Machine Learning for Predictive Maintenance

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SAP NATIONAL SECURITY SERVICES

BLUF: *Modernized technology can improve the performance, function, speed and cost of maintaining assests and resoucres for the warfighter.*

THE CHALLENGE

The time, costs and risks of maintaining assets for global operations is, in many scenarios, based on legacy capabilities. The platforms in use today were never engineered to process the millions of data points that can now be captured across weapons systems, supply chains, and operational requirements. And the speeds at which today's modern platforms can process and analyze data were not envisioned when current maintenance process were put in place.

THE GOAL

Shift from reactive maintenance to predictive maintenance, using Internet of Things (IoT) equipment sensor data processed with artificial intelligence and machine learning.

Today, there are thousands of sensors on equipment -- generating mountains of data across many parameters. This data can be leveraged for better maintenance practices, but it is not being fully leveraged--or in many cases, it's ignored. The only way to exploit this high volume and velocity of data is with machine learning automation.

There are two main benefits of using a predictive, machine learning, approach to maintenance:

1 Increase Readiness while reducing risk

- Empower asset operators and service providers with data science, helping them predict failures early and implement corrective actions – BEFORE there is a critical failure or malfunction.
- Analyze operational trends to minimize unplanned downtime. By better understanding defect and failure patterns, personnel can manage risk and tighten alignment of mission needs and maintenance operations.

2 Reduce maintenance costs while improving performance

- Gain the support of machine learning to provide recommended plans for your maintenance schedules, dynamically. This can improve how you use assets, help better plan downtime, and lead to more productive personnel. More focus on the mission, less on the process.

Better Maintenance Through Math

Machine Learning is based on algorithms, or a specified set of rules and processes to perform calculations. At its' core, maintenance is based on a set of processes. Putting in place high-speed computing that can perform exponentially faster calculations than a human operator gives us greater power and ultimately can predict better plans, performance and delivery of maintenance. Basically, we can combine all the knowledge of your best maintainers with enormous amounts of maintenance data to predict possible outcomes and take action in advance.

Examples of algorithms to use for predictive maintenance

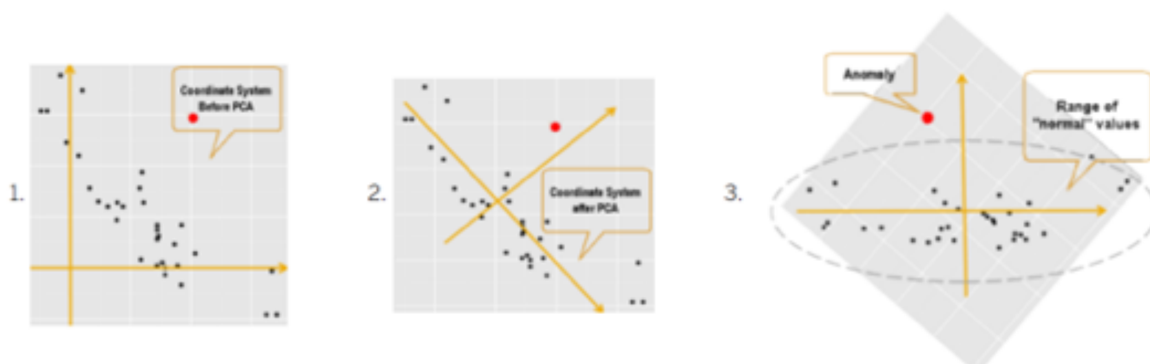
Tackle challenges like a flight data recorder

The first type of algorithm that can be used for improved predictive maintenance is Anomaly Detection with Principal Component Analysis (PCA). This machine learning method transforms data readings from an existing system into a new way to understand the data. From a very basic point of view, machine learning is used to map out everything that is considered normal data so you can identify the data that isn't expected or abnormal. The algorithm explains variance in your data beyond the speed and capacity of what a human operator could do.

Every input is analyzed, and the anomaly detection algorithm computes its projection on an axis, while also producing a normalized or expected error. You can then use the normalized error to score all your anomalies. The higher the score, the more anomalous the instance is. This allows you to find structure from randomness.

Consider a flight data recorder in a modern aircraft. More than 600 data parameters per second are processed. Everything from altitude to flap settings, cockpit switch positions, to engine power levels, geo location to aircraft pitch, and more are being tracked. At any given moment all the data is being clustered to determine normal or typical behavior. If anomalies happen, or something outside the scope of the clustered patterns develop, pilots, air traffic control, even the airline base operations can be notified – to catalog for maintenance action if the anomaly is not high risk or corrective action taken if the anomaly is potentially headed toward system failure. The same type of detection can help identify maintenance actions required, pending equipment failure or a breakdown in the maintenance process.

The PCA concept is depicted in the following sequence of figures (the closer data readings are to the center of the new coordinate system, the closer these readings are to an optimum value):



Uncover solutions similar to how FedEx might

Another type of machine learning is known as Distance-Based Failure Analysis using "Earth Mover's Distance" (EMD). This algorithm solves a linear optimization problem -- comparing a healthy asset to one of an unknown state. Similar to the PCA example above, this calculation assigns a predictive score.

A traditional example for EMD is a transportation problem – where you would need to deliver a fixed set of supplies to multiple recipients. Instead of determining the cost to move each, individual set of supply runs, you can use a machine learning algorithm to calculate distance clustering between each of the supply points and determine the most optimal supply routes for time, money, security risks, etc.

You can apply the same techniques to determine qualities and aspects of different supply sets, or tasks to mathematically determine the best maintenance actions to take by group, time personnel or whatever variable you determine are needed.

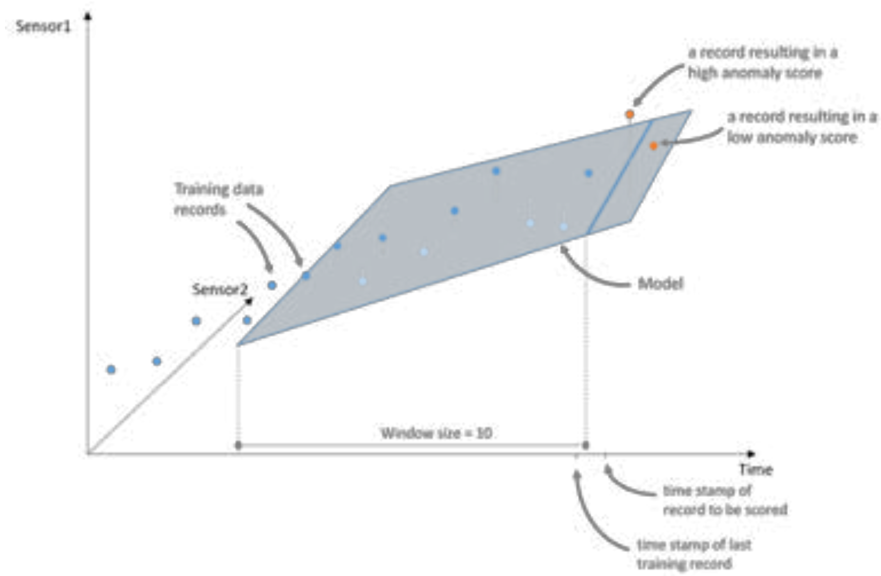
Using age to predict the future

The predictive analytics for Remaining Useful Life (RUL) Prediction uses a machine learning model known as Weibull Distributions. The Weibull algorithm calculates the distribution of equipment's lifetime based on its age. To pull this off, the algorithm considers the age at which identical equipment failed, along with the ages of the same type of equipment that still works. The result is an estimate of the remaining useful life (RUL) of each at the time of the calculation. The algorithm can also calculate the probability of failure of equipment within a certain time period.

Understanding what can go wrong by keep track of what is going right

The fourth algorithm for identifying anomalies to help with predictive maintenance is Multivariate Autoregression. Multivariate Autoregression can be used to detect anomalies in sensor data records varying over time. If machine learning is used with regular data (those without anomalies present), then the model is capable of learning the regular behavior of a system. When you present recently observed data to that system, the model can then predict a data record a step into the future. The system assigns an anomaly score based on the distance between the prediction and the observation. If there is large deviation, it can trigger an alert, report, notice or other mechanism to indicate abnormal behavior of the underlying system – giving you a window into what is going to most like or potentially happen before it actually occurs.

The following figure illustrates the predictive model for one input variable:



Determine what to fix based on the way Netflix figures out what movies you might like to watch

People tend to try and predict outcomes based on guessing. What we do as humans is based loosely on patterning a guess based on what we know about something. For machine learning, there is a similar method of finding a solution that is much more powerful and complex – and more accurate. The Tree Ensemble Classifier algorithm can be used to predict the failure of an item or process.

This approach combines multiple machine learning models to improve your results. The model also helps reduce bias and variance in your data. This algorithm trains a “boosted” decision tree model --which is a series of decision trees. Based on the values entered for a data record, the model is trained so each tree can decide which set of record groups the original record belongs to.

A comparative example of this type of decisioning is the rating and selection system on Netflix. On the Netflix platform millions of subscribers’ rate movies, there are also meta data associated with each movie title. There are also data attached to each subscriber. Combining all this data in various decision trees helps Netflix make better recommendations to each individual subscriber on what they may want to watch. And, each time that user updates their viewing habits or ratings, the decision tree gets more accurate. The model is an extremely sophisticated guessing engine that provides far more accurate results than any movie expert of employee at Netflix could. This same method can be used in predictive maintenance to accumulate data entered in maintenance records, while also allowing for possible data entry errors, and still provides near accurate predictions on analysis, cause, recommended actions.

The following figure illustrates the tree ensemble model created by the algorithm:

Understanding problems by keeping track of where everything should (and shouldn't) be

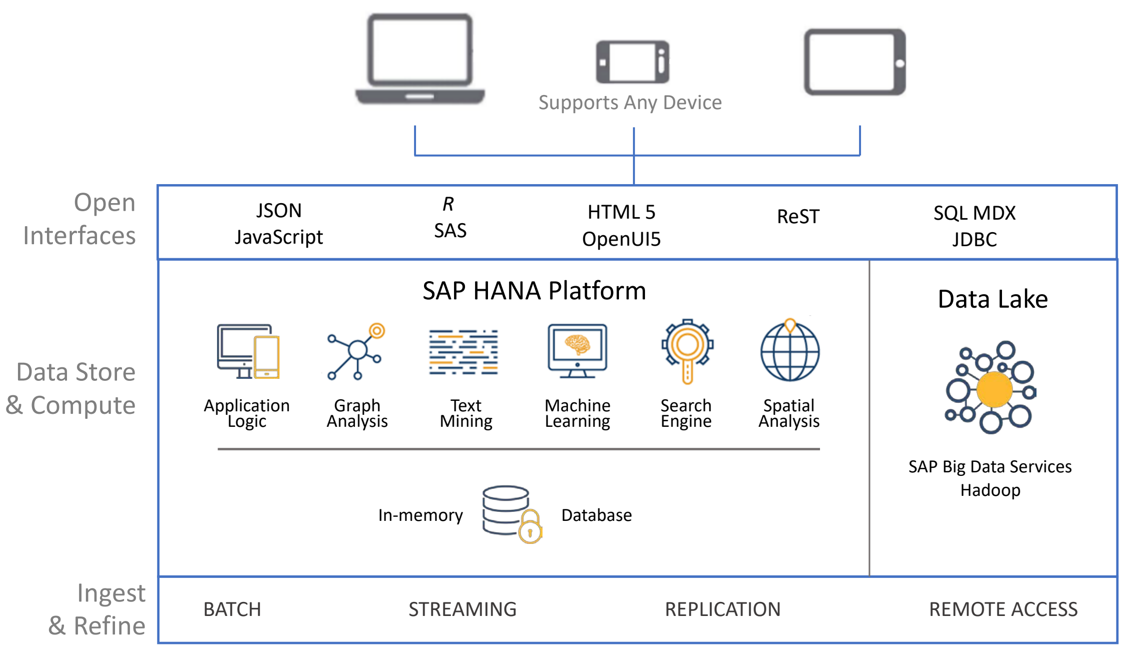
JRR Tolkien pointed out that "Not all who wander are lost" long before we started tracking modern technology. His point, though, fits well when talking about the last machine learning example to find maintenance anomalies. This model is known as Support Vector Machines (SVM)

In order to identify anomalous behavior of equipment, the current sensor values of particular equipment are compared with sensor values of a period when the equipment is working correctly. Given a set of training examples, each marked as belonging to one or the other of two categories, the SVM builds a model that is then used to classify the current sensor values as normal or anomalous.

An example of this might be tracking of ships in a strategic corridor like the Straits of Malacca near Singapore. The track and patterns of more than 150 large vessels each day are known, along with port and satellite surveillance, coastal radar and other data. After combining all of these data into a predictive analytic system, anomalies can be detected – providing better security and support for both the shipping and governmental organizations. This same type of vector-based machine learning can be applied to known patterns of maintenance data so that anomalies can be detected, and immediate action taken – whether it is the upcoming depletion of a critical part supply or maintenance performed on the wrong assembly or unplanned, out-of-cycle repairs on assets.

Software to enable Predictive Maintenance – there's an app for that

SAP has a capability that leverage in-memory computing technology to process data at exponentials rates. The platform is known as SAP HANA which can provide SAP Predictive Maintenance and Service. This service combines multiple types of machine learning to deliver deep, actionable insight across an enterprise or operation. The whole system is based on open, non-proprietary, data structures and interfaces, which makes it flexible and interoperable with other systems. This open architecture also ensures the service can process data from any type of equipment.



Technical Architecture of SAP Predictive Maintenance and Service software

Continuous Improvement and Futureproofing Predictive Maintenance

To support continuous performance improvement, you can use insight from systems-of-record and operational data from equipment sensors, as well as other documents from any source—even unstructured text. It can all be done on premise, or through the cloud.

The system also uses Natural Language Processing to automatically extract facts and entities from scanned forms and hand-entered free-form maintenance reports.

You'll be able to filter, analyze, visualize, search, sort and report on valuable insights with real-time data analytics, through a unified user experience.

Some of the other aspects of the system that can help operational maintenance include:

Indicator management

- Analytics indicators for equipment
- Ability to assign variable data types and threshold definitions
- Customizable rules engine for alerts and e-mail creation

Integrated machine learning engine

- Provides functionality for machine training and scoring models
- Offers a wide variety of algorithms, such as principal component analysis, earth mover's distance, Weibull distributions, multivariate auto regression, tree ensemble classifiers, support vector machines, logistic regression, and others
- Extensibility to other custom algorithms using R integration

Integration with back-end systems of record

- Can tackle master data replication and dynamic triggering of work items

Summary

The question of being able to process massive amounts of data for better outcomes and reduced risks is no longer if, but rather when to empower this capability.

Any predictive maintenance solution you choose should ensure you are empowered to scale your capabilities and achieve faster outcomes

You should be supported by a system roadmap that improves insights for the long term so you can keep pace with an ever-expanding world of threats and changing resources.

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877-972-7672
info@sapns2.com
www.sapns2.com

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