General Electric: Building Machine Learning Applications for the Industrial Internet

Source: Saleha Saulat Siddique, The Road to Enterprise Artificial Intelligence: A Case Studies Driven Exploration, MIT, 2018

About the Company

General Electric (GE), headquartered in Boston, Massachusetts, is a conglomerate company with products and services ranging from aircraft engines, power generation, and oil and gas production equipment to medical imaging, financing and industrial products. GE describes itself as a 'global digital industrial company, transforming industry with software-defined machines and solutions that are connected, responsive and predictive. In 2017, it served customers in over 180 countries, had over 313,000 employees worldwide, and revenues of $122 billion.

Consumer vs. Industrial Machine Learning

When we think of machine learning applications, often the first examples that pop into mind are from the consumer internet – Netflix's recommendation engine, Amazon's Alexa voice assistant, Google's Gmail Smart Reply etc. For these companies, data was already being aggregated and is relatively accessible.

Industrial machine learning is a field that is now emerging. Until recently the data was not available, but we are now reaching a point where every single asset in the field is laced with sensors, collecting data on short timescales, and transmitting it to the cloud, enabling more advanced analytic approaches. This unlocks a number of use cases across a number of industries. By 2020 the industrial internet had more than 50 billion connected machines.

This is an area of tremendous opportunity because even a 1% gain in efficiency can translate into tens of billions of dollars saved within GE's business units.

At the same time, this is also an area with a number of challenges as compared to the consumer internet, as summarized in the table below. Firstly, the Industrial Internet has much more data to manage – e.g. a day's worth of Twitter data is 500 GB but a single flight's data is double that at 1 TB. Connectivity is also problematic as these assets are in the field – e.g. a sensor could be in an aircraft engine – so getting connectivity at timescales that enable support is a challenge. Assets like engines and turbines are meant to be in operation for decades, so the sensors that are on it also need to work reliably for years/decades. Security is also far more necessary and many of these assets are 24/7 mission critical, e.g. in power, aviation and health care, and thus must be hack-proof. Finally, unlike the consumer internet, privacy in these industries is highly regulated.

Table 1 - Challenges for Industrial Internet vs. Consumer Internet

	Consumer Internet	Industrial Internet
Data Management	Day's worth of Twitter: 500 GB	Single flight: 1 TB
Connectivity	Biggest cell phone complaint: dropped calls	Mission critical, rough & remote
Device Support	Avg. wearables lifetime: 6 months	Lifetime of a Turbine: 20+ years
Security	Time to hack most devices: minutes	24/7 Mission Critical
Privacy	Privacy is no longer a 'social norm' – Mark Zuckerberg	HIPAA, ITAR, …

Considering all these challenges, it is not too surprising that most well-known machine learning applications happen to be on the consumer side, given the data there is easier to collect, manage and share. Just getting the infrastructure set up in the industrial internet to collect data at scale, aggregate it, send it to the cloud, and have people securely access it has been a complicated and time consuming process. However, GE made substantial progress on that front and was finally at the moment when the data infrastructure to enable machine learning applications was in place.

Acquiring Wise.io To Build Machine Learning Applications Across GE's Business Units

In the fourth quarter of 2016, GE acquired Wise.io to build and deploy machine learning applications for GE and its customers across all of GE's business units. Wise.io was a startup that had built and deployed more than 100 machine learning applications for its customers and that had a platform for deploying machine learning applications in production at scale. The Wise team sought to brought that mentality to GE – i.e. how to tackle common problems at a much larger scale, with an impact across millions of assets, in a way that is repeatable, scalable and unlocks real value.

Example: GE Aviation

About GE Aviation

GE makes 60% of the world's airplane engines. It has more than 33,000 engines in service worldwide, and each of those engines has 50-100 sensors on it, recording several times per flight, which will soon be upgraded to recording once per second (i.e. at 1 Hz). GE manufactures these engines and sells them to airlines, and also services these engines.

The Problem Statement

GE's Aviation Fleet Monitor process, which was built and refined over decades, was also very labor intensive, manual, and suboptimal (not in terms of engine parts failing, but in that GE tended to overmaintain/service when not needed).

The Fleet Monitor process supports GE's global engine fleet by capturing sensor data from engines multiple times per flight. This data is aggregated into the cloud, physics based models run on the data to identify anomalies and create alerts that get surfaced to the global Fleet Monitor team. This team has deep domain experts who then make a decision about each alert, and decide when to issue 'Customer Notification reports' to airlines when necessary and when to dispatch technicians on-site to perform inspections and repairs.

The bottleneck in this process was for the experts to review the alert and all the data associated with it, and to potentially look up in the knowledge base data about similar alerts. This was very time consuming, required many people hours and created delays.

Introducing Machine Learning

The Wise.io team aimed to inject machine learning into this workflow in a way that was not disruptive. The team took all the historical alerts and outcomes of those alerts, across the entire fleet, and used machine learning to learn the patterns that are associated with the actual outcome of each alert.

The machine learning application then served recommendations to the Fleet Monitor team, using machine learning to point them in a direction (serving both suggestions and confidence levels in those suggestions), and empowering the team with a tool to make their lives easier.

The Fleet Monitor engineers enjoyed working with the application. It decreased the time to case valid alerts, and it freed up time for the engineers to spend on more high value work, like communicating with the airline company, doing more proactive maintenance etc. It also drove higher consistency in the monitoring process.

Extrapolating to Other Business Units

What the team had improved was in fact a typical problem across many of GE's business units. There were many time consuming, repetitive processes where experts (analysts, engineers) looked at data and reference knowledge bases to make decisions. The team built similar machine learning applications for GE Power, and BHGE (Baker Hughes GE) Oil and Gas.

---THE END----