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MACHINE LEARNING AND THE INTERNET OF THINGS

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ABSTRACT

of	pattern	recognition	and
computational learning concept		in	artificial
intelligence. Machine	learning	determines the	

Machine learning is a part of computer science that developed from the study and construction of algorithms that can absorb from and make guesses on data. The Internet of Things (IoT) is the network of physical objects or "things" rooted with electronics, software, sensors, and network connectivity, which allows these objects to collect and exchange data. Collections of devices will act as systems that can be enhanced in new ways, and systems of systems will share data and perform as annetwork of data and devices. Machine learning - a term that describes numerous methods to evolving meaning from data - will have to be part of the calculation, but so will outdatedprofessional and data investigation techniques as organizations prepare for the Internet of Things (IoT). This paper will provide an overview of challenges and openings presented by this new model.

Keywords: *Internet of Things, Cloud computing, Machine learning, Smart Environments*.

I. INTRODUCTION

The term Internet of Things was first coined by Kevin Ashton in 1999 in the context of supply chain management [1]. However, in the past decade, the definition has been more inclusive covering wide range of applications like healthcare, utilities, transport, etc[2]. Although the definition of 'Things' has changed as technology evolved, the main goal of making a computer sense information without the aid of human intervention remains the same. A radical evolution of the current Internet into a Network of interconnected objectsthat not only harvests information from the environment(sensing) and interacts with the physical world (actuation/command/control), but also uses existing Internet standards to provide services for information transfer, analytics, applications, and communications. Fueled by the prevalence of devices enabled by open wireless technology such as Bluetooth, radio frequency identification (RFID), Wi-Fi, and telephonic data services as well as embedded sensor and actuator nodes, IoT has stepped out of its infancy and is on the verge of transforming the current static Internet into a fully integrated Future Internet [3].

The goal of machine learning is to program computers to use example data or past experience to solve a given problem. Many successful applications of machine learning exist already, including systems that analyze past sales data to predict customer behavior, optimize robot behavior so that a task can be completed using minimum resources, and extract knowledge from bioinformatics data [4]. In order to present a unified treatment of machine learning problems and solutions, it discusses many methods from different fields, including statistics, pattern recognition, neural networks, artificial intelligence, signal processing, control, and data mining. All learning algorithms are explained so that the student can easily move from the equations in the book to a computer program.

II. UNDERSTANDING ANAL YTICS AND MACHINE LEARNING

Data and functionality can be accessed from any location and through multiple devices. Specialized devices provide context in which the user accesses the data.A fitness bracelet can access data about the user's physical health via an iPhone or laptop in the specific context of exercise. In this case, the fitness bracelet acts as an IoT sensor as well as

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provides a means for accessing and consuming data. The device also subsumes other devices (such as a pedometer) through software functionality. The data provided by the device can offer additional insights about the consumer's usage and preferences, which can be leveraged when updating functionality and developing new features. If aggregated across a population of users and combined with other datasets, new insights can shed light on epidemiological data, activity levels across populations, lifestyles, and demographic data. This information has value to marketers, healthcare providers, insurance companies, and government agencies.

Machine learning algorithms can be used to make predictions based on these data patterns. For example, in a Mayo Clinic study, activity data was correlated with recovery rates for cardiac patients[5]. The same machine learning and predictive algorithms are the basis for a number of connected intelligent consumer devices. Nest thermostats are an example of a device that leverages data patterns to predict the preferred temperature in a specific room at a certain time of day. Other consumer devices include those that learn from voice patterns (such as Echo, a personal-assistanttype device from Amazon [6] to those that learn from much more complex behavior and activity patterns (such as Jaguar's Land Rover monitoring system, which "relies on a complicated software which enables the car to study, predict, check, and remind the car's occupants to help the driver auto-delegate his tasks and make him concentrate more on his driving [7].

Optimization algorithms use machine learning mechanisms to leverage data from both sensors and intelligent devices that interact under dynamic conditions. These variable conditions can't be precisely predicted beyond certain parameters. The algorithms will need to sense, respond, and adapt. For example, as cars take on more responsibilities from the driver, they will be interacting with more environmental sources of data (sensors, lights, other cars, and so on). Classes of applications in industrial automation, logistics and transportation, power grid and energy systems, traffic management, security systems, and other "systems of systems" will let machines communicate directly with other machines. Furthermore, such applications will help machines interpret dataflows based on algorithms that can evolve and adapt, so the machines can achieve the desired end states given certain operational parameters.

III. UNDERSTANDING IOT CAPABILITIES

When products are intelligent and connected to the Internet, they become variable and have the ability to change as the user's needs change. Now, physical objects become vehicles or containers for softwaredriven functionality. These levels of capability require increasingly sophisticated data analytics approaches - from collecting and applying data to allowing algorithms themselves to apply data and learn while doing so.

So, the first level of capability - monitoring - becomes a real-time mechanism to better understand field performance and user needs and offer new capabilities. This means that the boundaries of an organization's traditional products and services are blurred and extended. Consider field equipment that was traditionally maintained by a contract field service firm, not by the manufacturer. With intelligence and monitoring, equipment can inform the manufacturer of needed service ahead of a breakdown. Routine maintenance can become part of the manufacturer's offering, with complex repairs still being handled by a specialist contractor if the margins and logistics make sense for the organization. This disintermediation can extend to distribution chains as well. Equipment can automatically call for a replenishment of supplies, removing distribution costs and inventory from the supply chain[8].

Consider the role of humans in running a system or machine, where most of the functions are automated. Humans guide the operation and look for edge conditions, anomalies, and exceptions that weren't anticipated (or cost-effective) during the system design. Then, they use their judgment to make a change, correction, or adjustment. The human doesn't need to be with the equipment and might not need to be monitoring in real time (depending on the process). Monitoring is simply taking in the data and processing it (something must be done with the data at some point). Control is applying that data in real (or near real) time to the operation of the equipment or device. The strategic decision that organizations need to make is whether and when to make more control capabilities part of the product offering and whether to offer that as a service or to allow the customer to have that capability.

The third level of capability - optimization - can extend to the performance of an individual object, a fleet of objects, or an ecosystem of objects across multiple manufacturers and technologies. The strategic decision about whether to

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extend offerings to this realm hinges on the level of knowledge and sophistication around the value chain and the boundaries of the processes. A truck manufacturer, for example, would be poorly positioned to optimize complex mining equipment but would benefit from optimizing its fleet of trucks (and potentially a fleet of other manufacturer's trucks) if the industry dynamics made business sense.There are four types of IoT capabilities [4]: monitoring - sensors provide data about the operating environment and product usage and performance; control - product functions can be controlled and personalized; optimization - feedback loops from monitoring and control allow for improved efficiency, better performance, preventative maintenance, and diagnostics and repair; and autonomy - monitoring, control, and optimization allow for independent operation, coordination with other systems, interaction with the environment, personalization, replenishment, and self-diagnosis and repair.

Extending optimization to independent operation requires an extension of capabilities to allow for less constrained interaction with the environment and with other systems. Autonomy requires greater intelligence around algorithms that can deal with unplanned situations - those situations for which programmers and system engineers didn't explicitly design. Autonomous operations require incorporating adaptable machine learning approaches for dealing with novel situations into the core algorithms used for monitoring, control, and optimization.

IV. CHALLENGES FACING A SECURE INTERNET OF THINGS

While the full scope of security concerns is broad, Freescale sees four key challenges impacting the evolution to a secure IoT [9]:

1. Emergence of consumer IoT solutions introduced by startup companies, for which security may not be a focus.
2. A lack of system security standards for end nodes, where performance and low power requirements make security integration difficult.
3. Increasing complexity of end node security as the car itself becomes an end node. The more than 100 ECUs in the average car are now adding wireless connectivity, opening up new vulnerabilities to data privacy and driver safety.
4. New challenges of securing data with evolution of Software Defined Networking. The physical separation of the control and data plane in virtualized environments requires secure data over multiple miles versus inches in traditional networks. Other challenges exist in securing multiple channels for every communication versus one in traditional networks.

V. THE IMPORTANCE O F M ACHINE LEARNING IN T HE I NTERNET THINGS

Some of the most exciting work being done to reap value from the Internet of Things (IoT) involves taking data insights to the next level using machine learning (ML). A good IoT solution gives you an extraordinarily useful view of your organization's data; a great one allows you to build algorithms that can predict what's next—the next equipment breakdown based on historic failure data; the next tune-up needed based on lifespan data from component sensors; the best time to turn on the heat based on last year's data and next week's weather report [10]. When you put enormous compute against enormous data and you bring machine learning to bear along with it, and the Internet of Things feeding data into the cloud and streaming analytics running on live data. It is a very short time, to see a completely different picture of analytics.Some of the most exciting work being done to reap value from the Internet of Things (IoT) involves taking data insights to the next level using machine learning (ML). A good IoT solution gives you an extraordinarily useful view of your organization's data; a great one allows you to build algorithms that can predict what's next—the next equipment breakdown based on historic failure data; the next tune-up needed based on lifespan data from component sensors; the best time to turn on the heat based on last year's data and next week's weather report.

Machines are good at mechanical and physical processes, but still not that great at automating decision-making especially in very complex environments. The challenges associated with employment and wealth distribution in an environment of seemingly ever-increasing automation, but the panelists admitted they couldn't predict exactly how this trend might play out[11].The ML marketplace as a place where data scientists can publish their innovative ideas as web services, all panelists issued a call to action to the audience to be ever more data-driven in their work and build their ML skills, as there are many possibilities ahead of us to make products and services more intelligent.Next, the opinions on whether there is a danger to using ML systems as "black boxes" inside systems such as drones, cars, etc. without fully understanding what's inside.ML as being any different than any software algorithm collection, and there is a lot of software to ask the same question about. There must be systems in place to ensure reliability that mistakes can be made, and that experience and decision-making responsibilities have to be assigned appropriately. "People are teaching ML incorrectly. They teach what the need to learn statistical hygiene is inside the black box, but before that.There should be a test set, and no cheat, there should be confidence intervals, and need to worry about outliers. Learn statistical hygiene to avoid disasters"[12].

VI. CONCLUSIONS

Analysts expect that new Internet of Things (IoT) products and services will grow exponentially in next years. IoT-A relies on semantic types (Semantic Web, semantic clustering) to discover IoT resources and their vibrantrelationshipboard. IoT — as "a global set-up for the data society, enabling advanced services by interconnecting (physical and virtual) things based on, current and developing, interoperable information and communication technologies". To note that, in this view, the Machine to Machine (M2M) communication capabilities are seen as an essential enabler of the IoT, but represent only a subset of the whole set of abilities of IoT. Finally, the motivation for all is that through the collaboration and the integration of multiple data sources, it can be reached more powerful solutions, better data-analysis, more precise data-driven modeling, position awareness, and in absolute better solutions.

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