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Five Types of Analytics of Things

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For many years I have advocated for more sophisticated types of analytics. My goal has typically been to encourage companies to move from descriptive analytics (also known as reporting or business intelligence) to predictive (not surprisingly, analytics that allow predictions about the future) and prescriptive (analytics that make recommendations for human action) analytics.

One of the new frontiers for analytics involves analysis of Internet of Things (IoT) data—what might be called the "analytics of things." I'll argue in this essay that it's still a good idea to move up to more sophisticated forms of analytics with the IoT, but the picture is a bit more complex. With the IoT I believe it's necessary to distinguish between five types of analytics, and that with IoT data it's even more valuable and necessary than with other types of data to move beyond descriptive analytics.

Descriptive Analytics for IoT Data

The most commonly used type of analytics on IoT data by far is descriptive analytics, and the most common way of depicting these analytics is visually. Bar and especially line charts, for example, are common ways of displaying IoT data. Line charts are useful because they show variations in the values returned by sensors over time; they express just how much variation is taking place, suggest whether limits have been exceeded, and often indicate that a sensor is not working properly or not sending data for some reason.

However, such visual analytics are of somewhat limited value. They show variation in the past, but they don't say anything about the future. They don't provide any indication as to why the variation might be occurring, and they normally don't offer much insight about what to do about it. They require a human to stare at the charts for a while, take a stab at what is going on, decide what to do about it and take action. In many cases some of these steps never happen; so IoT data is often not converted into meaningful activity.

Another, somewhat more valuable form of descriptive analytics for IoT data are alerts. They require that someone has previously noted, "Let me know if the value of this variable goes above or below a certain level," presumably indicating a problem. Even if alerts require some thought in the setup process, they allow rapid action after the alert has been received. You don't have to follow the ups and downs of a line chart and decide what to do about it.

Diagnostic Analytics for the IoT

Gartner Inc. has for several years described diagnostic analytics, or those based on a statistical model with the key variables and relationships among the data.[1] They're typically based on some sort of regression model. The primary purpose of this with most types of data is serving as a basis for a predictive model; so I don't usually discuss them on their own.

But in the IoT, diagnostic models are particularly valuable for determining whether alerts are valid or not. As many makers and users of medical devices have learned, false or excessive alerts can quickly lead to "alert fatigue" for those designated to pay attention to them. IoT devices will generate millions if not billions of alerts, and they need to be qualified. If you have an underlying model that diagnoses different levels of data values, it can categorize and qualify alerts so that human tenders are not overwhelmed by them.

Diagnostic analytics are also valuable at an interim stage before an organization is ready to put its models into action. In fact, given the number of sensors and the volumes of data involved in the IoT, organizations will probably want to generate many different models and to put machine learning to work in generating them. Only when a good fit to the data is created does it make sense to move to predictive, prescriptive and automated models.

Predicting the IoT

Predictive analytics using IoT data are becoming increasingly well known, primarily because of one application: predictive maintenance. Companies that install sensors in equipment, and then use diagnostic models to learn what sensor data are associated with product problems or failures, can then create predictive models that suggest when failure is likely and what should be done to prevent it. These applications are typically found in industrial applications like gas turbines, windmills and locomotives, but firms are also using them in building elevators and point-of-sale devices. The health care equivalent of predictive maintenance uses medical device data to help predict the onset of serious health problems in humans or animals.

Predicting when things will go wrong, however, is not the only predictive application that uses the IoT. Organizations can also predict what's likely to go right, such as:

—What combination of seismic sensor signals predicts that underground oil is likely to be present?
—What patient behaviors gathered by fitness trackers predict lower blood sugar levels for a diabetic patient?
—What driving behaviors are most associated with low risk of having an accident (hence predicting an insurance discount)?

Indeed, it may be more effective to predict positive outcomes than negative ones. A Japanese insurance company, for example, found that when it used data from car-based telematics devices to price insurance, it was more effective to use the data and analytics to encourage positive driving behaviors than to discourage negative ones.

Prescription and the IoT

Think of prescriptive analytics as recommendations—analytical models that decide what is the best course of action and then inform a human about it. They may involve optimization models (what's the best price to charge to maximize profit on a product, for example), scoring models or predictive models. The human receiver of the recommendation normally has the ability to accept or reject it.

With the IoT, prescriptive analytics typically involve some of the same issues as predictive ones, but they are more explicit about recommending action. Analysis of sensor data might tell a pilot, "Shut down this engine now," or "Have this engine serviced as soon as you land." A fitness tracker might instruct its wearer to "Get moving—you rarely get to 10,000 steps if you don't have 4,000 by noon." A telematics system in a car might say, "Slow down—bad weather and unsafe speed have often yielded accidents in this area."

The benefit to prescriptive IoT analytics is that they reduce complex data and algorithms to recommendations that can be easily understood and used, often by workers at the front lines or nontechnical consumers. The challenge with them is that they require considerable human attention, and their recommendations may be a "black box" to users. The best prescriptive systems can explain the logic of their recommendations when asked.

Automating Analytics for the IoT

Given the need for human attention from other types of analytics, and the vast amounts of data that will be generated by the IoT, automation of decisions and actions is an obvious direction for the field. There will be way too few humans to make decisions on all the data and analyses coming from the IoT, so we're going to have to automate many processes involving it. Analysis of medical device data will have to lead to automated injections of certain drugs. Analysis of server farm data will have to generate automated reboots. Analysis of traffic data will have to change streetlight patterns automatically. We're not there yet with any of these IoT domains, but we will get there eventually.

We do have, of course, some automated and highly networked systems already, including financial markets and the energy grid. It's just that they don't always work very well. You may recall the "Flash Crash" of 2010. To my mind, we still don't have a convincing explanation for the sudden massive decrease in asset values, and one 2013 book argues that such rapid decreases have been common in the history of financial markets.[2] And in the U.S. energy grid, despite substantially increased automation we've seen increases in power outages over the last couple of decades.[3]

So we've got our work cut out for us on IoT decision automation. We can't link together our industrial, transportation, energy and other systems successfully until we've figured out the dynamics of complex automated networks.

A key with these multi-step models of analytics, however, is not to despair about how far you have to go, but simply to try to advance from where you are. If you are stuck on line and bar charts, try to use that data to run a diagnostic regression equation. If you've done that already, try predicting something—and so forth. The sooner we start employing more sophisticated analytics, the sooner we can get some real value from the Internet of Things.

—Produced by Tom Davenport, the President's Distinguished Professor of Information Technology and Management at Babson College, a Fellow of the MIT Center for Digital Business and independent senior advisor to Deloitte Analytics. This essay was originally published by Deloitte University Press.

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Endnotes

1. Gartner, “Diagnostic analytics,” http://www.gartner.com/it-glossary/diagnostic-analytics/.
2. Irene Aldridge, High-Frequency Trading: A Practical Guide to Algorithmic Strategies and Trading Systems, 2nd ed., Wiley & Sons
3. Jordan Wirf S-Brock, “Power outages on the rise across the U.S.,” Inside Energy</emM, http://insideenergy.org/2014/08/18/power-outages-on-the-rise-across-the-u-s/.