunderstandings; it is common to detect inconsistency in sensing data in case of several sensors monitoring an environment

Big Data in IoT (5/5)

- **Data interoperability**:
  - **Incompleteness** - in many IoT applications that detect and react to events in real time, the **combination of data from different sources is important to build a complete picture of the environment**; however, in this cooperation of mobile and distributed things who are generating the data, some problems related to the data quality from any source may negatively interfere in the whole system
  - **Semantics** - semantic technologies have been used to endow machines with the ability of **processing and interpreting IoT data**
- **Despite presenting all the aforementioned characteristics**:
  - the **data produced by IoT devices have additional features, not always observed in Big Data**
- **Typically, data produced by IoT sensors consist of**:
  - **time-series values**, which are **sampled over a defined period** and then **transmitted to a gateway for further processing**
- **Compared with Big Data produced by other sources, such as social data**, sensor data streams have additional features that call for a **shifting from the Big Data paradigm to the Big Data Stream paradigm**

Big Data Stream (1/3)

Data items arrive continuously and sequentially



- **Time-series data** are:
  - **not processed in the same way as the typical Big Data**,
  - **nor as easily interpretable such as, for instance, a document, video, or other data available on the Internet**
- **Data items**:
  - **arrive continuously and sequentially** as a stream, and
  - **usually ordered by a timestamp value** besides including other additional attribute values about the data item
- **Differently from Big Data** that is typically produced in controlled and owned data warehouses:
  - **data streams are usually generated by heterogeneous and scattered sources**
- In general, **IoT systems do not have direct access or control over such data sources**
- Moreover, **the input characteristics of a data stream are usually not controllable and typically unpredictable**

Big Data Stream (2/3)

Data items arrive in different rates

- Data streams are provided in **different rates**:
  - e.g., **from small number of bytes per second to several gigabits**
- The inherent nature of the input **does not allow one to easily make multiple passes over a data stream while processing** (and still retaining the usefulness of the data)
- **Big Data stream–oriented systems** need to:
  - **react effectively to changes**,
  - and **provide smart, semi-autonomous behavior to allocate resources for data processing**,
  - thus **implementing scalable and cost-effective services**
- The inherent **inertia of Big Data approaches, that commonly rely on batch-based processing**:
  - are **not proper for data processing** in IoT contexts with dynamism and real-time requirements
- The **Big Data stream paradigm**:
  - **enables ad-hoc and real-time processing** to connect streams of data and consumers,
  - benefiting **scalability, dynamic configuration, and management of heterogeneous data formats**

Big Data Stream (3/3)

Data items arrive are heterogeneous

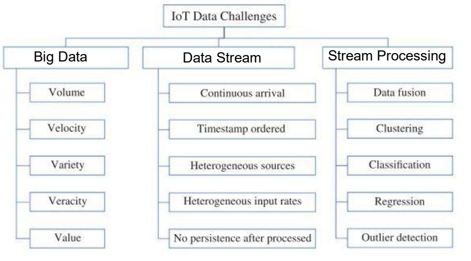
Data items are not kept

- Although **Big Data and Big Data stream cope with massive numerous heterogeneous data**:
  - **Big Data centers on the batch analysis of data**,
  - **Big Data stream deals with the management of data flows and real-time data analysis**
- **This feature has an impact** also on the **data that are considered relevant to consumer** applications:
  - **while for Big Data applications it is important to keep all sensed data in order to be able to perform any required computation**,
  - **Big Data stream applications might decide to perform real-time data processing on the raw data produced by IoT devices** to reduce the **latency** in transmitting the results to consumers, with **no need to persist such raw data**
- **Translating the huge amount of sensor generated data streams from their raw state into higher-level representations** and making **them accessible and understandable for humans or interpretable by machines and decision-making systems**:
  - one **promising approach to tackle this issue is by applying techniques of CI**
  - **CI refers to the ability of a computer system to learn a specific task from data or experimental observation**

Data Stream Processing (1/2)

Requires some processing applied to each data item

- **Data stream processing is a paradigm that deals with**:
  - **a sequence of data** (a stream),
  - and **a series of operations being applied to each element in the stream**
- **Integration with several data sources is particularly relevant for time-sensitive IoT applications**:
  - deal with **data provided by multiple data sources**, and
  - a **timely fusion of data is needed** to bring all pieces of data together
- **Information fusion and sharing** play a critical role for **fast analysis** and consequently providing **reliable and accurate actionable insights**



Data Stream Processing (2/2)

Information fusion in data stream processing

- **Information Fusion** deals with **three levels of data abstraction**:
  - **measurement**,
  - **feature**, and
  - **decision**,
- It can be **classified into these categories**:
  - **low-level fusion** - also referred to as signal (measurement) level fusion; **inputs are raw data that are joined with a new piece of more accurate data** (with reduced noise) than the individual inputs
  - **medium-level fusion** - attributes or features of an entity (e.g., shape, texture, position) are **fused to obtain a feature map** that may be used for other tasks (e.g., segmentation or detection of an object); this type of fusion is also known as feature/attribute level fusion
  - **high-level fusion** - also known as symbol or decision level fusion; **inputs are decisions or symbolic representations that are joined to produce a more confident and/or a global decision**
  - **multilevel fusion** - this fusion **involves data of different abstraction levels**, i.e., multilevel fusion occurs when both **input and output of fusion can be of any level** (e.g., a measurement is fused with a feature to provide a decision)

ML in Fog Computing

Computational Intelligence and Fog Computing

- To **minimize the communication latency and improve the computational performance of IoT applications**:
  - the **emerging paradigms of fog and edge computing** have been advocated as potential and promising solutions
  - the **compute nodes of the edge or fog tier** will perform all or part of the various data stream processing steps
- To **tackle the issues related to performance, scalability, and real-time responsiveness**, and considering the **massive amount of data produced by large IoT systems**:
  - researchers have investigated the **deployment of ML techniques in the fog computing paradigm**

ML is the creation and use of models learned from data

Machine Learning (1/4)

- **ML is a research field of CI**:
  - it has been **widely implemented in a number of domains** that depend on complex and massive data processing,
  - e.g., **medicine, biology, and engineering**,
  - providing **solutions to gather the information hidden in the data**
- The **central goal of CI** is to:
  - **provide a set of algorithms and techniques that can be used to solve problems that humans perform intuitively and near automatically but are otherwise very challenging for computers**
- ML is the **creation and use of models** that are **learned from data**:
  - **a model is a specification of a mathematical (or probabilistic) relationship that exists between variables**
- Typically, in **IoT scenarios the aim of adopting ML techniques is using historical and stream data to develop models** able to predict various outcomes for new data or to provide insights

ML examples and subdomains

Machine Learning (2/4)

- **Examples**:
  - **predicting the increase rate of energy consumption** based on the current temperature and power status of an IoT system
  - **predicting** whether a set of events represents a dangerous situation in some environment (for instance a smart building)
  - **predicting** an intersection congestion when the number of vehicles increases in a smart road application
- ML techniques can be divided into **three subdomains**:
  - **supervised**,
  - **unsupervised learning**, and
  - **reinforcement learning**

ML subdomains

Machine Learning (3/4)

- **Supervised** learning:
  - the **input data can be labeled** with the desired outputs of the algorithm
- **Unsupervised** learning:
  - you can interpret data based only on **input data** trying to find some hidden pattern or intrinsic structure
- **Reinforcement** learning:
  - differs from normal ML because it does not use training data set
  - it uses interactions with the **external environment** to constantly adapt and learn on given points as a kind of feedback

Learning types	Data processing tasks	Methodology	Learning algorithms	Example of IoT applications
Supervised learning	Classification/ Regression/ Estimation	Statistical classifiers	K-nearest neighbors Naïve Bayes Hidden Markov model Bayesian networks	Fruit identification through classification of data patterns
		Computational classifiers	Decision trees Support vector machine	
		Connectionist classifiers	Neural networks	
Unsupervised learning	Clustering/ Prediction	Parametric	K-means Gaussian mixture model	Anomaly detection in IoT healthcare system
		Nonparametric	Dirichlet pr. mix model X-means	
Reinforcement learning	Decision-making	Model-free	Q-learning R-learning	Urban traffic prediction
		Model-based	TD learning Sarsa learning	

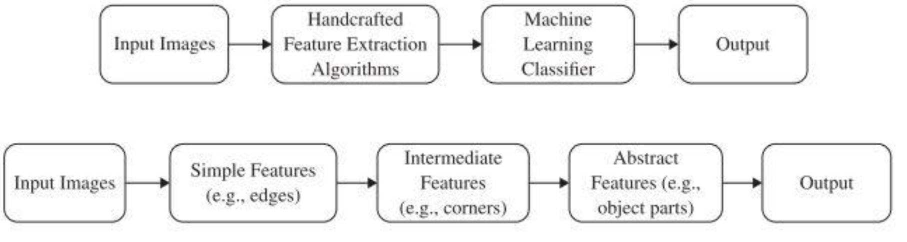
ML supervised, unsupervised, and reinforcement learning

Machine Learning (4/4)

- **Supervised and unsupervised learning** is suitable for **data analysis** while **reinforcement learning** is adequate for **decision-making** problems
- **For example**:
  - to **find unusual data points and anomalies in smart data**, the support vector machine (SVM) algorithm is suggested
  - to **predict the categories (labels) of data**, neural networks use approximation functions to obtain the desired output
  - to **find hidden patterns or intrinsic structure in data**, unsupervised learning applies the clustering technique
- **K-means is the most widely used clustering algorithm for exploratory data analysis**
- **K-means is one of the most naive ML algorithms being used for classification and regression problems**
- **Decision tree algorithms are used to develop classification models in the form of a tree structure**

Deep Learning (1/5)

- In **recent years, with the increasing computational capacities**:
  - **new generation IoT devices have been able to apply more advanced neural networks** to capture and understand their environments
  - e.g., in recent years, with the increasing computational capacities, new generation IoT devices have been able to apply more advanced **neural networks** to capture and understand their environments
- **Using a cascade of nonlinear processing units (layers) for feature extraction and transformation**:
  - a **deep learning (DL)** method can extract from an image a hierarchy of concepts that correspond to different levels of abstraction

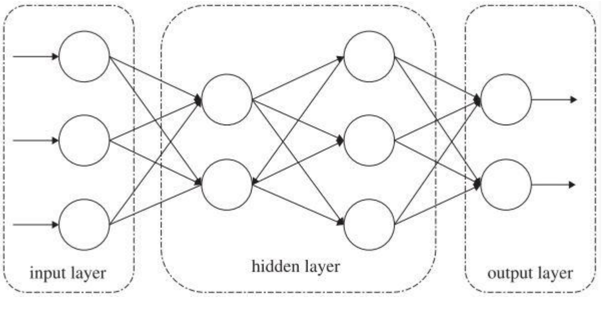


Deep Learning (2/5)

- DL architectures such as **Deep Neural Network (DNN)** and **Convolutional Neural Network (CNN)** are classes of **ANN (artificial neural network):**
  - have been **applied to many fields including computer vision, audio recognition, speech transcription, and natural language processing**, where they have produced results comparable to human experts
- A **DNN is basically a feed-forward neural network with several hidden layers of interconnected neurons** (or processing units):
  - collectively, the **neurons of the hidden layers** are responsible for transforming the data of the input layer into the desired output data (inference classes) of the output layer
  - **each hidden layer neuron has a vector of weights** with a size equal to the number of inputs as well as a bias
  - **these weights are optimized** during the training process
  - the **hidden layer neuron** receives the inputs from the previous layer, calculates a weighted summation of these inputs, and calls an **activation function** to produce the output, passing the resulting sum as a parameter
  - **these weights are what make each neuron unique**
  - **they are fixed during the test of the network**, but during the training these weights are changed in order to teach the network how to produce the expected output for the respective data inputs

Deep Learning (3/5)

- An **artificial neural network (ANN), or neural network for short, is a technique inspired by the way the brain operates**:
  - a **collection of neurons** wired together
  - the **neurons** that represent processing units are **organized in layers** – input layer, one or more hidden layers and output layer
  - **each neuron in a layer** receives the outputs of the previous layer neurons, does a calculation with an activation function, and then forwards the results to the next layer neurons
- The **algorithms used in neural networks form a framework for many ML techniques capable of dealing with complex data inputs**

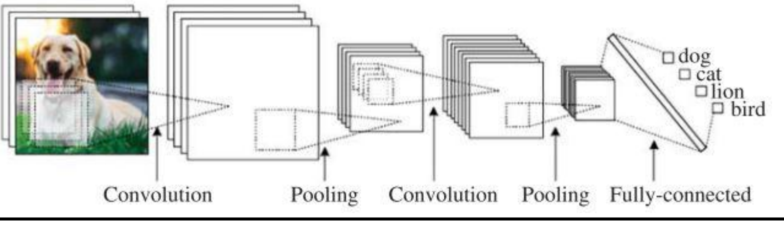


Deep Learning (4/5)

- A **CNN is a class of ANN and an alternative to DNN** when applied to:
  - **analyzing visual imagery due to scalability issues** (e.g., high resolution images imply thousands of neurons), and
- **DNN might not learn the features that undergo minor changes in some images**, like a rotation of the face:
  - **CNN has solved these problems**
- **As any ANN, a CNN also consists of**:
  - **input layer, multiple hidden layers, and an output layer**
  - **the hidden layers of a CNN typically consist of one or more convolutional and pooling layers**, and **finally a fully connected layer equivalent to those used in DNNs**
- **Convolutional layers** apply convolution operations to the input, **called filters**, extracting the features from data, reducing the number of parameters and passing the result to the next layer

Deep Learning (5/5)

- In the training process, **a CNN automatically learns the values for these filters**, which represent hierarchical feature maps (e.g., edges, corners and object parts) of the input images
- The **pooling layers** operate on the feature maps produced by the filters combining the outputs of neuron clusters at one layer into a single neuron in the next layer
- **Max and average pooling** uses the maximum and average value, respectively, from output of a cluster of neurons at the prior layer causing dimensionality reduction and the representations to be invariant to translations
- The **last layers (i.e., a DNN fully connected) are applied to complete classification**



Challenges for Running Machine Learning on Fog Devices (1/7)

- **Traditionally, ML algorithms run on powerful computers** hosted in cloud data centers to accommodate their high demand for computation, memory, and power resources
- **Data streams are generated (and eventually processed)** by devices located at the edge of the network that have limited power and hardware resources
- **Smart applications that use large sets of sensing data**, such as audio and images, aggravate the memory demand and bandwidth consumption
- Therefore:
  - **applying modern data analytics processing using ML techniques without imposing communication overheads is a challenge**, and
  - **researchers have recently investigated how to deploy CI on fog devices in an efficient way**
- **Challenges for running any resource demanding program on fog devices are related to**:
  - **processing time**,
  - **memory demand**,
  - **bandwidth**, and
  - **power consumption**

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Challenges for Running Machine Learning on Fog Devices (2/7)

- **Processing time and bandwidth consumption** are directly related to the performance and the energy required to run the application:
  - so, **any reduction in these two factors** is important to save energy and increase the overall efficiency of the system
- Studies have shown that:
  - **running on a low-capacity computer is still possible**, but
  - the **response time and energy consumption** will probably make the solution infeasible for most Smart IoT applications
- **One way to overcome this problem is to use GPUs**:
  - **CNN algorithms require a huge number of mathematical operations** using **large matrices of floating-point numbers** that are intensive time-consuming if performed in pipeline mode by the CPU
  - however, **the hundreds or thousands of processing cores of GPUs** can easily speed up the execution of a huge set of mathematical operations such as the ones required by CNN algorithms

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Challenges for Running Machine Learning on Fog Devices (3/7)

- **Hardware** resources found and analyzing capacities for running ML algorithms
- Proposed **classes of devices** with the respective suitable algorithms
- Devices class 1 are the **smallest and least computational powerful** of them, and its role is only to produce data:
  - **class 1 devices are known as the IoT sensors** by the research community, with some basic computational resources

Class	Hardware capacity	Power consumption	Suitable algorithms	Main application
1	No storage Low CPU and memory	≤1 W	Basic computation	Data generation
2	Storage ≤4 GB Memory ≤512 MB CPU single-core	≤2 W	Basic statistic	Measurement level fusion
3	Storage ≤8 GB Memory ≤2 GB CPU quad-core	≤4 W	Classification/ Regression / Estimation	Feature level fusion
4	Storage ≥16 GB Memory ≥4 GB CPU and GPU	≤8 W	Prediction/ Decision-making	Decision level fusion
5	Very large	Very high	Any	Autonomous system

Challenges for Running Machine Learning on Fog Devices (4/7)

- **At the other end**:
  - **class 5 devices are the highest powerful computational equipment** and can be considered as the unlimited resources available in cloud data centers
- **Devices of class 2, 3, and 4** showed that they have capacity to perform the three levels of information fusion:
  - **measurement**,
  - **feature**, and
  - **decision**

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Challenges for Running Machine Learning on Fog Devices (5/7)

- **Unlike class 1 devices that have microcontrollers**:
  - **devices of class 2, 3 and 4** have true CPU, RAM memory and a multitask operating system
- **Devices class 3 and 4 are the ones really used for running ML algorithms on the fog**:
  - the **main difference between them** is that class 4 devices have a **powerful GPU** for parallel processing,
  - which is **very important for the execution of algorithms for training DNNs**, for instance

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Challenges for Running Machine Learning on Fog Devices (6/7)

- **Class 3 device** can use a trained neural network to make the mid-level data fusion and extract the relevant features of the data, like a detection of an object
- **Class 4** device can go further and taking decisions using a set of higher-level data fusion

Class	Hardware capacity	Power consumption	Suitable algorithms	Main application
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Challenges for Running Machine Learning on Fog Devices (7/7)

- On the one hand:
  - **IoT devices are to be deployed in non-refrigerated environments and with limited power sources**, less computation requires less power and yields less heat
- On the other hand:
  - **devices with high computational power are more expensive**, require a lot of energy to work and yield more heat, so that they should be used with care in IoT projects

Class	Hardware capacity	Power consumption	Suitable algorithms	Main application
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5	Very large	Very high	Any	Autonomous system

Conclusion (1/2)

- There is a **consensus that IoT is the leading technology to enable advanced, ubiquitous and intelligent systems**
- Using all kinds of data, provided by a **growing number of heterogeneous devices** (from wearables to cameras), a **huge diversity of information** can be extracted and interpreted to enhance the user experience
- The **gathering and analysis of this Big Data** is one of the main challenges faced by the community nowadays
- As we have seen, **ML techniques have been applied** to perform advanced data analysis in a very efficient way in order to allow for valuable inferences even in resource-constrained devices
- Looking at the opportunities of a new market, the **industry has developed new hardware** to overcome the limitations of running heavy ML algorithms on edge devices

Conclusion (2/2)

- The **limited hardware of edge/fog device** is only part of the problem, and there are further issues that have been addressed by researchers developing IoT intelligent systems:
  - **accuracy vs. energy consumption**
  - **lack of complete training data set for each domain**
  - **security and privacy**
- We can conclude with a final thought that the **ML algorithms will evolve along with IoT devices**, pushing forward the development of new hardware, software, and network protocols to address all the challenges presented