When applied in an industrial IoT (IIoT) deployment, artificial intelligence (AI) can enable predictive insights to solve pragmatic and complex business problems. Since the quality of AI decisions improves with relevant data, having mechanisms to meaningfully express the immense volumes of data in an IIoT to an AI service would represent an important step to its performance.

This paper examines a case study proving the value of AI in a smart city application, and goes on to examine a practical solution for delivering data from the network edge to AI and cloud services – a data fabric known as the IoT Access Protocol (IAP).
Introduction

As we begin the widespread use of contact tracing to mitigate the effects of the current pandemic, we are witnessing the exemplary power of data to illustrate events and create insights. With the ability to harvest information about distributed events through a system of networked devices on a massive scale, we can generate better outcomes. This is a core value proposition of the Internet of Things (IoT).

The Industrial IoT (IIoT) expands this value proposition to businesses by managing their costs, risks, scale and complexity in heterogeneous industrial deployments. The vast heterogeneity of the IIoT is the result of a seemingly never-ending collection of legacy and emerging devices, sensors and protocols all being applied to a widely varying list of requirements such as compliance, safety, efficiency, and security. Irrespective of the scale, complexity, goals and requirements, all IoT deployments share one thing in common – that data is the glue that binds this cooperating framework of things.

Over the past two decades, the ‘big data’ movement has perfected the art of using large amounts of data (as well as different types of data) to drive future outcomes. Tremendous strides in machine learning (which automates the normally arduous process of human intervention) in improving the accuracy of predictions is ushering in a resurgence of artificial intelligence (AI).

It should therefore come as no surprise that AI, when applied in an Industrial IoT deployment, can enable predictive insights to solve pragmatic and complex business problems. This relationship between AI and IIoT is particularly symbiotic. AI is well positioned to address the very complex nature of IIoT deployments. Conversely, the vast amounts of previously untapped sources of data in the IIoT can be applied to improve the accuracy and value of AI predictions. With the emergence of AI frameworks today, as well as the increased computation capacity for AI, the symbiotic relationship between AI and IoT can evolve into the perfect vehicle for driving better business outcomes for industrial deployments.

An Example Study of AI and the IIoT

Addressing the difficult problem of urban traffic congestion is one potential use of AI services in an IIoT (smart city) deployment. We undertook a limited proof of concept (POC) for a mid-sized North American city with the goal of accurately detecting traffic flow within the city. We built an AI enabled computer vision camera called a ‘cognitive camera’ to be deployed at street corners. The cameras were designed to be integrated into an existing Industrial IoT platform that provides a connected streetlight solution for many cities (Figure 1).

By leveraging an existing Industrial IoT infrastructure, our traffic counting POC was cost-efficient to deploy, and potentially scalable into every corner of the city. This use of edge-based AI computer vision allowed us to explore the per-lane count of vehicular traffic at an intersection without having to send the entire raw video stream to the cloud for processing. Not only did this edge processing translate into bandwidth savings, it also allowed the system to perform real-time actions needed in the city streets without incurring the latency of a round trip to the cloud.

Once the cameras were mounted at cross intersections of streets, they could be identified and provisioned on a street map through a centralized IoT management console (Figure 2). A city
planner could then select any camera and send it a very tiny set of instructions, e.g. a logical translation of the instruction: “Report back to the cloud every five minutes, each car with its speed, BUT ONLY in lane two, AND only between 10:00 a.m. and 11:00 a.m. every day.”

Based on this instruction, the camera will process the features (speed, lanes, timestamp, etc.) in the image and upload the information to the cloud at five-minute intervals, giving the timestamp and the speed of every car in lane two. Since software drives the cognitive camera system, it could be easily adapted to accommodate different requirements and additional opportunities for the city (e.g.: “Find free parking spots on the street”).

Our traffic detection accuracy was very high (greater than 98%) and was the result of extensive training under many challenging conditions such as light, weather, angles, and camera height. It should be noted that we were reaching the computing thresholds of the edge processing units and would have needed AI-assisted hardware if we had to expand our edge processing requirements.

The red dots in Figure 3 represent our cognitive camera’s traffic count readings (y-axis) at different times in the day (x-axis). The blue dots represent the industry-proven tube flow device used to compare the traffic flow against our system.

Discoveries from our Proof of Concept Deployment

Cities are not typical ‘businesses,’ and while they have budgets (limited or otherwise), their return on investment is measured by citizen satisfaction. A key factor to city-wide deployment of a cognitive camera lies in lowering the barrier to entry of this technology for cities with limited (or diminishing) budgets. To that end it was important to:

1. **Simplify the deployments**: Time is money, and anything that would speed up deployment time involving a bucket truck would translate into savings. The camera units with edge-based image recognition capabilities were completely self-contained, allowing an installer to simply bolt on the camera unit and plug in the power, piggybacking over the same power line for communications. These camera systems could speed deployments and translate into huge savings for the city.

2. **Reduce the cost of ownership**: The computer vision industry is in a state of hyper acceleration resulting from a deluge of image recognition frameworks and other deep learning advances. A lot of these systems were built under the assumption that processing would occur in a cloud. Sending the raw data stream to the cloud from every deployed camera is a recurring expense that any city would like to avoid. Having edge-based image recognition with hardware assist would be much more accommodating for cities to adopt.

A problem that we faced in this POC had to do with the goal we set ourselves of minimizing the time to deploy cameras throughout a city. Most installers would be given a general angle at which to point the camera onto the road, but the resultant image recognition quality would be dependent on conditions such as height and angle of the camera, different illumination conditions (time of day and seasonal), reflections on the road, and even shadows from trees and objects which may not have been there at the time of deployment. These issues have a strong influence on the ability to correctly detect objects in an image.

While it may be practical to accommodate camera adjustments with human intervention on a one-off basis, scaling to thousands of cameras deployed in a city requires a more automated resolution. One approach to the solution that we implemented in this POC was to have each camera spend a week at the outset of deployment to self-learn and adjust to its unique surroundings.

Such real-world conditions are critical considerations, but there was one significant observation that stood out beyond all others. This revelation had less to do with AI techniques and everything to do with the symbiotic expectation between an...
AI and an Industrial IoT. The basic idea is that AI systems rely on data as their basic currency, and an IIoT generates a lot of meaningful data. However, if an AI system cannot easily access and process this data, and an IIoT cannot interpret, distribute, and act on AI decisions, then, their symbiotic relationship becomes non-optimal and puts a cost burden on the business.

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Today, many AI services and IIoT platforms are developed, installed, run, and managed in relative isolation from each other. While data is the glue to the symbiotic relationship between AI and IIoT, it is also a challenge to interoperability because of the very heterogeneous nature of the Industrial IoT.

Consider the following example of an Industrial IoT deployment sending temperature data to an AI system. One temperature gauge in the deployment expresses its temperature data in Celsius, while a temperature gauge in the same IIoT deployment may express its readings in Kelvin. An AI service that needs access to temperature data in this scenario would be faced with an ambiguous representation of the data (temperature format) being exchanged between the IIoT and the service. The AI service could try to resolve this ambiguity through human intervention, but at a much higher cost of integration. While it may even be feasible to resolve the data incompatibility issues through human intervention for this simple use case, it is impractical to assume that this same high-touch approach could scale to solve issues in complex heterogeneous IIoT deployments. The solution to this problem can be better addressed by the IIoT platform rather than the service.

Similar integration challenges needed to be addressed in our POC. With the successful completion of our car counting investigation (figure 3), the city wished to conduct a different experiment with the cognitive camera. Their desire was to turn down the streetlights late at night to conserve energy and create a more calming environment for residents. But with safety in mind, the city wished to reuse the camera as a motion detector to turn up the streetlights for passing vehicles. This would also test the time-sensitive collaborative nature of the platform. Our POC did accurately detect vehicle motion, and the camera could immediately send instructions to turn up the luminosity of the surrounding streetlights.

The camera needed to also quickly alert neighboring streetlights to turn up their luminosity to ensure safe driving conditions for fast-moving cars. To perform this function at the edge, the cognitive camera needed to “know” how to communicate with all other neighboring streetlights. As in the example of the temperature gauge, not all streetlights have the same format or “language” of communication. For example, communicating with a streetlight from company ‘X’ may be very different than communicating with a streetlight from company ‘Y’.

Adesto’s approach would resolve these data interoperability challenges in the underlying IIoT platform through a medium we call the ‘data fabric’. By addressing the data interoperability in the IIoT platform (and not at the service level), the platform could extend this data interoperability solution to any type of application (AI or otherwise). This support for data interoperability in the platform also made the overall solution more extensible and adaptable to change, with minimal disruption to the service.

A Data Fabric: Orchestrating Data for AI Services on an IIoT Platform

Any large distributed system like an IIoT has at its core some form of a manager (or service) to coordinate the activities of the system. One can look at it as a fabric that inter-connects all devices into an IIoT.

Going from being connected to being collaborative is what establishes the symbiotic relationship between AI and IIoT deployments. Connected things are made collaborative when they can interoperate with each other through an agreed upon interpretation of the data. The support for such behavior is typically done through an abstraction protocol at the application layer. Such a protocol transcribes the data into a universal description and is an essential step in the process of comprehending the data being exchanged between heterogeneous devices.

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A data fabric is a distributed manager that has the support for well-defined application layer protocol and device communication protocols and is core to the collaborative nature of an IIoT deployment. It unifies end points including devices, applications and microservices and provides consistent capabilities across the fabric.

Figure 4 shows devices connected into this data fabric through edge servers. These edge servers transcribe device-specific data into the universal description of the data fabric. Conversely, these edge servers will convert the data back into the device-specific data formats. It is important to mention that edge devices with the correct protocol support could connect directly into the data fabric as well (bypassing the edge server). The data fabric forms the foundation that builds the collaborative nature between an IIoT deployment and AI services that can either run at the edge (as in our case of the cognitive camera) or in a cloud.

The IoT Access Protocol (IAP) is a powerful example of this data fabric. The IAP is an open protocol initially created by Adesto and which is now being standardized through ANSI and CTA. Using a well-defined set of REST and MQTT APIs to access device data or invoke services, developers can easily interface to the IIoT from anywhere. Through IAP, developers at all levels will be less dependent on needing to understand the complexities of IoT protocols or industrial field buses to access data needed for their AI. The IAP has the potential to define a new era of interoperability as AI comes to the IIoT.

Conclusions

The extraordinary promise of AI allows businesses to predict an event or a failure in their IIoT deployments before they occur. Since the quality of AI decisions improves with relevant data, having mechanisms to meaningfully express the immense volumes of data in an IIoT to an AI service would represent an important step to its performance. Consequently, the ability to have an AI system’s decisions easily distributed, and understood, by edge devices in the IIoT is key to establishing operational excellence. The data fabric is a key ingredient to this symbiotic relationship between AI and the IIoT.

As AI becomes an increasing part of our daily lives, more demands will be placed on access to data and the distribution of intelligence into every aspect of our lives. Perhaps in the future we can imagine a world where we no longer need to extract the intelligence from the data; but instead simply expect that the data intrinsically has the intelligence to be part of the new fabric of the Internet. An Internet 2.0.

![Figure 4. A virtual data fabric view](image)

![Figure 5. A return on investment by the layering of services in an IIoT](image)
About Adesto

Adesto is a leading provider of innovative, application-specific semiconductors and systems that comprise the essential building blocks of Internet of Things (IoT) edge devices operating on networks worldwide. Our broad portfolio of technologies are optimized for connected IoT devices and systems used in industrial, consumer, and communications applications. Through expert design, unparalleled systems expertise and proprietary intellectual property (IP), our offerings enable customers to differentiate their IoT systems and product designs, leading to improved efficiency, greater reliability and security, integrated intelligence and ultimately lower cost.

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