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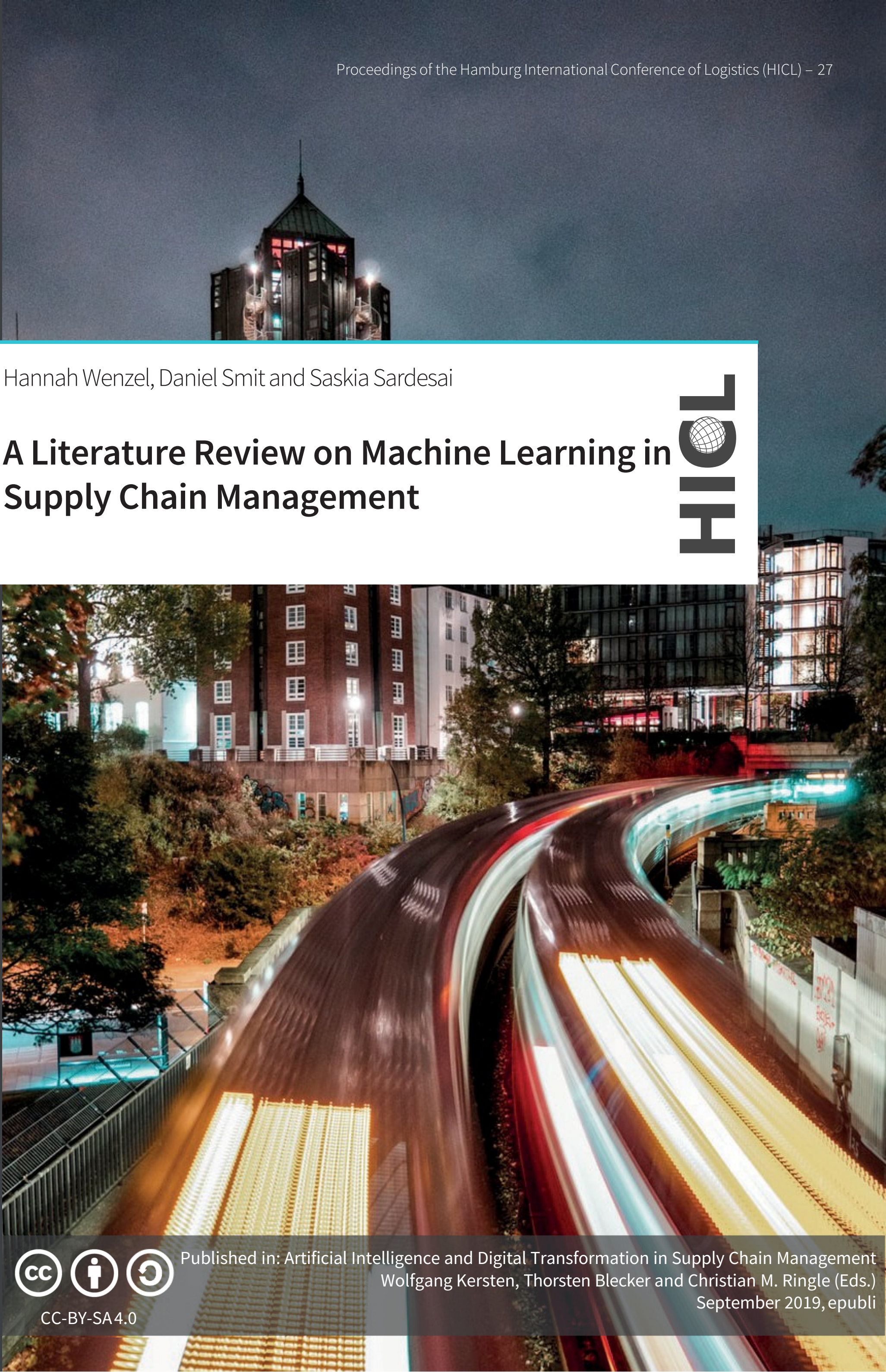

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A Literature Review on Machine Learning in Supply Chain Management

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Purpose: In recent years, a number of practical logistic applications of machine learning (ML) have emerged, especially in Supply Chain Management (SCM). By linking applied ML methods to the SCM task model, the paper indicates the current applications in SCM and visualises potential research gaps.

Methodology: Relevant papers with applications of ML in SCM are extracted based on a literature review of a period of 10 years (2009-2019). The used ML methods are linked to the SCM model, creating a reciprocal mapping.

Findings: This paper results in an overview of ML applications and methods currently used in the area of SCM. Successfully applied ML methods in SCM in industry and examples from theoretical approaches are displayed for each task within the SCM task model.

Originality: Linking the SC task model with current application areas of ML yields an overview of ML in SCM. This facilitates the identification of potential areas of application to companies, as well as potential future research areas to science.

Keywords: Supply Chain Management, Machine Learning, Literature Review, Predicitve Analytics

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1 Motivation

In the age of information technology and increasingly complex technical and industrial processes, agile and efficient logistics processes play a central role. High logistic requirements such as reliability, transparency and flexibility combined with optimal economic conditions form the foundation for a successful supply chain (SC). Dynamically changing processes require a technology that is able to cope with the increasing complexity of supply chains.

The growth in data volume and diversity has led to data sets larger than ever before. Processing with conventional, practical management tools is often inefficient or impossible. To manage and evaluate these new and potentially valuable data sets, new methods and applications have been developed in the form of predictive analytics (Waller and Fawcett, 2013, p. 77). One of these predictive analytics methods is machine learning (ML). The success of this methodology is achieved through the invention of sophisticated ML models, the availability of large data sets ("big data") and the utilization of hardware architectures such as GPUs (Abadi et al., 2016, p. 256; Copeland, 2016; Steinbach, 2018, p. 32).

Current applications of ML focus on specific areas within SCM, while some areas remain unexploited. Thus the paper intends to create a link between current ML applications, actual research work and the SCM task model. This allows for a visualization of tasks wherein ML techniques are already applied and a deduction of potential areas of future research within the SCM task model.

The paper is based on a literature analysis by querying the "IEEE Xplore Digital Library", "Scopus" and "ScienceDirect" databases using the search term "Supply Chain Management [AND] Machine Learning". Due to the recent developments in ML, the results were restricted to publications from 2009-2019. Based on the abstracts, a total of 38 relevant papers have been identified.

Along with the full papers, the specific SCM task and the applied ML methods have been extracted. The papers have been categorized by the source of the datasets they used. 20 of the papers used real-world datasets acquired mostly from enterprises. 9 papers used synthetic datasets (e.g. generated by a simulation). For the remaining 9 papers, the types of datasets used were not mentioned. Furthermore, with the support of the Google search function several practical applications of ML within SCM were identified. This was done to provide a complete picture of current practical applications.

The paper is structured as follows. Firstly, the different tasks of SCM are explained, ensued by a general introduction to ML including the different types and methods, and explaining the process of applying ML techniques for solving real-world issues. This is succeeded by application examples of ML in SCM and a mapping to the SCM task model. The paper concludes with an overview on possible areas of future research within the SCM task model. The result of this paper addresses researchers in their future course of research work as well as Supply Chain Managers in applying ML in their field of work.

2 Supply Chain Management and its Task Model

According to Arnold et al. (2008) the primary goal of SCM is to fulfill customer needs while optimizing costs in terms of inventories, resources and processes in the network at the same time. To ensure that this goal can be achieved, it requires a number of subgoals e.g. improving customer orientation and satisfaction, increase of delivery capability and reduction of lead times (Arnold et al., 2008, 460 f.). The achievement of the preceding goals must be carried out by internal and cross-company tasks of SCM. A representation of these tasks is shown in Figure 1.

The three main tasks of the model are Supply Chain Design, -Planning and -Execution (Kuhn and Hellingrath, 2002, 142 f.). The inner circle of tasks is discussed briefly hereafter as it is of relevance for mapping ML applications.

Supply Chain Design

Supply Chain Design (SCD) deals with long-term planning in terms of location decisions, make-or-buy decisions, supply relationships, capacity dimensioning, logistics strategy and general tasks (Hompel and Wolf, 2013, p. 148). Another important task is cost-optimized structuring of the logistics and production processes. Consequently, this area involves a financial evaluation of changes in the logistics network (Kuhn and Hellingrath, 2002, 143 f.).

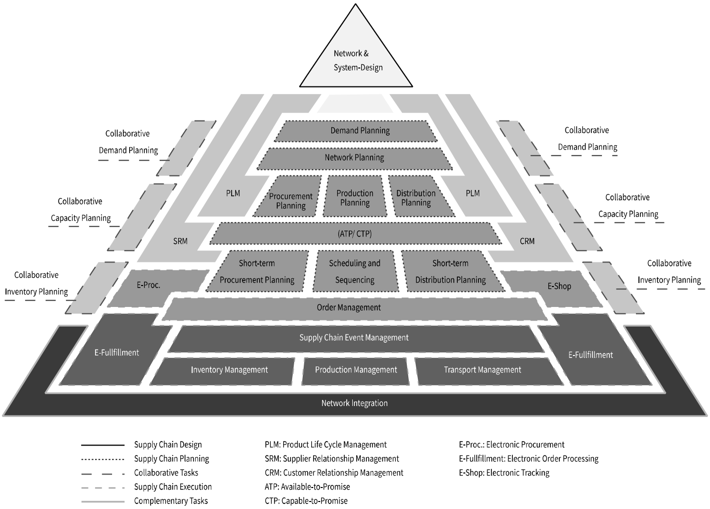

Figure 1: Supply Chain Management task model (Hompel and Wolf, 2013, pp. 146–147)

Supply Chain Planning

The goal of Supply Chain Planning (SCP) is medium- to long-term program planning across the entire SC. The area of SCP reflects the planning of production and logistics resources to fulfill customer orders. Hence, the basis of resource planning are forecasted customer requirements. The tasks for SCP include the areas of demand and network planning, which set the basis for procurement, production and distribution planning and enabling available-to-promise/ capable-to-promise checks. In the short-term, procurement planning, scheduling and sequencing and short-term distribution planning support SCP (Kuhn and Hellingrath, 2002, p. 144). Thus, demand information creates an important basis in order to coordinate decisions and planning along the logistics chain.

Tasks of demand planning are forecasting and visualization of short-term and long-term requirements. These are particularly important when it comes to fulfilling customer requirements, planning the utilization of the value chain, or carrying out inventory optimization (Kuhn and Hellingrath, 2002, 144 f.).

The next task, network planning, deals with the coordination between partners within the value chain. Through network planning, requirements as well as material and capacity resources are coordinated. It is possible to trace the fulfillment of the production program through network planning, due to its orientation towards production programs and sales plans (Kuhn and Hellingrath, 2002, 145 f.).

Procurement planning takes into account the preceding areas of demand and network planning and determines the planning of the parts supply. This is followed by production planning, which has the task of creating a production plan for each production unit in the SC. The aim is to achieve a high level of readiness for delivery while at the same time keeping inventory costs as low as possible (Kuhn and Hellingrath, 2002, 146 f.).

Distribution planning deals with the fulfilment of requirements, which are achieved through optimized planning and coordination of deliveries. It is based on the results of production planning and the specifications of network planning (Kuhn and Hellingrath, 2002, p. 147).

In order to satisfy customer requirements or customer orders, their feasibility is examined via available-to-promise/ capable-to-promise. Due to the gap in the task model between the anonymous planning tasks and the planning tasks with customer reference, this area represents an important task of SCM (Kuhn and Hellingrath, 2002, 147 f.).

Short-term procurement planning, scheduling and sequencing, as well as short-term distribution planning deal with more detailed tasks of procurement, production and distribution planning. For more detailed information, please refer to Kuhn and Hellingrath (2002).

Supply Chain Execution

The area of Supply Chain Execution (SCE) considers cross-company processes such as SC management and control. The aim of this area is to support decision-making at the operational level (Kuhn and Hellingrath, 2002, 152 f.). Its executive area includes the processing and monitoring of orders. Inventory management is also part of SC Execution, taking care of movements of stocks and materials including their documentation. Two further components are production management, which manages all information on production processes, and transport management, which handles transport orders on the procurement and distribution side.

An additional major task is Supply Chain Event Management. It controls the activities within the SC, announces plan changes and initiates corrective measures. The task aims to create transparency about parameters such as disruptions, inventories and requirements. Therefore, it includes all reactive risk managing activities (Kuhn and Hellingrath, 2002, p. 154).

3 Machine Learning

The following section interprets the term "Machine Learning" and covers types of ML methods. This supports a common understanding of the methods used in the different application areas of ML in SCM. Challenges are also addressed.

3.1 Interpretation of Machine Learning

ML is a sub-area of artificial intelligence and represents another way of programming. Example data replaces rigid calculation rules of a program. From the given example data, learning methods or algorithms extract statistical regularities, and represent those in the form of models. The models can react to new, unknown data and classify them into categories or make predictions (Hecker et al., 2017, p. 8).

ML deals with the computer-aided modelling and realization of learning phenomena (Görz, Schneeberger and Schmid, 2013, pp. 200–201). It is defined as a process that uses experience to improve performance or make concrete predictions. The experience refers to past information, which is provided to the procedure from an electronic data collection. ML involves the design of effective and precise algorithms (Mohri, Rostamizadeh and Talwalkar, 2012).

3.2 Types of machine learning

Several types of ML can be distinguished. Well-known ones are supervised, unsupervised and reinforcement learning. Further types can be found in e.g. Géron (2017).

Supervised Learning

The most widely used type of ML is Supervised Learning (Marsland, 2015, p. 6). Supervised Learning is a process in which a computer program is trained by using known example data. As the output is also known, this learning process aims at finding a connection in the form of rules, which relate input data to output data and finally apply the learned rules to new data. At this point the computer program is getting trained. With this newly gained knowledge it is now able to predict future input and output data. Two important tasks are classification and regression (Kirste and Schürholz, 2019, 25 f.).

Unsupervised Learning

Unsupervised learning describes a system that is able to discover knowledge. Correct answers are not provided in this type of learning, thus, there are no pre-labelled target values. This approach is also called "learning without a teacher". A well-known task of unsupervised learning is clustering. The method identifies similarities between the inputs to categorize inputs by common patterns. Similar tasks are e.g. Association Rules, Self-Organizing Maps, Multidimensional Scaling and Nonlinear Dimension Reduction (Marsland, 2015, p. 281; Russell and Norvig, 2016, p. 694; Hastie, Friedman and Tibshirani, 2017, 485 ff.).

Reinforcement Learning

With reinforcement learning, the optimal solution is unknown to the system at the beginning of the learning phase and therefore must be determined iteratively. In this process, sensible approaches are rewarded, and wrong steps tend to be punished. With this approach, it is possible that the system takes into account complex environmental influences and reacts accordingly. Hence, the system finds its own solutions autonomously through directional rewards and punishments (Gentsch, 2018, 38 f.).

3.3 Machine Learning Methods

Machine Learning methods can be categorized by the task they are solving. As described in 3.2 classification and regression are two tasks of supervised learning. Examples of tasks in unsupervised learning are clustering and association rule mining. Another common type of learning is reinforcement learning. Figure 2 shows selected methods of ML, grouped by the task they commonly solve. It is important to mention that this selection of methods is far from complete and some methods can be used to solve more than one task. Also, there exist several variants of algorithms for each method.

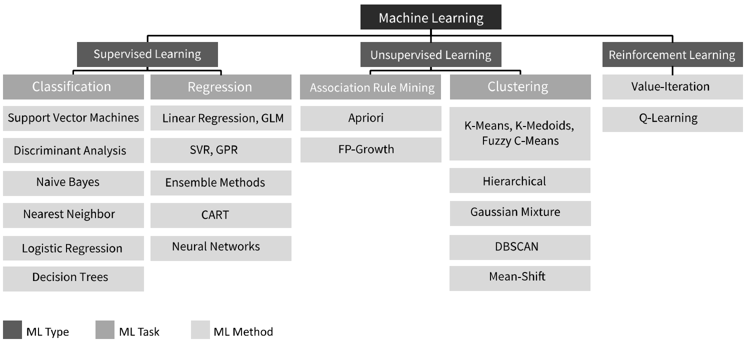

Figure 2: Overview of Machine Learning Methods based on (Witten, Eibe and Hall, 2011, pp. 116–216; The MathWorks, 2016, p. 7; Seif, 2018)

Part of the ongoing research in ML is the development of further methods, models and algorithms. Selecting a model and an algorithm depends on many factors and there is no one-method-fits-all-solution - also known as "There is no free lunch in statistics" (James et al., 2013, p. 29). The selection of an appropriate method for a given problem and dataset is one of the most challenging tasks in data analysis (James et al., 2013, p. 29).

When using ML methods and algorithms, some challenges may occur. Two different reasons can be mentioned when it comes to the development of error sources. On the one hand, the problem can be found in the data. The availability of a large amount of data which is necessary for the training of a model is still a frequent challenge, as well as insufficiently representative training data. Another challenge is poor data quality. In order to make patterns visible in data sets, they first must be detected. If the data contains errors or outliers, it is difficult to identify such patterns. Another issue is redundant features, which do not provide added value to the model. An important step for the success of a ML method is therefore to select suitable features for training (Géron, 2017, pp. 23–26). On the other hand, a poorly chosen algorithm can create difficulties in the form of overfitting and underfitting (Géron, 2017, p. 22). Overfitting means that ML algorithms can sometimes generalize incorrectly although the model works on a training data set. A model can be too complex, which means that the model follows noise or errors in the data too closely (James et al., 2013, p. 22). Underfitting is the opposite of overfitting and describes a model that is too simple for the structure of the data to be recognized and learned (Géron, 2017, p. 29).

3.4 Machine Learning Process

Real world machine learning applications are usually developed as part of a larger project. Several process model frameworks have been developed for such projects. One popular one is the Cross Industry Standard Process for Data Mining (Shearer, 2000; Piatetsky, 2014).

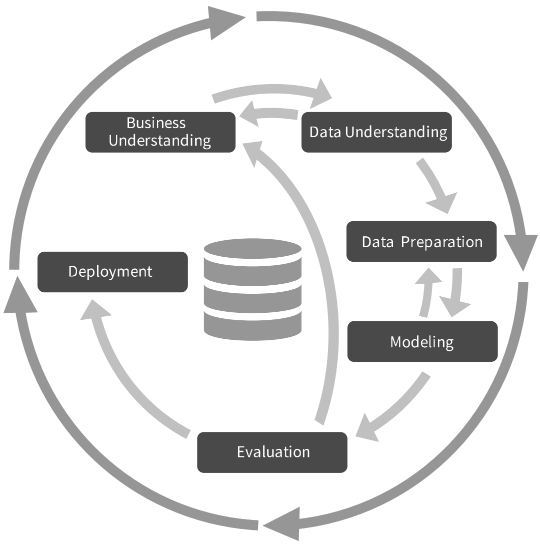

Figure 3: Cross Industry Standard Process for Data Mining (Shearer, 2000, p. 14)

The illustrated process in Figure 3 is also used for ML projects and acts as a common standard for ML (Cohen, 2017). The process defines six phases with specific tasks. Starting from "Business Understanding" to "Data Understanding", "Data Preparation", "Modeling", its "Evaluation" and ending with "Deployment". The goal of the framework is to improve results while reducing costs and time for the project. Shearer (2000) describes the specific tasks in more detail.

The paper is focused on presenting ML methods that are usually used during the modeling phase, as this was also the focus of the examined papers.

4 Machine Learning Application Areas in Supply Chain Management

This chapter portrays practical applications of ML by using three examples. Each of these examples represents one of the three main tasks of the SCM Model and is intended to show the reader how to use ML in practice. The three applications are selected as each of them represents a concise structure, a comprehensible explanation and gives a first impression of ML application.

4.1 Selecting Supply Chain Partners

In the field of SCD, one of the major challenges remains to find suitable business partners such as customers or suppliers to exploit new opportunities. This is especially valid regarding the globalization and the fast development of technology. To simplify finding new plausible business partners, Mori et al. (2010) use ML techniques based on company profiles and transaction relationships.

For data collection, the authors obtained company data of suppliers and customers via the "Teikoku Data Bank". A total of 30,660 companies from the manufacturing industry could be retrieved from the databank, all of them located in the Kanto and Koshinetsu areas of Japan. The training data consisted of 34,441 supplier and customer pairs from the existing inter-firm network. Those pairs are used as positive examples. Negative examples are defined as randomly chosen supplier and customer pairs, which are not related.

A Support Vector Machine (SVM) was applied to model the existing relationships by using features inherent to the company, such as number of employees and capital, as well as features defined by the interlinkage of firms, like customers of a supplier and common Industrial categories. The accuracy of the SVM-model reached up to 85%.
The most important determinants of customer-supplier relationships were identified as number of employees or industry category. The authors explain the relevance of these categories with country specific characteristics such as hierarchical structures. This shows that different determinants might be relevant when applying the method elsewhere. Along with the SVM, the ML model provides a tool to predict plausible candidates for future customer-supplier relationships (Mori et al., 2010).

4.2 Demand forecast for DM

One of Germany's largest drugstore companies, dm, uses machine learning algorithms to predict future demands. With 3,350 stores worldwide, the dm drugstore chain runs six distribution centers to ensure the availability of goods. The distribution centers have to ensure that the incoming goods of the industry partners are arranged for the individual stores in such a way that there is no product deficit and customer satisfaction remains high. Frequently, stores require a delivery of products within a short time frame, but the manufacturers have relatively long delivery times. This remains the biggest challenge for the distribution centers. Planning well in advance is accompanied by long-term orders, resulting in high storage costs and tied up capital.
To overcome this issue, artificial intelligence algorithms are used to create weekly demand forecasts based on SKU level over a time horizon of half a

year. For training of the algorithm, the data from the last 2.5 years of the particular distribution center has been used and the seasonality factor has been taken into account.

As a result of the artificial intelligence algorithms, the demand forecasts became so precise over a period of six months that a significant improvement in forecast quality could be achieved and industrial partners are now able to plan much earlier. Delivery reliability and product availability can thus be significantly optimized, which is supported by an automated information flow of future requirements to industrial partners. The advantages of using the algorithms are obvious for the industrial partners as well as for the dm drugstore market. The industrial partners can count on increased planning and ordering security through valid forecasts and the drugstore chain has secure product availability and less excess stocks. The results are satisfied customers and lower costs (JDA Software, 2019, pp. 8–9).

4.3 Detecting False-Positive RFID Tag Reads in Transport Management

One of SC's key processes is the shipment of goods from distribution centers. An error-free shipment depends on several factors, be it the picking process or the assignment of pallets to the allotted truck. To integrate a control mechanism, the METRO Group Cash & Carry implemented RFID portals to check on outgoing pallets. In its distribution center in Unna, Germany, loading ramps are equipped with RFID portals to automatically detect goods leaving the warehouse. For the detection of a pallet, it carries a transponder. As soon as the pallets pass the portals, the reading device records goods leaving the warehouse and automatically adjusts the available inventory via direct communication with the warehouse management system.

The RFID identification supports the shipment of goods and the automatic inventory adjustment but carries one major issue. The antennas of the portals have ranges of several meters and therefore identify all pallets in range, pallets to be shipped and pallets placed for intermediate storage. This means that during a collection cycle it is not possible to distinguish between a moving pallet loaded into a truck and a static pallet that is not relevant for the current shipment and hence, has been accidentally read. The non-relevant pallets represent a false-positive reading of the RFID portals.

In order to differentiate between the moving and static pallets, METRO Group Cash & Carry applied ML techniques based on the recorded attributes by each pallet. The attributes include the reception of the signal strength indicator (RSSI), the time stamp of each tag event and the number of reads per antenna based on the low-level reader data. It became apparent, that the tags of static and moving pallets submit different RSSI values, based on frequencies submitted to the portals. This is where ML comes in, as classifying two characteristics according to their threshold value is a well-known ML task. If the RSSI average value is below -58.1dBm, it is a static tag (false positive); otherwise it is a moving tag.

To automatically evaluate the attributes by ML, a very large data set is required for the training phase. The distribution center installed RFID portals on all 70 loading ramps and monitored them over a period of 7 months. A total of 53,998 pallets were monitored, of which 40,743 were static and 13,245 were moved through the outgoing goods portal.

After completion of the data acquisition, the used algorithm could correctly classify more than 95.5% of the data. Thus the pallets can be quickly identified and false-positive pallets can be captured directly. This minimized faulty inventory adjustments and deliveries (Keller et al., 2010).

4.4 Mapping of Use Cases to the Supply Chain Task Model

The analysis of the papers resulted in an assignment of the ML use cases to all three main task areas of the SCM model, which are outlined below. Out of illustration purposes in Figure 4, a number is assigned to each paper.

In the area of SCD, all retrieved papers deal with supplier selection. The authors apply different ML methods. While Kong and Xue (2013) utilize Radial Basis Function (RBF) neural networks [1], Zhang et al. (2017) use ensemble learning, decision trees and logistic regression [2]. Similar to the case of Mori et al. (2010) [3], the authors apply SVM, too. Another paper by Cheng et al. (2017) integrates Adaboost on expert knowledge basis to deal with supplier selection [4].

In the area of SCP, ML topics address the task of demand planning and procurement planning. The number of papers in relation to other tasks is very comprehensive. Based on the literature analysis carried through, fourteen use cases could be assigned to this area.

The authors Xue et al. (2018) use machine learning to solve the dynamic forecasting problem of the supply of goods in the event of a catastrophe [5]. Gamasaee, Zarandi and Turksen (2015) [6] and Sarhani and El Afia (2014) deal with approaches to demand forecasts of SC. It should be noted that all three papers use Support Vector Regression (SVR) as the ML method [7]. Ap-

plication examples for artificial neural networks are provided by the authors Gaur, Goel and Jain (2015), who apply a data set from Walmart to forecast demand for the SC [8], and Yang and Sutrisno (2018), who distribute perishable goods among franchise companies [9]. Adhikari et al. (2017) contribute with an ensemble technique to combine different ML methods in order to obtain demand forecasts [10]. The described practical application of the drugstore chain dm can be assigned to SCP, too, as the methodology creates a planning basis for a more effective SC to the stores. JDA Software (2019) mentions that the goal is to achieve high store availability [11]. Souichirou (2015) deals with commodity demand forecasting and systematization of SCM by using heterogenous mixture learning, and uses this to simulate sales measures [14]. As one of the rare studies so far, Cui et al. (2018) [12] and Lau, Zhang and Xu (2018) [13] integrate social media sources to forecast sales. The last three authors base their analysis on real data.
In the area of procurement planning, Hogenboom et al. (2009) apply RBF Networks [15] to deal with product pricing as well as Kiekintveld et al. (2009) who use a Bayesian Network and artificial neuronal network [16]. In addition to the two authors mentioned above, Lee and Sikora (2016) also deal with product pricing by using Q-learning softmax function [17]. In the same context, Ketter et al. (2009) use gaussian mixture models [18]. It is interesting to mention that all three authors deal with the same topic based on the same synthetic data, but use different methods.
Within distribution planning Mokhtarinejad et al. (2015) outline vehicle routing and scheduling problems in cross-docking systems by using Bi-Clustering, K-means and artificial Neural Networks [19].

In the third, operationally structured SCE, the literature addresses the areas of Order Management, Supply Chain Event Management, Inventory, Production and Transport Management.

Order management contains a total of four use cases. Based on synthetic data, the authors Sun and Zhao (2012) present a multi-agent coordination mechanism using reinforcement learning to derive an optimal ordering strategy for the entire SC with several levels [20]. Wang, Ng and Ng (2018) group SKUs according to their demand and performance attributes by unsupervised learning [21]. Real data is used in Wang and Liu (2009) to train a model using neural networks, which represents an index system for evaluating order priority [22]. Zhu, Ma and Zhang (2014) determine the manufacturing priority of an order with the help of RBF neural networks, Kriging and SVR [23].

There are four use cases in the area of Supply Chain Event Management. Among them, Arumugam, Umashankar and Narendra (2018) create an intelligent logistics solution that negotiates contracts, and includes logistics planning and condition monitoring of the facilities [24]. The early detection of supplier risks, Frerichs (2018) [25], as well as the identification of fraud and deceptive practices Zage, Glass and Colbaugh (2013) [26] are topics addressed in the context of risk management. Both applications rely on real data. Hiromoto, Haney and Vakanski (2017) use neural networks to identify vulnerabilities within SC's and mitigate the consequences of unforeseen risks [27].

A total of four use cases could be assigned to inventory management. The authors Barbosa de Santis, Pestana de Aguiar and Goliatt (2017) use ML classifiers to identify material residues within an inventory management system that have negative effects on inventory management [28]. Furthermore, Inprasit and Tanachutiwat (2018) use neural networks to optimize safety stocks and reorder points for products, taking into account various influencing factors such as performance and lead time [29]. The applications outlined above rely on real data. Another application is the identification of technically obsolete spare parts in the warehouse. Supervised learning methods were used to solve this problem (Cherukuri and Ghosh; Inprasit and Tanachutiwat, 2018) [30]. The authors Priore et al. (2018) use decision trees on the basis of synthetic data to determine the optimal replenishment rule [31].

Production management contains four use cases, while all of the papers had access to real data. Ali Ahmadi et al. (2016) use machine learning approaches to differentiate between the manufacturing locations of products. ML distinguishes products that were manufactured in a ratified factory from the ones which originate from unknown sources [32]. In the paper of Tirkel (2011) predictive models of ML and data mining are used to determine the cycle time [33]. By using linear regression and tree based methods, Dávid Gyulai et al. (2018) and Lingitz et al. (2018) estimate production lead times [34], [35].

The described use case of Keller et al. (2010), whose authors use ML to distinguish between static and moving pallets, is assigned to transport management [36]. In addition, the authors Gulisano et al. (2018) formulate a challenge to predict the arrival time and destinations of vessels [37].

An interesting approach is taken by Kao, Niraula and Whyatt (2018) who analyze part identification to enable data curation. Hence, the paper can cover several areas within the supply chain task model and is a rather general topic.

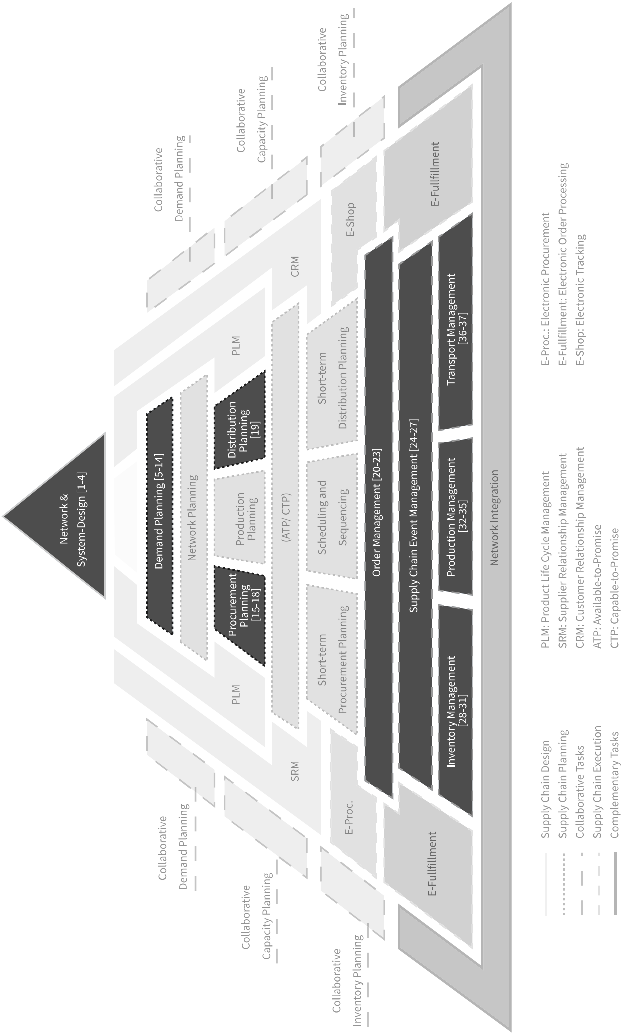

Figure 4: Illustration of the ML use cases in the SC model with numbers of the use cases based on (Hompel and Wolf, 2013, pp. 146–147)

Figure 4 depicts the ML application cases described above sorted into the respective supply chain tasks. The papers have been integrated into the task model along with their assigned numbering. All tasks with ML use cases are highlighted.
It shows that with four papers, SCD contains the lowest number of ML applications, all of them in the area of supplier selection. SCP has a total number of 15 use cases in the area of demand, procurement and distribution planning, most of them allocated to demand planning. Within SCE, each component of the SCM task model has at least one use case assigned. The highest number of applications, 18, could be found in SCE. Many of the applications are based on real data, in some cases synthetic data serves to verify the applicability of ML methods.

5 Conclusion

This paper assigns use cases of machine learning to the task model of Supply Chain Management, resulting in an overview of ML applications within the different supply chain tasks. It was demonstrated that in the SCM task model a single area could have different ML methods applied for a common goal. A large portion of research focused on demand planning, with 10 out of 38 papers handling this task. An investigation of ML methods for intercompany areas such as SRM and CRM could be promising for SCM. Future research should review relevant literature to suggest which methods apply best to certain SCM tasks.
With regard to the standard process model, the research focus lies in the modeling phase. Further research emphasizing on and explaining the concepts used in Business, Data Understanding and Evaluation is required. The

examined papers cover these phases, but hardly present useful insights and concepts for SCM. The Deployment phase is not treated at all.

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