“Scope of Machine Learning in Mechanical Engineering”

(Based on Machine Learning)

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ABSTRACT

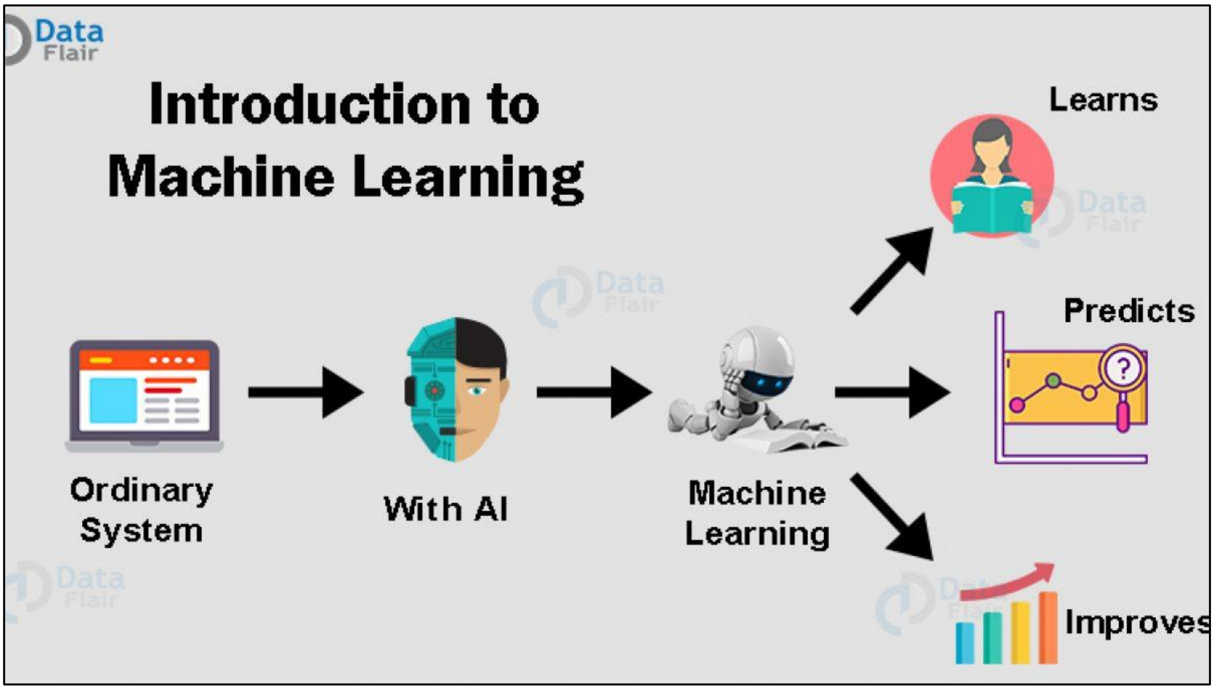
Machine learning is concerned with enabling computer programs automatically to improve their performance at some tasks through experience. Manufacturing is an area where the application of machine learning can be very fruitful. However, little has been published about the use of machine-learning techniques in the manufacturing domain. This paper evaluates several machine-learning techniques and examines applications in which they have been successfully deployed. Special attention is given to inductive learning, which is among the most mature of the machine-learning approaches currently available. Current trends and recent developments in machine-learning research are also discussed. The paper concludes with a summary of some of the key research issues in machine learning.

INTRODUCTION

Machine learning is a method of data analysis that automates analytical model building. It is a branch of artificial intelligence based on the idea that systems can learn from data, identify patterns and make decisions with minimal human intervention.

Machine learning is the science of getting computers to act without being explicitly programmed. In the past decade, machine learning has given us self-driving cars, practical speech recognition, effective web search, and a vastly improved understanding of the human genome. Machine learning is so pervasive today that you probably use it dozens of times a day without knowing it. Many researchers also think it is the best way to make progress towards human-level AI. In this class, you will learn about the most effective machine learning techniques, and gain practice implementing them and getting them to work for yourself. More importantly, you'll learn about not only the theoretical underpinnings of learning but also gain the ractical know-how needed to quickly and powerfully apply these techniques to new problems.

Today's Artificial Intelligence (AI) has far surpassed the hype of blockchain and quantum computing. This is due to the fact that huge computing resources are easily available to the common man. The developers now take advantage of this in creating new Machine Learning models and to re-train the existing models for better performance and results. The easy availability of High-Performance Computing (HPC) has resulted in a sudden increased demand for IT professionals having Machine Learning skills.



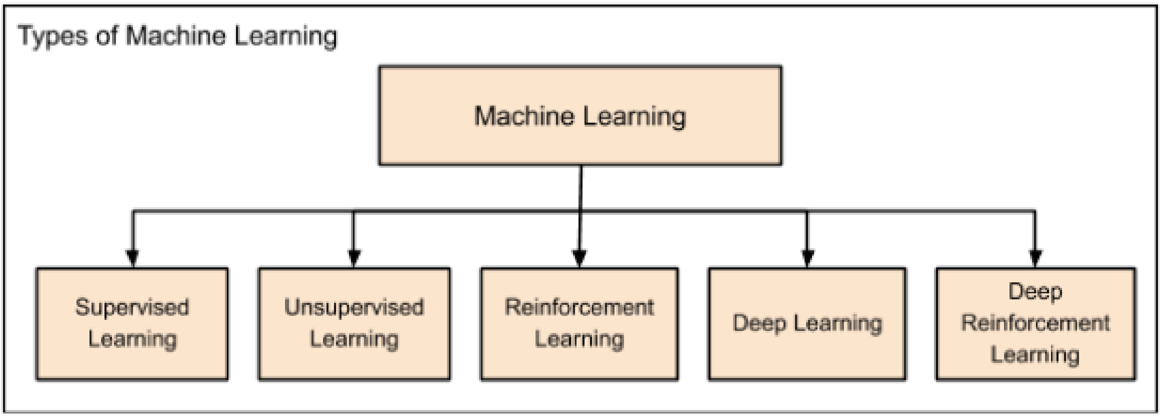
Predictive causal analytics – If you want a model that can predict the possibilities of a particular event in the future, you need to apply predictive causal analytics.

Prescriptive analytics – If you want a model that has the intelligence of taking its own decisions and the ability to modify it with dynamic parameters, you certainly need prescriptive analytics for it. This relatively new field is all about providing advice.

Machine learning for making predictions — If you have transactional data of a finance company and need to build a model to determine the future trend, then machine learning algorithms are the best bet.

Machine learning for pattern discovery — If you don't have the parameters based on which you can make predictions, then you need to find out the hidden patterns within the dataset to be able to make meaningful predictions. This is nothing but the unsupervised model as you don't have any predefined labels for grouping

Machine Learning – Categories of Machine Learning



Machine learning evolved from left to right as shown in the above diagram.

- Initially, researchers started out with Supervised Learning. This is the case of the housing price prediction discussed earlier.
- This was followed by unsupervised learning, where the machine is made to learn on its own without any supervision.
- Scientists discovered further that it may be a good idea to reward the machine when it does the job the expected way and there came Reinforcement Learning.

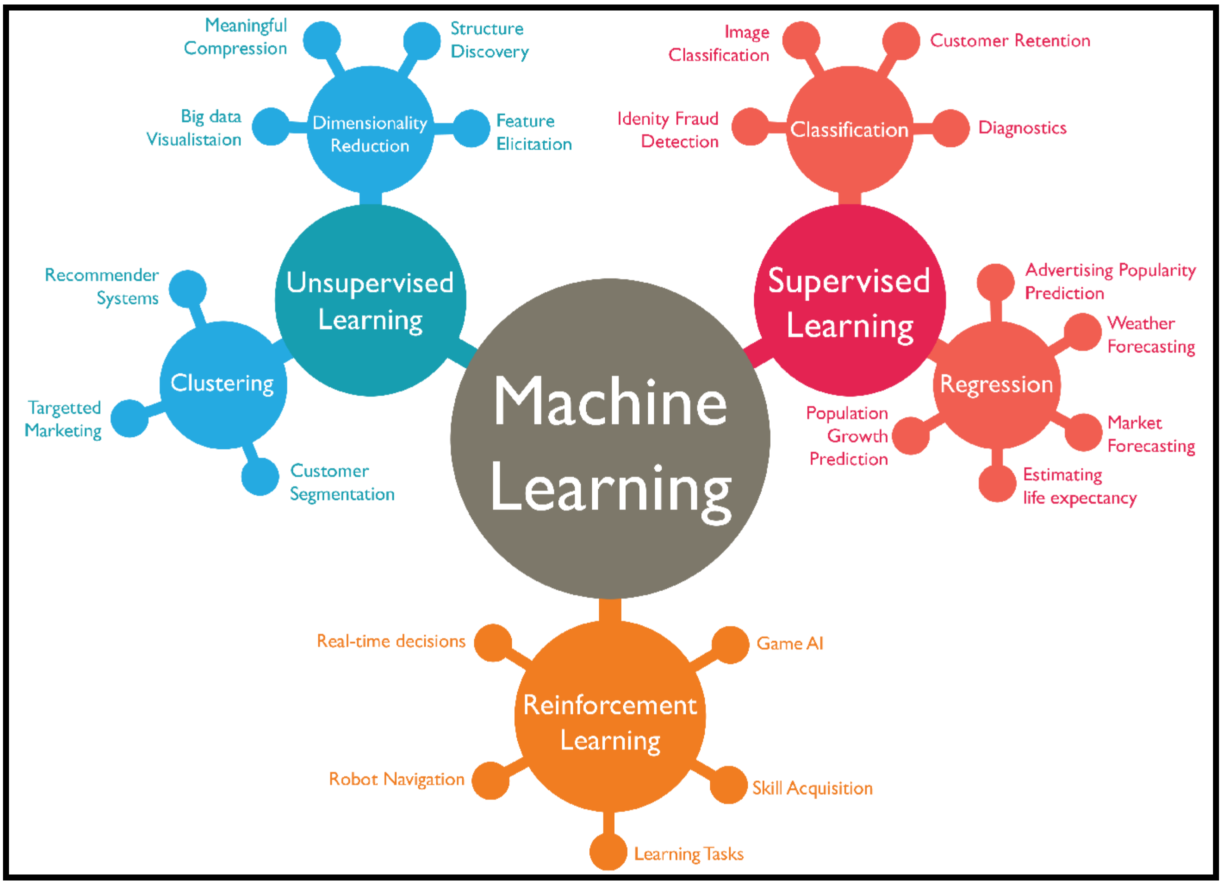
- Very soon, the data that is available these days has become so humongous that the conventional techniques developed so far failed to analyse the big data and provide us the predictions.
- Thus, came the deep learning where the human brain is simulated in the Artificial Neural Networks (ANN) created in our binary computers.
- The machine now learns on its own using the high computing power and huge memory resources that are available today.
- It is now observed that Deep Learning has solved many of the previously unsolvable problems.
- The technique is now further advanced by giving incentives to Deep Learning networks as awards and there finally comes Deep Reinforcement Learning.

Supervised learning algorithms are trained using labelled examples, such as an input where the desired output is known. For example, a piece of equipment could have data points labelled either “F” (failed) or “R” (runs). The learning algorithm receives a set of inputs along with the corresponding correct outputs, and the algorithm learns by comparing its actual output with correct outputs to find errors. It then modifies the model accordingly. Through methods like classification, regression, prediction and gradient boosting, supervised learning uses patterns to predict the values of the label on additional unlabelled data. Supervised learning is commonly used in applications where historical data predicts likely future events. For example, it can anticipate when credit card transactions are likely to be fraudulent or which insurance customer is likely to file a claim.

Unsupervised learning is used against data that has no historical labels. The system is not told the "right answer." The algorithm must figure out what is being shown. The goal is to explore the data and find some structure within. Unsupervised learning works well on transactional data. For example, it can identify segments of customers with similar attributes who can then be treated similarly in marketing campaigns. Or it can find the main attributes that separate customer segments from each other. Popular techniques include self-organizing maps, nearest-neighbour mapping, k-means clustering and singular value decomposition. These algorithms are also used to segment text topics, recommend items and identify data outliers.

Semi supervised learning is used for the same applications as supervised learning. But it uses both labelled and unlabelled data for training – typically a small amount of labelled data with a large amount of unlabelled data (because unlabelled data is less expensive and takes less effort to acquire). This type of learning can be used with methods such as classification, regression and prediction. Semi supervised learning is useful when the cost associated with labelling is too high to allow for a fully labelled training process. Early examples of this include identifying a person's face on a web cam.

Reinforcement learning is often used for robotics, gaming and navigation. With reinforcement learning, the algorithm discovers through trial and error which actions yield the greatest rewards. This type of learning has three primary components: the agent (the learner or decision maker), the environment (everything the agent interacts with) and actions (what the agent can do). The objective is for the agent to choose actions that maximize the expected reward over a given amount of time. The agent will reach the goal much faster by following a good policy. So the goal in reinforcement learning is to learn the best policy.



Technique Under

Supervised Learning

- Linear Regression

Regression analysis is a set of statistical methods used for the estimation of relationships between a dependent variable and one or more independent variables. It can be utilized to assess the strength of the relationship between variables and for modelling the future relationship between them. Regression analysis includes several variations, such as linear, multiple linear, and nonlinear. The most common models are simple linear and multiple linear. Nonlinear regression analysis is commonly used for more complicated data set in which the dependent and independent variables show a nonlinear relationship. Regression analysis- simple linear regression. Simple linear regression is a model that assesses the relationship between a dependent variable and an independent variable. The simple linear model is expressed using the following equation:

“$Y=a + bX + \varepsilon$”

Where:

- Y- Dependent variable
- X- Independent (explanatory) variable
- a - Intercept
- b - Slope
- ε – Residual (Error)

- Multiple Linear Regression

Multiple linear regression analysis is essentially similar to the simple linear model, with the exception that multiple independent variables are used in the model. The mathematical representation of multiple linear regression is:

$$Y= a + bX_1 + cX_2 + dX_3 + \varepsilon$$

Where:

- Y- Dependent variable
- X_1, X_2, X_3- Independent (explanatory) variable
- a - Intercept
- b, c, d - Slope
- ε – Residual (Error)

- Logistic Regression

Logistic regression is a statistical model that in its basic form uses a logistic function to model a binary dependent variable, although many more complex extensions exist. In regression analysis, logistic regression[1] (or logit regression) is estimating the parameters of a logistic model (a form of binary regression). Mathematically, a binary logistic model has a dependent variable with two possible values, such as pass/fail which is represented by an indicator variable, where the two values are labelled "0" and "1".

Consider a model with two predictors, x_1 and x_2, and one binary (Bernoulli) response variable Y, which we denote $p=P(Y=1)$. We assume a linear relationship between the predictor variables and the log-odds (also called logit) of the event that $Y=1$. This linear relationship can be written in the following mathematical form (where ℓ is the log-odds, b is the base of the logarithm, and βi are parameters of the model):

$$\ell = log_b \frac{p}{(1-P)} = \beta_0 + \beta_1 x_1 + \beta_2 x_2$$

We can recover the odds by exponentiating the log-odds:

$$\frac{p}{(1-P)} = \mathrm{b}^{\beta_0 + \beta_1 x_1 + \beta_2 x_2}$$

Unsupervised Learning

- Kmeans Algorithm

Kmeans Algorithm is an iterative algorithm that tries to partition the dataset into Kpre-defined distinct non-overlapping subgroups (clusters) where each data point belongs to only on group. It tries to make the intra-cluster data points as similar as possible while also keeping the clusters as different (far) as possible. It assigns data points to a cluster such that the sum of the squared distance between the data points and the cluster's centroid (arithmetic mean of all the data points that belong to the cluster) is at the minimum. The less variation we have with the clusters, the more homogeneous(similar) the data points are within the same cluster.

The way kmeans algorithm works is as follows:

1. Specify number of clusters K.
2. Initiate centroids by first shuffling the dataset and then randomly selecting K data points for the centroids without replacement.
3. Keeping iterating until there is no change to the centroids. i.e assignment of data points to clusters isn't changing.

- Compute the sum of the squared distance between data points and all centroids.
- Assign each data point to the closest cluster (centroid).
- Compute the centroids for the cluster by the average of the all-data points that belongs to each cluster.

The approach kmeans follow to solve the problem is called Expectation-Maximization. The E-step is assigning the data points to the closet cluster. The M-step is computing the centroid of each cluster. Below is a break down of how we can solve it mathematically.
The objective function is:

$$J = \sum_{i=1}^{m} \sum_{k=1}^{k} W_{ik} \| x^i - \mu_k \|^2$$

Where W_{ik}=1 for data point xi if it belongs to cluster k, otherwise, w_{ik} =0. Also, μ_k is the centroid of x^i's cluster.
it's a minimization problem of two parts. We first minimize J w.r.t W_{ik} and treat μ_k fixed. Then we minimize J w.r.t μ_k and treak W_{ik} fixed. Technically speaking, we differentiate J w.r.t W_{ik} first and update cluster assignments (E-step). Then we differentiate J w.r.t μ_k and recompute the centroids after the cluster assignment from previous step (M-step). Therefore, E-step is:

$$\frac{\partial J}{\partial w_{ik}} = \sum_{i=1}^{m} \sum_{k=1}^{K} \|x^i - \mu_k\|^2$$

$$\Rightarrow w_{ik} = \begin{cases} 1 & \text{if } k = argmin_j \ \|x^i - \mu_j\|^2 \\ 0 & \text{otherwise.} \end{cases}$$

In other words, assign the data point x_i to the closest cluster judged by its sum of squared distance from cluster's centroid. And M-step is:

$$\frac{\partial J}{\partial \mu_k} = 2\sum_{i=1}^{m} w_{ik}(x^i - \mu_k) = 0$$

$$\Rightarrow \mu_k = \frac{\sum_{i=1}^{m} w_{ik}x^i}{\sum_{i=1}^{m} w_{ik}}$$

Literature review

Irrespective of the industry, production systems usually comprise a selection of manufacturing processes in accordance with DIN 8580 [1] and handling operations as defined in VDI 2860 [2] (Fig. 1). In the following, exemplary ML use cases in the respective subcategories as well as cross-process applications will be given for a rough orientation on ML potentials.

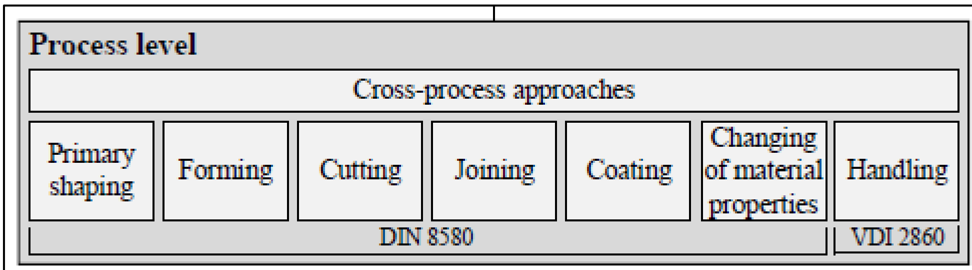


Fig. 1. Structure for classifying ML use cases into process and industry level

Primary Shaping

According to DIN 8580, primary shaping is the manufacturing of a solid body from shapeless material by creating cohesion. In literature, ML-based approaches can already be found for individual processes, such as casting. For instance, by evaluating process data and detecting implied correlations, Saleem et al. apply ML for enabling an intelligent process control in foundries. In addition, Rössle and Kübler present a ML approach for real-time quality prediction in die-casting based on process data acquired by high-resolution sensors. Although a clear allocation of additive manufacturing into the main groups of DIN 8580 is not possible, most additive pro-cesses can be assigned to primary processing. By using ML, powder feedstock can be characterized by its microstructure. During layer generation, the process can be monitored by evaluating acoustic emissions or image data.

Forming

Forming represents the manufacturing through plastic change of the form of a solid body by preserving both the mass and the cohesion. As with primary shaping, some ML approaches already exist. In a novel approach for categorizing forming processes into multiple failure classes based on ML is presented, already showing a good prediction of the on-set of necking. Moreover, Dib et al. [10] apply ML for defects prediction in metal forming processes. In another example, ML is used for anomaly detection in press-hardening.

Cutting

According to DIN 8580, cutting describes processes in which a form is altered by means of reducing material cohesion. In this context, machining represents the most important subgroup, summarizing cutting processes in which layers of material are mechanically separated from a workpiece in the form of chips by means of cutting tools. As summarized in different ML use cases have already been implemented in machining processes, e.g., for diagnostics and prognostics of machine tools, parameter optimization or product quality prediction. For instance, Al-Zubaidi et al. provide an overview of applying ANN in milling processes, focusing on the prediction of surface roughness and cutting force as well as on the estimation of tool life and wear.

Joining

As stated in DIN 8580, joining is defined as bringing together two or more workpieces of geometrically defined form or such workpieces with amorphous material. Starting with the field of welding, a large number of ML approaches already exist. Petković presents a supervised learning approach for quality prediction in welding processes using support vector regression. In ML algorithms are applied for the classification of welds based on arc sound signals. In contrast, Khumaidi et al. present a visual inspection system for the classification of welding defects based on CNN.

Coating and changing of material properties

The last two main groups of DIN 8580 constitute the coating as well as the changing of material properties. While the former processes apply a firmly adhering layer of shapeless material to the surface of a workpiece, e.g., painting, the latter change the material properties within the product itself, e.g., tempering. In thermal spraying, for example, an ML-based vision system can be used to evaluate the alignment of the plasma gun nozzle using images of a test spray pattern. With regard to heat treatment, Oh and Ki introduce a deep learning model for predicting the hardness distribution in laser heat treatment of tool steel.

Handling

In accordance with VDI 2860, handling is a part of material flow and principally defined as the realization, defined change or temporary maintaining of a specified 3D arrangement of geometrical bodies in a reference coordinate system. It can be grouped into multiple different domains, including object manipulation and insertion but also localization, inspection and support functions such as environment evaluation. So far, a lot of ML applications address the autonomous planning and optimization of trajectories for articulated robot arms as well as sensor data processing, e.g., for 6DoF pose estimation.

APPLICATION OF MACHINE LEARNING IN AUTO INDUSTRY

From parts suppliers to vehicle manufacturers, service providers to rental car companies, the automotive and related mobility industries stand to gain significantly from implementing machine learning at scale. We see the big automakers investing in proof-of-concept projects at various stages, while disruptors in the field of autonomous driving are trying to build entirely new businesses on a foundation of artificial intelligence and machine learning.

There are huge opportunities for machine learning to improve both processes and products all along the automotive value chain. But where do you focus? And how can you make sure your investments in machine learning aren't just expensive, "one-and-done" applications? We've rounded up four machine learning use cases that can be implemented using open-source technologies and offer long-term value beyond the initial application.

1. Quality Control

Image recognition and anomaly detection are types of machine learning algorithms that can quickly detect and eliminate faulty parts before they get into the vehicle manufacturing workflow. Parts manufacturers can capture images of each component as it comes off the assembly line, and automatically run those images through a machine learning model to identify any flaws. Highly-accurate anomaly detection algorithms can detect issues down to a fraction of a millimetres. Predictive analytics can be used to evaluate whether a flawed part can be reworked or needs to be scrapped. Eliminating or re-working faulty parts at this point is far less costly than discovering and having to fix them later. It saves on more expensive issues down the line in manufacturing and reduces the risk of costly recalls. It also helps ensure customer safety, satisfaction and retention.

To implement an image recognition and analytics model, the manufacturer needs an accurate dataset containing hundreds or even thousands of parts images, each one tagged with information such as pass, fail, issue A/B/C, etc. The data scientist constructing the model must also have domain expertise regarding allowable tolerances and the potential performance and safety impact of various flaws.

The same approach can be used for all component manufacturing as well as throughout the vehicle assembly line. Image recognition and analytics models can play multiple roles across the automotive value chain — such as recognizing and evaluating tiny variations in tread wear patterns to help develop new and better-performing tires, providing quality control for paint and other finishes, and enabling hazard avoidance for Advanced Driver-Assistance Systems (ADAS) and autonomous driving systems. For this reason, many organizations would realize greater value from an enterprise data science platform, rather than a point solution designed for a single use case.

2. Root Cause Analysis

When an issue arises at any point in the product lifecycle — whether it's something found early in the manufacturing process or an issue affecting multiple vehicles in the field — organizations scramble to determine the exact cause and how to resolve it. The brand's reputation (and possibly consumer safety) is at stake.

During the manufacturing phase, identifying the root cause(s) of an issue is a lengthy and painstaking process. Root cause analysis uses massive amounts of testing data, sensor measurements, manufacturer parameters and more. Performed with traditional methods, it's also incredibly hard.

Root cause analysis for issues in the field isn't any easier. Today's vehicles are highly complex, and each driver has unique behaviour, maintenance actions and driving conditions. Some issues arise only under very unique circumstances that were unseen in the manufacturing process.

Machine learning techniques can vastly accelerate root cause analysis and speed resolution. Anomaly detection algorithms can analyze vast amounts of system and driver data efficiently. And they can perform this analysis using additional data types and in far greater quantities than traditional methods can handle.

For example, during the manufacturing phase, the use of image data as an input for root cause analysis helps organizations correlate failure modes to possible flaws in the underlying manufacturing procedures.

With issues arising in the field, text recognition and Natural Language Processing enable the inclusion of service provider notes in the analysis process. Each of these approaches can reveal very specific root causes months faster than traditional analysis — and oftentimes diagnose issues that may not be uncovered any other way.

3. Predictive Maintenance

Machine learning can provide far more precise and — importantly — evolving maintenance recommendations to help drivers protect their vehicle investment as well as their safety. Rather than a static maintenance schedule that gets updated a few times a year, a predictive analytics model can continue to learn from thousands of performance data points collected from manufacturing plants, suppliers, service providers and actual vehicles on the road. The industry is well on its way to completely customized maintenance schedules that evolve over time to be increasingly more tailored to individual drivers and vehicles, and can even adapt to changing conditions and new performance information.

Predictive maintenance helps increase customer satisfaction and brand reputation, while also improving compliance with recommended maintenance. It can also be a source of additional revenue for car makers as an added-value service.

Note: The same technologies enable predictive maintenance for fleet management, saving on major repairs and protecting the ROI on each vehicle. Predictive maintenance can also help keep manufacturing systems working at optimal performance levels — protecting yield, helping to ensure quality and safety, and ultimately saving time and money.

4. Supply Chain Optimization

Throughout the supply chain, analytical models are used to identify demand levels for different marketing strategies, sale prices, locations and many other data points. Ultimately, this predictive analysis dictates the inventory levels needed at different facilities. Data scientists constantly test different scenarios to ensure ideal inventory levels and improve brand reputation while minimizing unnecessary holding costs.

After analyzing the gap between current and predicted inventory levels, data scientists then create optimization models that help guide the exact flow of inventory from manufacturer to distribution centers and ultimately to customer-facing storefronts. Machine learning is helping parts and vehicle manufacturers — and their logistics partners — be more efficient and profitable, while enhancing customer service and brand reputation.

Staying Ahead of the Curve

The automotive sector is nothing if not competitive. Machine learning and data science are the new frontier, enabling organizations to discover and harness hidden value in their operations — and create new opportunities for growth. The open-source community is the engine of innovation across most of data science, which is why automotive executives would be wise to embrace a platform that leverages innovation from open source. Cutting-edge open-source software packages and libraries in a centrally managed, enterprise-class data science platform enable data science teams to do more than just bolt on various point solutions. They can collaborate, learn and evolve to address thousands of use cases with just one platform.

What are machine learning use cases in the automotive industry?

Innovations became an integral part of automotive development, moreover, we are already familiar with self-driving cars, real-time parking systems, and other trends in this area. But what else can we expect from active using machine learning and artificial intelligence in the automotive domain? Let's figure it out in our article on the example of seven AI&ML use cases.

QUICK NAVIGATION

With self-driving cars under development, the adoption of artificial intelligence and machine learning in the auto industry is well underway. Leading car manufacturers use these technologies in their business processes from design development to the sale of a car. Let's find out what the use cases for artificial intelligence (AI) and machine learning (ML) in the automotive industry are, and what benefits automakers can get by adopting these technologies.\

MACHINE LEARNING ADOPTION IN THE AUTOMOTIVE INDUSTRY

Artificial intelligence in self-driving cars is the future of the industry, while machine learning in the automotive industry is becoming more common.

- The market for AI in cars will reach $215 billion of annual value by 2025.
- AI machine-learning car installations are expected to rise by 109% by 2025.
- BMW uses artificial intelligence to create autonomous cars that are expected to be available next year.
- Tesla machine learning is used to create a very sophisticated system capable of deep learning to improve its computer vision, predicting, and route planning skills.
- Artificial intelligence and machine-learning self-driving cars are predicted to be here very soon since the recent pandemic has accelerated innovation in the auto industry because of the need for contactless delivery.

MACHINE LEARNING USE CASES IN THE AUTOMOTIVE MARKET

Below are the main artificial intelligence and machine learning use cases in the automotive industry. What’s more, we outline the paths you can take to make your car manufacturing business more optimized, customer-centric, and innovative.

DESIGN AND DEVELOPMENT

The use of artificial intelligence begins at the development stage for a new car. At this stage, innovative technologies work together. With the help of augmented and virtual reality, it is possible to create a more thoughtful design concept and eliminate possible errors before they become costly.

The current level of development of artificial intelligence in cars is quite impressive. An intelligent system can suggest thousands of designs for future parts and models, and auto manufacturers can choose the best options. Volkswagen is already using this approach. It is called Generative Design and is based on a specific idea or problem that you need to address for the car’s design like making it more compact without losing quality and a sense of space.

QUALITY CONTROL

Once the parts are developed, approved, and put into production, it is necessary to carefully control their quality. In the auto industry, the quality of every part is critical as it can make the difference between life and death in a critical situation. Using object recognition technologies as well as built-in comparison capabilities, sensor-based artificial intelligence assesses the quality of every part on the production line. Defective objects are immediately removed. Moreover, the artificial intelligence of Audi recognizes not only defects but also the smallest scratches so that even little things won’t disappoint the future car owner.

PREDICTIVE MAINTENANCE

Predictive analytics is one of the strongest capabilities of artificial intelligence and machine learning. This is also one of the most promising ways to use machine learning in the automotive industry, which can be implemented in two ways.

1. **With predictive intelligence**, automakers can monitor the health of their equipment. The advantages of this approach are obvious because it allows for the uninterrupted operation of the parts manufacturing plant since all possible problems of maintenance, repair, and replacement of equipment are solved before they arise (reactive maintenance).
2. **The predictive ability of artificial intelligence** for cars can be used to help car owners keep their cars running. For example, the Tesla AI app notifies drivers of the need for technical inspections, oil changes, and other maintenance operations. There are even remote diagnostic capabilities.

CAUSE ANALYSIS

The essence of predictive maintenance is that the system analyzes the equipment, compares its specs with industry and safety standards, adds specific information about the operation of the enterprise, and receives a forecast about when a certain part will fail. The essence of reactive maintenance is to prevent this situation and replace a critical part before it crashes the production system. If an unforeseen situation has already happened though, this is a good reason to analyze the prerequisites and find the root cause.

Artificial intelligence and machine learning cannot live without data. These systems can analyze a huge stream of historical and current information, find anomalies and invisible patterns, and draw conclusions about what led to a certain breakdown.

SUPPLY CHAIN OPTIMIZATION

Supply chain optimization is challenging for any business, and auto production is no exception. In the case of the auto industry, its supply chain is extremely complex. This business is highly influenced by political and social factors, it's quite difficult to manage inventory, the cost of raw materials fluctuates, plus low-quality production increases product recalls. Fortunately, all these problems can be solved with AI automotive solutions.

For example, with the help of the Blue Yonder AI and ML project, it becomes possible to optimize an automotive supply chain, plus take into account the fluctuating prices of the resources and adjust the final price accordingly. What’s more, using machine learning and artificial intelligence in self-driving cars to optimize their routes will be one of the future challenges.

AUTONOMOUS AND ELECTRIC VEHICLE OPTIMIZATION

Autonomous and electric vehicles are still in the early stages so there is no established trust in them. To get these technologies adopted worldwide, especially with the pandemic and the need for autonomous delivery, machine-learning start-ups are focused on making these devices manageable, predictable, and safe. For example, the British project Spark collects driving data to better understand the strengths and weaknesses of the machine-learning-based autonomous vehicles.

INTELLIGENT PARKING MODE

Smart parking is no longer just a dream. It has become a common component of a smart city ecosystem. In response to this trend, car manufacturers are creating cars that have built-in smart parking systems that tell the driver about the presence or absence of free parking places saving him time and fuel.

To do this, automakers need strong systems for analyzing data on city traffic and driver behaviour, plus they need to equip the car with sensors and computer vision features.

MARKETING FOR AUTOMAKERS

It would be a shame to miss out on the marketing opportunities that have opened up with artificial intelligence and machine learning in the automotive industry. With its help, auto manufacturers can attract more qualified leads and competently guide them through the sales funnel taking into account the specifics of car sales.

Plus, you can dramatically improve the user experience by combining artificial intelligence for marketing with virtual reality as Porsche has already done. This company invites drivers to test the vehicle in a virtual environment before purchasing. Of course, the data on driver behaviour in the application is collected and carefully analyzed to develop marketing strategies.

Conclusion

As can be seen from the exemplary applications, ML holds great potential in production. However, missing industry-specific guidelines as well as the unstructured way of representing possible use cases prevent companies from applying ML to own production problems. Therefore, this paper provides a structured overview of various ML use cases from a process and an industry sector perspective. The process perspective mainly covers the manufacturing process groups of DIN 8580, handling operations according to VDI 2860 as well as cross-process approaches. On the industry level, exemplary ML use cases in the production of electronics, electric motors, automotive transmission components and medical devices are out-lined. Although the structured overview is anything but complete, it is already a good basis to identify own use cases from an opportunity-push perspective. However, most of the approaches mentioned are still subject of research and not yet ready for practical use or even widespread. Therefore, research on the application of ML must be further promoted and, above all, the necessary data be provided. As always, it is important to get started to avoid falling behind in the long run.

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