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Machine Learning in Supply Chain Management

Magnus Tilmar Hoppe, 29774

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Professor José Crespo de Carvalho

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Lisbon, 4th January 2019

Magnus Hoppe
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Magnus Tilmar Hoppe

Abstract

Almost every day newspapers and online media publish articles about the ongoing development of machine learning and related applications. Eventually, the practical use cases seem infinite and the potential especially for the efficient organization of supply chains is difficult to determine. This paper examines different applications as well as the underlying operating principles of self-learning algorithms in order to derive implications for supply chain management. Furthermore, an outlook for the prospective development of machine learning and the related further establishment of cognitive automation will be presented.

Keywords

Machine Learning, Supply Chain Management, Predictive Maintenance,
Cognitive Automation

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List of Abbreviations

CPU	Central Processing Unit
DL	Deep Learning
IT	Information Technology
JIT	Just-in-Time
ML	Machine Learning
SC	Supply Chain
SCM	Supply Chain Management
SCP	Supply Chain Planning
SQL	Structured Query Language

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1.0 Introduction:

1.1 Importance of Machine Learning in this Day and Age

The continuous development of the digitization and integration of IT-systems lead to constantly new achievements and establish new trend topics. With the unstoppable progress in these research areas more and more terms came into the focus of the public which a few years ago were mainly discussed in blockbusters or novels. Especially the field of machine learning (ML) under the guise of artificial intelligence (Siau et al., 2018). Many immediately think of movies like "Terminator" or "I, Robot" and fear the superior power of those technologies. But the reality seems different: Today self-learning algorithms are already integrated into everyone's products like smartphones or cars. Our private and business life is increasingly determined by intelligent programs that learn from data and generalize what they have learned. Speech recognition and route planners are largely controlled by those algorithms as well as spam filters inside your mail account. Clearly stated we are often in contact with learning systems, without knowing it (Harvard Business Manager, 2018).

But strictly speaking ML is based on pattern recognition research that was already carried out in the 1980s. The field stagnated for quite a long time due to technical limitations (Bishop, 2006). Just a few years ago ML underwent a breakthrough caused by the development of much more powerful processors. The new technical standard enabled software-engineers to work with complex algorithms. Today self-learning algorithms belong to the "Breakthrough Technologies For 2018" (Forbes Magazine, 2018) which have the potential to change our lives in dramatic ways according to the Massachusetts Institute of Technology.

Furthermore, companies are already recognizing the value of ML when it comes to optimizing their business or saving costs. Algorithms can process much more data than humans and more quickly derive patterns and models from them as well as make more accurate calculations and forecasts. The emerging automation reduces routine work and frees up resources for value-adding activities and additional investments. Spending for advanced algorithms will rise to $

52.2 billion by 2021 in mainly all industries according to the International Data Corporation (IDC) forecast.

1.2 Problem Definition

The term ML is still a confusing field because there are many different conceptual and especially theoretical approaches and the possible potential as well as the dangers remain unclear (Kourou et al., 2015). Eventually, the practical use cases for enterprises seem infinite in terms of quantity and complexity beyond the barriers of different industries. As a consequence the desire for structured overviews and clear depictions along the complete supply chain (SC) accrues.

1.3 Purpose and Research Questions

This work aims to give a profound overview of possible applications within different industries and should analyse the challenges and advantages by integrating ML into consisting business processes along the SC. Concerning this issue, this work addresses four main research questions:

(1) What lays beyond the term Machine Learning and which operating modes exist?

(2) What are the applications of Machine Learning and where should they apply?

(3) What are the risks and potentials in the integration of Machine Learning?

(4) How does Machine Learning change supply chain management (SCM)?

2.0 Methodology

2.1 Research Approach

In order to ensure the practical approach of this thesis a mix of two different research methods was used to give the reader complete as well as valuable insights about the fields of applications and the influence on SCM. Thus, the method of Saunders (2012) was adopted who recommends a prefixed literature review and qualitative research by the help of in-depth interviews to justify the results of the review.

At first, secondary research was conducted to examine the status quo of the technology. This information was collected from leading information technology and business journals like the *International Journal of Logistics* or the *Cutter Business Technology Journal* as well as business reports from consulting firms like the *McKinsey Global Institute* or *Deloitte Development LLC*. Additionally, my sources of information were complemented by technical literature with books like The "*Field Guide to Data Science"*. The results should give the reader a fundamental understanding of the basic operating principles of ML which could be seen as requirement to understand the hereinafter analysed applications and challenges within the industries.

Secondly, the primary research process took place by the help of expert interviews and should give the reader specific insights of global acting enterprises. Gratefully a data scientists from the Porsche AG as well as from the Otto Group and a managing data scientist from KPMG Lighthouse Germany have expressed their willingness to provide their experience and know-how about algorithms and the possible effect this technology can have on enterprises. More information about the interviewees can be found in part five of this work.

2.2 Scope and Limitations

This work cannot consider all industries which try to use the technology for their business operations owing to the limited number of pages. But the retail-, automotive- and courier-industry were selected, because those use the technology extensively and invested huge amounts into the further development of their algorithms and additionally have the highest disruptive potential to be transformed by ML in the next years according to Michael E. Porter (Harvard Business Manager, 2018). It should be mentioned that this chapter only deals with ML or in other words self-learning algorithms which is only a small part of the large area of narrow artificial intelligence. Both concepts are often called in the same breath. In fact, both are quite different. ML entirely represents the preliminary stage during the development of narrow AI applications like natural language processing or computer vision (Dickson, 2017). However, ML is currently considered as one of the most central and successful narrow AI disciplines (Marr, 2016).

Last but not least I want to clarify that the statements of the experts are subjective and are characterised by their experiences from different projects during the last years. The answers of the intentional open asked questions rather aim for practical insides of business operations.

3. Literature Review: Status Quo

3.1 Definition of "Machine Learning"

ML is a subfield of computer science as well as an application which enables IT-systems to identify patterns out of existing data and develop solutions by the help of algorithms (Flach, 2012). Hence, it is a generic term to describe the process when an algorithm learns from given examples and is able to generalize this information into rules which will improve the system in every cycle. A simple algorithm in comparison would just be able to follow a systematic, logical rule or procedure which are predefined by humans (Hamilton, 2013). Eventually ML is an application that enables computer systems to independently acquire and expand knowledge by a learning process to solve a given problem.

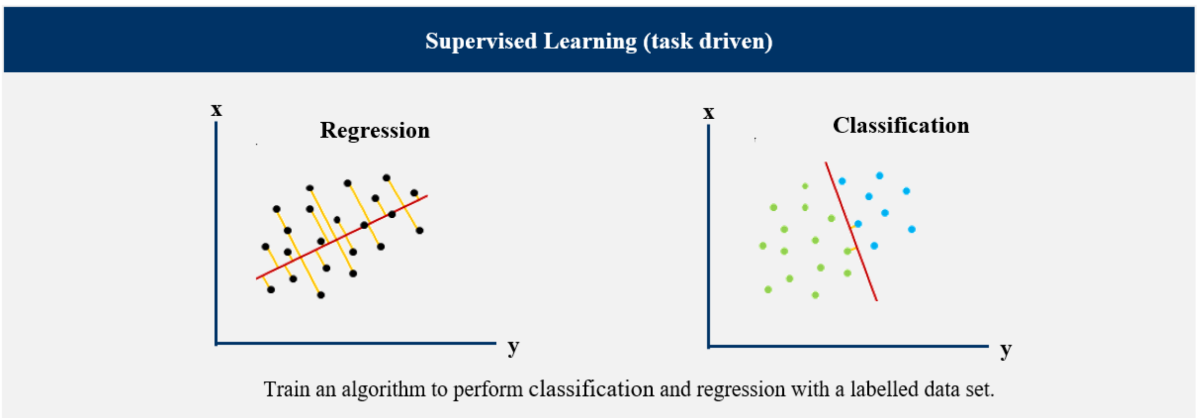
3.2 Enabler of Current Technology Status

There are four factors which allow firms to implement ML useful and fast into their IT-infrastructure compared to the possibilities they had ten years ago (SAP SE, 2017): The (1) **continuously storing of data** by global acting enterprises (big data approach), the (2) **processor power** of efficient superchips which allow complex algorithm-computations and eventually (3) the establishment of the **cloud-technology** which allows infinite and instant expansion capabilities of storage space and processor power (CPU) whenever it is necessary. Especially, global acting cloud- and software providers like Google Cloud Platform, Amazon Web Services and Microsoft Azure enable quick access and usability of the technology for nearly every business, regardless of size. Even if it appears obvious: The (4) **mathematical models** especially from the last century provide the basis for every single algorithm on this world (Kolbjørnsrud, 2016).

3.3 Basic Operating Principles

This part will describe the underlying technical operation principles of self-learning algorithms in order to make the reader aware of the fundamental concept.

Previous actions by humans are necessary in order to empower the algorithm to learn independently and find solutions. The systems must first be supplied with the data which are relevant for the solution. In addition, rules must be set up for the analysis of the data stock and the recognition of the patterns. If matching data is available and rules are defined, ML- systems can start with the learning cycles. The underlying systematic is based on statistical and mathematical models (Manyika et al., 2017). Certainly, the classification of those models like k-means algorithms, linear regression or gamma classifiers would go beyond the scope of this thesis. Out of this reason the procedures of self-learning algorithms are simplified but can be distinguished between three types of learning processes:



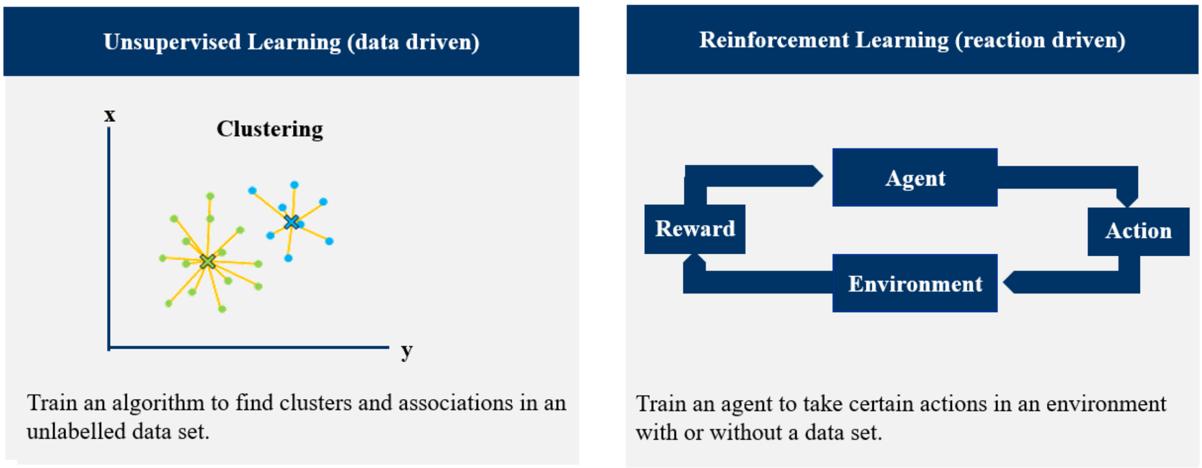


Figure 1: Three types of learning processes (own illustration based on Manyika et al., 2017)

The term (1) **supervised learning** describes the process if the algorithm learns from given pairs of inputs and outputs. The result for a specific input has to be given inside a labelled data set (at least by probabilities). The system is trained to recognise meaningful connections with different inputs and outputs after several cycles and should fill the gap between them. The supervising only refers to the "learning-process". After the algorithm is trained it should predict outputs by itself. Since it can be used for regressions (predictions) or classifications (allocation to already defined groups).

By comparison the (2) **unsupervised learning** process should identify hidden structures inside the given data. The possible outputs are completely unknown. Therefore, we cannot train the algorithm by given results. But we use the algorithm to explore the structure of the unlabelled data set and build meaningful clusters (building of groups by similarities) or associations (detection of dependencies). This method is mainly used for data mining (preparation and evaluation of data).

(3) **Reinforcement Learning** differs from the two other types because a data set is not mandatory. The learning method can be seen as kind of conditioning in which the algorithm is rewarded if it has answered correctly and punished if the result does not meet the expectation. Briefly speaking it works like a trial and error-process and remembers correct and incorrect behaviour (Biamonte et al., 2017).

3.4 General Application Fields

There definitely exist various possibilities to use self-learning algorithms for business operations in different industries. In order to keep an appropriate overview four general fields of applications were classified out of McKinsey's Global Institute Report (2016) and will be analysed by practical examples:

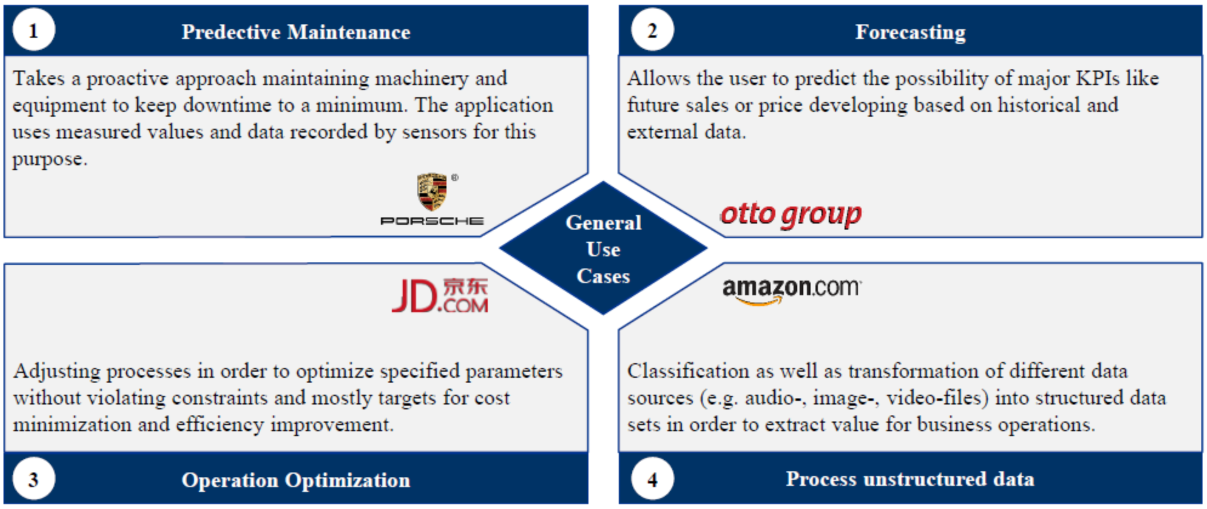


Figure 2: General application fields of machine learning (own illustration)

By (1) **forecasting** we understand the prediction of future KPIs like sales, inventory level or price development depending on other factors like season, weather or customer satisfaction of a past sale. The usage of forecasting tools is definitely not a new innovation but the self-learning algorithm is able to integrate new variables into the statistical model completely autonomous out of the given data. The algorithms provide information for important decisions on a daily basis after a one-time integration into the given IT-infrastructure.

In 2016 The Otto Group, one of the biggest online-retailers in Germany was faced with the challenge to eliminate out-of-stock situations which had tremendous impact on sales and customer online reviews. Accordingly, the company tried to forecast the required quantities by the help of a self-learning algorithm. Data was aggregated (weekly basis) and various external influencing factors such as holidays and seasonal effects were integrated into the statistical model. The new application was a complete success. Corresponding actions could be planned and carried out both in the short term and in the medium term due to the forecast horizon of three months as well as the precise predictions. The algorithm is still in action and keeps optimizing itself for even more exact outcomes according to a data scientist from the Otto Group (business intelligence department).

The term (2) **predictive maintenance** refers to a maintenance process that is based on the evaluation of process and production machine data. The real-time measurement by sensors as well as parallel data analysis leads to a minimization of downtime and consequently to cost reduction (Ernst & Young GmbH, 2016). It mainly applies in big production facilities for example of car manufacturers or aeronautical engineering. The advanced development of self-learning algorithms offers reliable results in the area of predictive maintenance and is a key technology for manufacturers according to a study of Roland Berger in 2018.

The Porsche AG for example has developed a new solution which recognizes noises and vibrations and uses deviations from normal behaviour to interpret machine errors. The incurring amount of data from various sensors has to be combined to recognize slight differences. In consequence self-learning algorithms are necessary to detect tiny deviations which are as individual as a human fingerprint. The algorithm uses the current status as well as historical data to predict breakdowns and upcoming repairs. Each cycle of the algorithms improves specific recommendations of the system. Eventually, the car manufacturer was able to reduce cost-intensive total failures of plants by the constant monitoring of the actual state of the machines and could also use the innovation to develop their products: A small version of this data-driven application will be installed into cars as a self-diagnostic facility in order to inform the driver about future repairs according to a senior data scientist of the Porsche AG. This integration is directly related to the “Connected-Car”-strategy most of the competitors in the automotive sector pursue.

The application field of (3) **operation optimization** refers to the improvement of manufacturing processes in real time as well as the optimization of logistics, procurement timing and inventory distribution across warehouses and stores according to the definition of McKinsey's Global Institute (2017). It includes the dedication of resources to reduce bottlenecks and cycle time. Additionally, specific applications are able to analyse lane choices and path routing to reduce the length of a trip. 20% of all logistic and transportation providers in Europe already use this application according to a potential analysis by Hermes Europe (2017).

A good example to illustrate the usage of self-learning algorithms for operation optimization would be the automated warehouse of JD.com which fulfils 200.000 packages units daily and employs only four people to monitor the process (Freightwaves, 2018). The Chinese online platform is one of the two big B2C online retailers in Asia by revenue and transaction volume (Fortune Magazine, 2018). The whole automation process of the warehouse is based on ML. Different algorithms compute ideal driveways for the autonomous robots which take historical as well as real-time data from sensors to assure fast distribution of different products. The new warehouse enables much better same-day-delivery quotes and are directly noticeable for customers. JD.com is in direct competition with the tech giant Alibaba and has to adjust their business concept by operational excellence. The future will tell whether the intensive usage of self-learning algorithm in warehouses can make the difference.

To (4) **process unstructured data** basically means the classification and transformation of collected data from various sources like videos, audio-files or sensors to make it usable for later analytics. It directly refers to the unsupervised learning process which was described briefly before in this chapter. Unstructured data has an unidentifiable data structure while structured data has a normalized form and can be stored in a row and column oriented database. Consequently, the information could not easily uploaded into SQL-databases (Hamilton, 2017). Unfortunately most of the information companies try to use consist of unstructured data. As a result ML can also be applied to make better use of this data type. The self-learning algorithm is able to recognize patterns and tries to find similarities to assort the given information into general clusters. Just imagine that the system tries to find the right headings for a column inside an Excel-spreadsheet.

The online giant Amazon integrated ML into their software-product “Amazon Comprehend”. This NLP-algorithm (Natural Language Processing) is able to identify the language of a text, keywords, places, people, brands or events and recognizes how positive or negative a post or comment is formulated. For example it can be used to analyse customer feedback on the online platform and classifies frequently mentioned characteristics or the seriousness of the post. Therefore, thousands of product reviews can be analysed in a few minutes (by given processor power) and offers the possibility to act fast and spontaneous. According to Amazon (2017) the direct impact on sales or customer satisfaction of this application is very difficult to measure. But we can state that the product already recorded strong demand by external customers. Since 2016 Amazon also sells the application under the umbrella of AWS (Amazon Web Services) which is currently one of the biggest cloud-service providers.

3.5 Potentials and Challenges of Implementation

The mentioned general use cases were presented and discusses with a senior manager from KPMG Lighthouse Germany in order to work out resulting potentials and challenges which are summarized in the following overview (Figure 3):

Potentials (Advantages)	Challenges (Disadvantages)
– Fast processing and real-time predictions – Process automation – Applicable in various industries – Multi-dimensional and multi-variety datasets possible – Useable in dynamic or uncertain environments – Continuous improvement of the outcome quality	– Huge amounts of data needed – Acquisition of relevant data as major challenge – Lack of variability (error diagnosis and correction) – Risk of early integration into the IT-infrastructure – Time constraints in learning

Figure 3: Potentials and Challenges of machine learning implementation)

3.6 Outlook: Future Development of Machine Learning

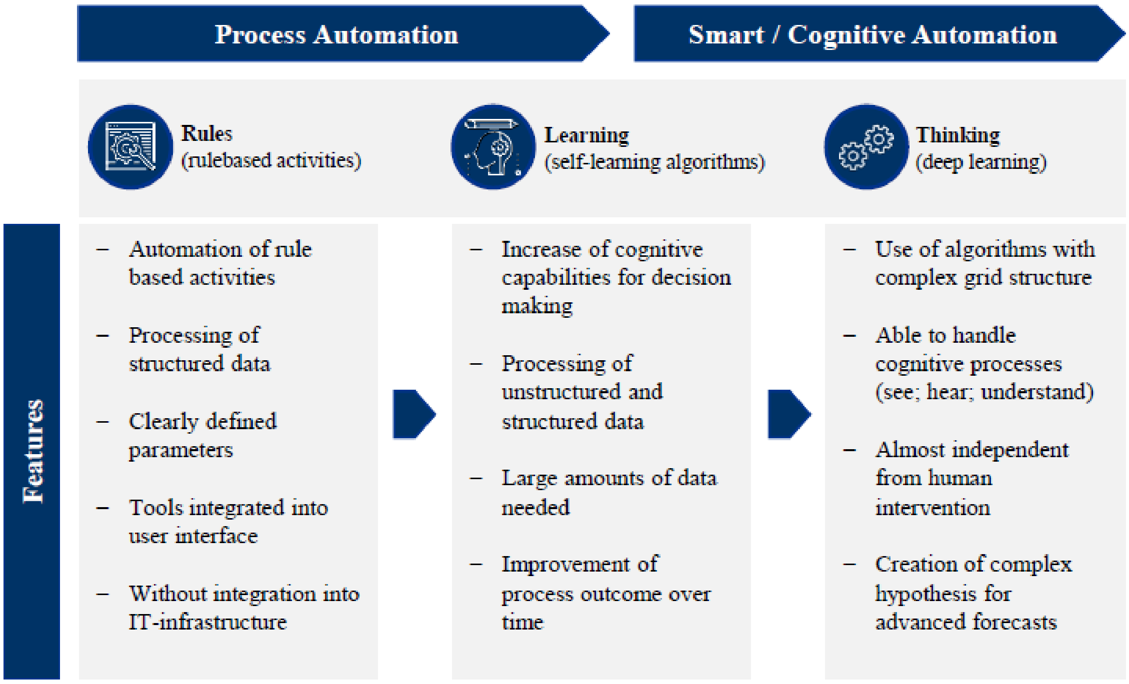


Figure 4: Development stages of process automation by algorithms (own illustration inspired by KPMG Germany, 2018)

The functions and complexity of advanced self-learning algorithms increase year by year. Especially caused by the enormous amount of available data and the abiding interest of companies for business usage. The next level of automation by complex algorithms will enable the so-called cognitive automation (KPMG Germany, 2018). The term basically describes an advanced decision making tool which is able to handle cognitive processes – especially image and voice recognition as well as natural language processing and combines them with the needed self-learning capabilities. The solutions can be used to accept or reject sophisticated hypotheses for better predictions. Both the media as well as scientists already found a term for this advanced version: Deep learning (DL). With DL-applications users are able to create new models independently from human interventions. At the moment these applications are still very cost-intensive and the development and integration requires long lead times according to the data Scientist from KPMG Lighthouse Germany. Additionally, the calculations require much bigger amounts of processor power. But the chip-industry already introduced new superchips which are distinctly more powerful. In the coming years, a rapid increase in the number of such solutions is likely to be observed. Already realized DL-applications can be found in call centres where voice processing is used to accelerate customer interactions or on online-platforms with automatically created product descriptions by text generation algorithms.

4.0 Machine Learning in Supply Chain Management

4.1 Definition of Supply Chain Management

The Council of Supply Chain Management Professionals (CSCMP) defines supply chain management (SCM) as a series of key activities that must be completed in an efficient as well as a timely manner in order to make the desired products or services available for the customers. Mostly more than one company is involved in the SC-activities. There are different roles like suppliers, manufacturers, logistic- or other service providers, to name but a few. The cooperation among those companies has to be organized and monitored. This is where SCM comes into play which has the overall goal to provide timely fulfilment of customer demand through the organization of effective product flows from the point of origin to the point of consumption. However, two-way information- and data flows among the whole SC are key for managers to make the right decisions based on demand development or problem detection at an early stage. This information is required to execute the five processes of SCM:

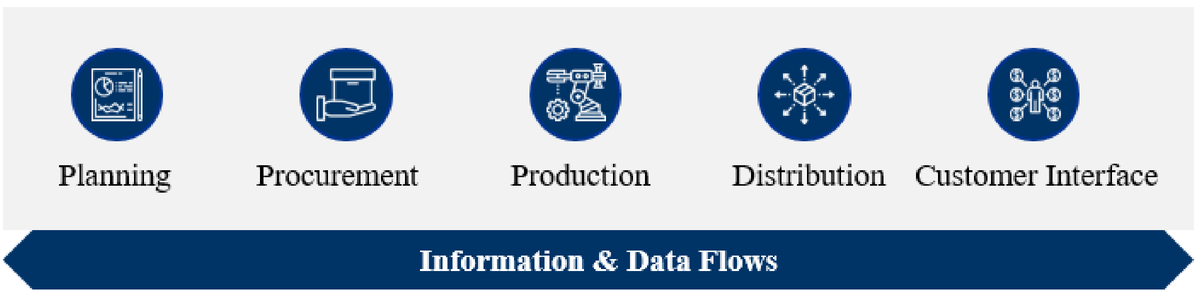


Figure 5: Supply chain management processes (own illustration)

The (1) **Planning** process aims for the integration of SC-strategies and includes the design of the network and the consideration of market data like demand predictions or special customer requirements. The (2) **Procurement** basically consists of finding and acquiring products or raw materials. The supplier management plays an important role in this phase. The (3) **Production** process is defined as the act of creating outputs like goods which have a value for the customer. By (4) **Distribution** we mean the logistical flow of output across the whole SC. In this phase third party transportation companies are key to ensure the efficient and trusty delivery of the product. The so called "last-mile" of the product matters a lot to customers and is often a complicated aspect of SCM (Yu et al., 2017). The (5) **Customer Interface** includes all types of interactions with the customer and has the overall aim to satisfy him at every stage of the customer life cycle. The choice of the right communication channel can make a huge difference in the customer perception.

In order to help the managers decide how to proceed with this five processes David Anderson (1997) defined seven fundamental principles of SCM which are used up until today even though they are more than two decades old. Those principles focus on the customer and emphasize the importance of coordination activities:

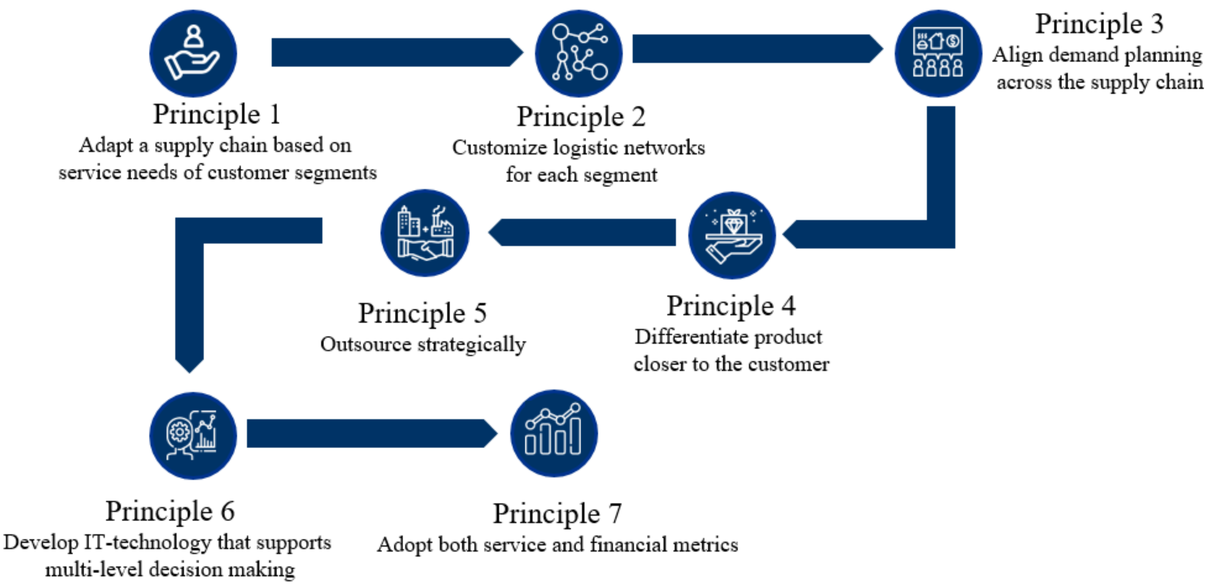


Figure 6: Seven principles of supply chain management by David Anderson (own illustration)

4.2 General Applications in Supply Chains

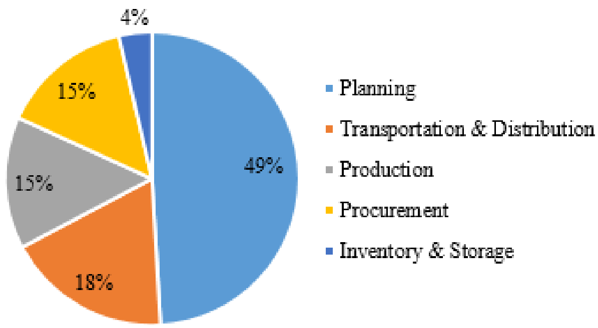


Fig. 7: ML-algorithms applied in each area of the supply chain (Source: Bousqaoui et al., 2018)

Self-learning algorithms are used in many phases of the SC, both downstream as well as upstream, but mostly in the following processes: The planning, the procurement, the production, the warehousing and last but not least the transportation and logistics (Bousqaoui et al., 2018). Figure 7 shows the distribution of different ML algorithms that are used in each of these different phases according to a study from 2018 which analysis 42 certified academic articles with examine practical applications in different industries. We can clearly see that most of the applications take place in the area of **planning**. The concept of Supply Chain Planning (SCP) includes the modelling of the network structure along the whole supply chain with different suppliers, sub steps of production and third party providers. The most important tasks in this field are the selection of suppliers as well as the just-in-time (JIT) -management with the aim to optimize the cost structure (Wild, 2018). Simply put, the JIT-concept is an organizational principle which describes the process if materials are delivered only when they are actually needed for production. Both tasks target the ideal selection of possible scenarios and the consideration of numerous influencing factors. This impossible seeming challenge can be accomplished by the help of self-learning algorithms which integrate constantly new indicators for better decision-making.

The second most named application field inside supply chains would be the **transportation and distribution** area which includes the often mentioned vehicle routing problem. Its objective is to find the best routes for a truck to travel in order to deliver a product to the corresponding production facility or directly to the customer. Becker et al. (2016) address this problem by using a self-learning algorithm against human decisions and various routing heuristics in the literature. They find that the performance of the algorithm was 48% better than that of the best routing heuristic.

The third mostly mentioned field according to Bousqaoui et al. (2018) are all use cases which have influence on the **production process**. Juez et al. already published an article in 2010 which analyses the influence of algorithms on the lead time of components batches in the aerospace engine production. Lead time calculations or better predictions of the manufacturing time before the start of the production helps to avoid delays of the delivery to customers. Reorders can be placed much earlier and default risks can be minimized. I already mentioned the usage of predictive maintenance and operation optimization in part two of this chapter. Those general use cases can also be classes as applications in the production phase of SC.

The **inventory and storage** phase includes the challenge to identify the best price-value ratio from different possible suppliers for the needed material. Deloitte's "Global Chief Procurement Officers Survey" (2018) describes how ML has the potential to tighten the procurement and SC-synchronization. Good examples would be an automated supply assignment sourcing by self-learning algorithms or predictive contract consumption. The first mentioned application is able to assign the right supplier and amount for an order by using pattern recognition on historical data. By every new order the algorithm learns how to make decisions based on factors such as supplier evaluations, delivery time or the price. The predictive contract consumption enables the procurement department to automatically predict the date of the contract's full consumption. The instructed employee is now able to identify contracts that should be modified at the right time and avoid poorly negotiated prices and terms due to past contracts. Especially, the warehousing of raw-materials and finished goods generates important costs but is necessary to guarantee a fast availability of products for the customer. The yearly stock-costs for a single unit of inventory can range up to 35% of its actual value. Hence the success of SCM depends highly on its ability to capture data and organize inventory at minimum costs while ensuring customer satisfaction (Min, 2010). Out of this reason companies like Nike and many more use multi-echelon inventory optimization (MEIO) which only become possible by the integration of self-learning algorithms. The concept of MEIO allows you to integrate all your storage facilities and adjusting the total stock amount across the whole network by taking into consideration the interdependencies among stocking locations according to the Association for Operations Management (2017). One of the core capabilities are ML- implementations to automate model switching and handle the variability in customer demand across the whole SC.

4.3 Case Studies: Machine Learning in Supply Chain Management

This part will have a more detailed focus on major applications of ML in SCM at the example of three well known enterprises with global connected SCs:

	amazon.com	Walmart	Hermes
Industry	Online Retail	Retail	Courier
Application	Anticipatory shipping	Inventory forecasting	Intelligent route planning system
SCM-Process	Planning	Planning	Distribution
Main Parameters	Buying behaviour: (1) Shopping card (2) Past purchases (3) Retention time	(1) Stock level - shops (2) Stock level - suppliers (3) Purchase history	(1) Past traffic data (2) Vehicle parameters (3) Route information (3) Weather conditions
Achievements	+ Shipping time improvement + Reduction of logistic costs + Increase of customer satisfaction	+ Increase of sales + Cost reduction	+ Reduction of transportation costs

Figure 8: Overview of illustrated case studies (own illustration)

I decided to use those companies to illustrate experiences with the technology because they already used self-learning algorithms at an early stage to manage the complexity of their SC and improved it to reach today's state of the art (Harvard Business Manager, 2018). Additionally, the algorithms are key resources of their core business by now. All three described applications should improve the efficiency and leverage the huge amount of data collected by warehousing-, logistic- and other systems of the companies.

In 2013 **Amazon** was faced with a high degree of customer and competitive dynamic inside the online retail-market. Faster product life cycles and a wide range of the assortment were the results. Furthermore, their Business Intelligence (BI) tool at the time was just based on historical data like past purchases and returns. However, this kind of reactive inventory and procurement management was to slow for the highly competitive market. Mainly out of this reason the online giant decided to extent the forecasting methods to minimize out-of-stock situations and lower the stock level at the same time. They introduced the patented "Anticipatory Shipping"-tool and integrated it into the IT-infrastructure. The algorithm uses real-time information or more precisely the current behaviour of online customers and takes it into consideration. Shopping cart fillings, the amount of clicks, retention time on specific article pages and also past orders are evaluated. The system automatically creates a forecast about the expected orders within the next days by recognizing (unknown) patterns and calculating probabilities. With this method Amazon is able to already send articles to one of their fulfilment hubs in the vicinity of the customer before receiving the online order. After the purchase the article will only be provided with the final address label and will be delivered to the customer's front door in just a few hours. In brief, the algorithm sends the product on the way to the customer even before he ordered it. The more people visit the online domain of Amazon and place an order (or not) the better the forecasting of the tool will be.

With the new tool Amazon was able to reduce shipping times and logistic costs. At the same time they increased customer satisfaction to the next level according to product reviews and an independent survey. The exact numbers are not published but the success of this method was also confirmed by McKinsey & Company (2017): The new integrated technology by Amazon is able to reduce loss of sales through out-of-stock situations by 65% and can reduce from 20 % up to 50 % of the average stock levels depending on the explanatory power of the data. Furthermore, the Anticipatory Shipping makes Same-Day-Delivery possible and could be seen as leading edge in a highly competitive market.

Another interesting use case would be the inventory management algorithm of the biggest multinational retail corporation with over 11.000 stores worldwide: **Walmart**. Since 2017 the company connects all physical stores as well as their online business by the help of the world's largest private cloud architecture according to Forbes (2017). The cloud system called "Data Café" is able to process around 2.5 petabytes (one petabyte = 1 Mio. gigabytes) of data every hour and is based on the database management system SAP HANA. This offers almost unlimited possibilities for ML-algorithms. In addition to the transaction data from the physical and online stores the calculations integrate about 200 external data sources for example from various suppliers. Consequently, the company is able to analyse the stock level inside the whole SC almost in real time. On one hand the automatic recognition of inventory problems by the algorithms are identified early and can be rectified already when they emerge. On the other hand, potential optimization actions are displayed by the system and can be considered by supply managers. The use of the "Data Café" is a success story according to Walmart Inc. (2018) and the huge investments are already paying off. In the first year, data analysts at the headquarter were able to recognize that a special cookie was very popular in most of their stores during Halloween. But there were few stores where it wasn't selling at all. The alert by the algorithm allowed the analysts to investigate. A simple stocking oversight had led to the problem and Wal-Mart was able to avoid further lost sales. This is just a single story to illustrate the detailed analysis of self-learning algorithms within complex global SC.

Last but not least I want to introduce the intelligent route planning system of **Hermes**. The parcel delivery company had to find a solution for high traffic load in German major cities. Last-mile delivery costs increased significantly caused by long traffic jams and the occurring delays. After that the company tried to explore new technologies like alternative transportation vehicles and also innovative software solutions. As quickly as possible they developed a route planning tool which is based on self-learning algorithms with the ability to create customized route adjustments even before a traffic jam takes place. The new tool should help couriers to organize their route planning in the most efficient manner (Hermes Europe, 2018). The software is based on the "Nunav Courier"-algorithm and combines past traffic data with time, weekday and wheatear conditions with specific stop variables such as the opening hours of pick-up points or delivery windows and also route-specific factors like working hours, break times of drivers and various parameters from the vehicle. The system calculates the best possible route option and adjusts the sequence in real time. Currently the application is still in the test phase but the company expects a huge increase in route productivity as a result of the algorithm according to Markus Haller (Head of network optimization and design at Hermes Germany).The parcel delivery provider will benefit from the tool by lowering the risk of transport delays and couriers are able to adjust to spontaneous situations on their delivery route. This results in a better use of working time and can decrease transportation costs for the expensive last mile. In the near future Hermes plans to integrate the intelligent route planning tool with the consumer mobile application after the successful test phase. In this scenario spontaneous deliveries to the workplace of the customer or on the way home would be imaginable.

4.4 Outlook: Future of Machine Learning in Supply Chain Management

The intensive use of the ML-technology currently lays the groundwork for fundamental changes in the way managers will organize the flow of goods across the SC (Accenture Strategy, 2017). Especially the transparency at each stage of the chain will increase massively through fast evaluation of data and reliable forecasts. This will constantly lead to a proactive SCM in warehouses, on the road and eventually in the store and has the potential to significantly reduce logistic costs and shipping times. The connection of various applications in one integrated infrastructure instead of independently working algorithms in one stage of the SC will be the standard in mainly all industries according to the data scientist from Porsche AG. Innovative approaches to bridging the last mile will allow retailers to provide even better customer service and new shopping models. To do justice to this expectations, the companies will have to increase the autonomy of the algorithms and will constantly look for a close linking of deep learning algorithms with data collecting tools like sensors, voice and image recognition.

Eventually, the level of automation will increase to a much higher level by the help of cognitive systems which go well beyond the mentioned use cases in this work. But despite the high level of automation the systems will just provide information for better decision making and human management skills remain a key capability for operational excellence in SCM (McAfee, 2018).

5.0 Interviews

Three interviews were carried out to accompany the results out of the literature review and case studies. First, a managing data scientist form KPMG Germany Lighthouse (Center of Excellence for Data & Analytics) was asked to answer general questions about current technology trends and the influence of ML independently from a specific industry. The interviewee has about ten year's professional experience in the field of data science and was part of various consulting projects with focus on intelligent automation. Second, a senior data scientist from Porsche AG was interviewed who has long standing experience in the area of ML and data analytics especially in the automotive industry. Last but not least, a data scientist from the Otto Group was asked to share his knowledge out of practice. The expert has more than ten years of experience in the effective processing of big data volumes and allows an insight into future challenges of one of the world's biggest e-commerce companies regarding the intensive usage of algorithms. The following table summarizes the results of the interviews and shows the impacts of ML on different covered topics:

	All Industries (KPMG Germany)	**Automotive Industry** (Porsche AG)	**Online-Retail Industry** (Otto Group)
Impact on cost structure	◕	◕	◕
Impact on just-in-time strategy	◔	◕	◔
Impact on maintenance processes	◔	◕	◔
Impact on customer experience	◑	◑	◕
Impact on IT-infrastructure	◑	◑	◑

Figure 9: Evaluation of expert interviews (own illustration)

5.1 Impact on All Industries

The automation through self-learning algorithms for example in the areas of document processing, predictive analytics and anomaly detection are the most important terms during the next ten years independently from a specific business sector according to the managing data scientist from KPMG Lighthouse. He additionally emphasized the enormous potential of those algorithms to make already existing processes much more efficient and better predictable and already lead to massive cost reductions since first implementations in business processes in the early 1990s. Out if this reason the expert expects a multiplication of sales and productivity by ML-based optimization until 2030. Especially the areas of production and transportation will play an important role caused by efficiency gains through automation.

Regarding the JIT-approach of mainly manufacturing sectors: This strategy does not make sense for all industries especially if those are faced with steady adjustments of production processes and deliveries. ML can be an immense help to reach the next step of efficiency if this approach was already integrated during the last years. In particular, the automotive industry strives to improve their supplier management by the help of ML-tools and has been hugely successful.

Most of the consulting projects of KPMG Lighthouse had the focus on professional support of system integration and implementation of new tools like ML-applications into the scalable production system. However, those adaptions of the exiting ERP- and CRM-systems add additional value to the whole infrastructure. Mainly because the ML-technology is able to eliminate problems that are a part of traditional enterprise software solutions. General speaking, traditional systems are built on relational databases and take weeks to provide insights that can be expected immediately by the help of self-learning algorithms.

For and efficient integration into the infrastructure interdisciplinary teams with infrastructure specialists, data engineers, software engineers and data scientists are mandatory. Those teams should consider four types of actions which improve process reliability. First, ensure sufficient quantity and quality of training data. Second, avoid obscure “black box algorithms” without any knowledge of its actual systematic. Third, involve all stakeholders throughout the process to create transparency and confidence during the development. At the end of the day sufficient commitment of decision-makers and budget providers to invest in technologies beyond short-term profitability are key factors which should not be underestimated.

5.2 Impact on Automotive Industry

In particular car manufacturers deal intensively with different use cases along the whole supply chain in order to optimize the cost structure. Especially in the field of production and development. Predictive maintenance algorithms and the detection of production faults play an important part in this according to the data scientist of the Porsche AG. Since last year the concern intensively tries to analyse driving data from different customers all over the world by complex algorithms. The implications should improve the next production cycle and should point out production faults which could be avoided. The expert could not share specific numbers but estimates a cost reduction potential of about 15% especially through the integration of vehicle usage data and the quality measurement by vision or sound inside the manufacturing and development processes during the next five years. This statement fits to the results of the McKinsey Center for Future Mobility inside their report from 2018.

Since three decades the subsidiary of the Volkswagen Group adapts the lean-management approach initial established by a Japanese automotive manufacturer and evaluate the pursing development of ML and the associated impact as relatively high especially in the area of supplier management through applications like integrated pricing and inventory management across suppliers and channels and also the improved utilization of transport capacity based on real-time information.

But also the customer can benefit directly by the technology in the field of aftersales and services. For example the Startup Engie Motors from Tel Aviv offers a software product called

“Engie App” which is able to interpret extracted data of car diagnostic devices in order to recommend the best possible repair shop in town. This application would be a good example for the use of ML in after-sale services and would improve the customer experience by early recall detection and a transparent service pricing model.

Regarding the impact on the IT-infrastructure: The expert emphasized that independent applications in single steps of the SC (stand-alone applications) are not the best option for big car manufacturers like Porsche or others. The whole analysing process by algorithms should be considered over the entire chain which makes the integration much more complex and risky.

5.3 Impact on Retail Industry

Currently the field of transportation services and warehousing is one of the most cost-intensive areas the retail industry has to manage. For that reason there is a strong need of improvement of the cost structure by algorithms in general according to the data scientist of the Otto Group. An overall improvement of efficiency can be achieved by the establishment of an end-to-end predictive analytics tool for sales and the automation of warehousing based on real-time information. The integration of both are cost intensive investments and need long development time but at the end will lead to significant cost savings.

The JIT-approach is still a difficult area in the whole retail industry because there exist large variations in demand and small margins on product sales. Since an intensive use of self-learning algorithms will not change this fact. But the expert emphasized the impact of ML on the “last-mile” to the customer. New route planning systems which are based on self-learning algorithms enable parcel delivery providers to improve the positive awareness of the customer.

The estimation of future sales and the customer’s buying patterns are essential for this sector. Online channels are being further automated and becoming even more personalized. Additionally, customer communication (especially the first "communication loop") is becoming increasingly automated with massively increasing quality of automated solutions.

The response times will be drastically shortened and the service level will be increased which in the end has a positive impact on the customer overall experience.
In addition the expert mentioned that the technology also includes a risk in the upcoming years because European retailers have to face the competitive pressure of technology giants like Amazon or Alibaba in the market. For both self-learning algorithms are part of their success story. The Otto Group have to stay in touch in order to defend their current position in Germany and also to expand their platform strategy with more external vendors.

6.0 Conclusion

Within the scope of this thesis four initial research questions (see 1.3) have been elaborated and answered to show major applications as well as the fundamental concepts behind the technology.
(1) In summary, ML can be seen as an application that enables IT-systems to identify patterns and characteristics of already existing data by the help of self-learning algorithms. All of them are based on statistical models and make predictions, classifications or the exploration of the underlying coherences possible. Simply speaking, those algorithms help users to automate complex calculations for better decision making.
(2) There exist various use cases for business operations like sales predictions, predictive maintenance and optimization of existing business processes or simply the transformation of unstructured data into useful data sets. The forecasting of future sales avoids out of stock situations by taking external factors like wheatear conditions into account. The maintenance algorithm is a real-time-measurement tool which minimizes downtime of production machines by the help of sensors. Additionally, the dedication of previously unknown optimization potential or the classification and transformation of collected data from various sources help global acting companies like Amazon, Walmart or Hermes to decrease risk, cut costs and offer additional services like same-day-delivery.

(3) But the implementation involves both, potentials as well as challenges. On one hand, the technology leads to more automation and is also useable in dynamic and uncertain environments. Additionally, the algorithms improve themselves and the outcome quality with every new cycle. But on the other hand, the algorithm is dependent on the quality and quantity of the collected data. The lack of variability can also lead to problems, because only experienced data scientist are able to interpret the outcomes in the right way which makes error diagnosis and corrections costly. Therefore, an early integration holds immense dangers and should be well-prepared.

(4) The companies which take those implications into consideration are able to benefit by better organization of their SC-activities especially in the areas of logistics and demand forecasting to improve the customer experience or company's cost structure. All three mentioned applications from practice show how ML helps to leverage the huge amount of data in the most effective way. In the near future, we will see more connected applications through all SC-phases instead of single algorithms in one activity. Some players have already taken the first steps towards the future by the use of voice and image recognition. These examples show which enormous changes self-learning algorithms can bring with it. Anyone who reacts adequately to the associated challenges today will reap the benefits tomorrow because only smart SCM by the help of self-learning algorithms guarantees that companies will retain their competitiveness.

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Appendix

Interview Questions:

Managing Data Scientist KPMG Lighthouse Germany

(1) What do you think are the most relevant technology trends that every CIO should consider?

(2) What influence does the intensive use of complex algorithms have on the IT-infrastructure of companies?

(3) How do you evaluate the impact of an integration for cost-reduction purposes?

(4) Which special requirements does this technology call for on today's leaders in different industries?

(5) What future applications would be possible if processor performance and network speed are no longer limiting factors?

(6) In your opinion, what are the biggest cost factors when implementing complex algorithms?

(7) How can we minimize the risk factors which should be considered to integrate self-learning algorithms into the IT-infrastructure?

(8) How do you see the role of young (agile) companies focusing on the use of self-learning algorithms?

(9) Are there specific business models or companies that become superfluous due to the emerging technology?

(10) Which role do legal restrictions play especially the renewal of the "General Data Protection Regulation" which is binding for companies since May 2018?

Senior Data Scientist Porsche AG

(1) Which overall application areas of self-learning algorithms do you regard as most effective in the automotive industry in terms of sales growth or cost-saving potential?

(2) Does the Porsche AG aims for a JIT-strategy and how does ML can change this approach?

(3) Does the integration of ML lead to massive changes in the IT-infrastructure?

(4) In a simplified supply chain consisting of (1) procurement, (2) production, (3) distribution and (3) retail: Where do you see the greatest impact of self-learning algorithms?

(5) How does this technology influence the production as well as the development of new products/ models?

(6) What about applications in the area of after-sales services?

(7) Which risk factors should be considered to integrate the technology into the IT-infrastructure of car manufacturers?

Data Scientist Otto Group

(1) Which application areas of self-learning algorithms do you generally consider as most effective in the retail industry?

(2) How would you evaluate the impact of ML for cost-reduction purposes?

(3) Does the Otto Group aims for a JIT-strategy and how does ML can change this approach?

(4) Does the intensive implementation of this technology create new distribution and communication channels in the retail industry?

(5) What significance do self-learning algorithms have for the platform strategy of many online retailers?

(6) Are applications in cost-intensive areas such as customer service or "last-mile" conceivable?