Development of a Conceptual Framework for Machine Learning Applications in Brick-and-Mortar Stores

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Abstract. The growing prevalence and impact of e-commerce puts traditional brick-and-mortar stores under pressure. More and more customers prefer the variety of goods, easily comparable prices, and personalized recommendations online to conventional shopping experiences in stationary retail. A major asset of online stores is their potential to collect, analyze, and interpret data. The collection and analysis of customer behavior and transaction data to improve website design, the assortment, and pricing strategies – so-called 'web analytics' – are common practice in e-commerce for more than fifteen years already. Advancements in technologies and the ongoing digitalization of brick-and-mortar stores unveil the potential of Retail Analytics for conventional stores as well. Yet, a structured overview of diverse factors relevant for implementing Retail Analytics is missing. In light of this context, this article derives a conceptual framework harmonizing the relations between different technologies, collected data, analysis methods, method outputs, and application purposes.

Keywords: Retail Analytics, Machine Learning, Brick-and-Mortar-Stores, Stationary Retail.

1 Introduction

Over the last decade, the rise of online retailers has started to endanger the continued existence of brick-and-mortar stores. Thus, ghost town city shopping centers have been a point of discussion [1–4]. While in 2014 the amount of goods sold via electronic commerce (e-commerce) totaled to 1.3 billion U.S. $, it has doubled within four years to 2.8 billion U.S. $ in 2018. As this already decreases the share of traditional brick-and-mortar stores, it is projected to steadily increase to 4.8 billion U.S. $ in 2021 [5]. Thus, resulting in online retailers holding a total market share of 17.5 % in 2021, which indicates an increase of 10 % within six years [6]. This increase in market share can be attributed to digital retailers already utilizing new technologies to reach customers on multiple channels. Thus, allowing them to offer their products and services as conveniently as possible and adopt new customer experiences suited for nowadays customer needs [7]. Traditional brick-and-mortar

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stores usually operate on a single physical channel without adopting new technologies within their stores.

A major asset of online stores, leveraging their dominant position, is their immense potential to collect, analyze, and interpret data about their businesses. The collection and analysis of customer behavior and transaction data to improve website design, the product assortment, and pricing strategies – so called 'web analytics' – are common practice in e-commerce for more than fifteen years already [8]. These techniques have considerably contributed to the success of e-commerce. Davenport's Harvard Business Review article "Competing on analytics" [9], which has been cited more than a thousand times, underlined the immense power of data analytics for business purposes and can be seen as the first seminal paper on this topic leading to the emergence of a whole new research area, which has significant relevance for stationary retail as well. Yet, most brick-and-mortar stores restrict their analyses to simple methods like implementing customer counters or sending test customers into their stores, while further customer touchpoint within the store are not investigated [10]. Furthermore, brick-and-mortar stores are not necessarily used to data-driven decision making, which would lead to better decision making. Since the domain knowledge as well as experts, applying their knowledge, are missing, they are in need for support, which could offer additional benefits to them and their customers. During the literature search, nearly no real holistic, structured overview over possible opportunities for brick-and-mortar stores to adopt new technologies or machine learning could be found. However, multiple sources show single implementations of technologies and/or machine learning in the context of brick-and-mortar stores, providing them with examples to improve their business. An overview over these applications could offer brick-and-mortar stores the first point of contact in order to engage with different ideas and possibilities.

This led to the question of how brick-and-mortar stores could be supported in discovering and adopting new technologies as well as machine learning in order to offer new customer experiences as well as smart, data-driven decision making? To solve this question, this article aims to offer a structured overview of existing applications. Thus, showing brick-and-mortar stores what they can achieve by implementing machine learning with their currently present data as well as possible technologies they could introduce to improve their business. This can guide brick-and-mortar stores on their way to discover new technologies and implement machine learning. Additionally, it also closes a research gap by providing a structured overview over the topic of applied machine learning in the context of brick-and-mortar stores.

The remainder is structured as follows: section 2 delineates our research design and section 3 presents the research background. In section 4, the Retail Analytics framework for brick-and-mortar stores is explained. The discussion and evaluation are presented in section 5 followed by limitations, implications for research and practice and the conclusion in section 6.

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2 Research Method

In order to identify all relevant publications for developing the conceptual framework, we followed the guidelines of [11] to conduct literature reviews of every needed aspect relevant for the development. Therefore, the scope of the reviews need to be defined. The focus during the search were research outcomes, which provide the necessary information as foundation for the framework, which resulted from previous research. The goal is to depict the central issues on the topic of applying machine learning to brick-and-mortar stores in order to provide an overview. Coherent with the goal of the literature review, the information conveyed is of conceptual nature. Thus, the organization is done in a conceptual manner. Besides, it is not in the interest of this article to espouse a certain position. As the framework is meant to help brick-and-mortar stores discover possible new ways of improving their businesses through the use of technologies and the application of machine learning algorithms, it is mostly intended for retail practitioners. However, these retailers might not have any knowledge in the field of machine learning. Therefore, the audience can be described as general scholars, which do not have to be specialized in the fields of retail or machine learning but should have some kind of understanding for both areas. As only the most important information needed to understand the creation of the framework is needed, the coverage will be reduced to reflect the most central up to representative points of previous research [11]. Based on this scope, literature reviews have been carried out for all relevant areas like machine learning algorithms, Retail Analytics, application scenarios etc. An overview of the results is given in the remainder of this article.

The process of framework creation is divided into six steps according to [12]. (1) The **initialization** is the first step of developing the framework and purposes to deduce the requirements for the framework. These requirements should guide the creation as well as keeping the finished framework accountable. (2) Followed by the **identification of individual cases,** this step is responsible for identifying individual application cases of machine learning in the area of brick-and-mortar stores, which are forming the foundation for the creation process. (3) In the next step, **preparation of the individual cases**, the gathered cases of machine learning applications in brick-and-mortar stores are mapped to the derived classes. (4) In the fourth step, **production of the framework**, a framework is designed from the homogeneous cases created in the third step. This step results in a first draft of the desired framework. (5) The fifth step, **follow-up of the framework**, aims to refine the first draft of the framework. If a framework is split into different parts, these parts are now combined and linked. The results of the fifth step should be the finished framework. (6) Next, the **evaluation** takes place. The evaluation can be viewed from different perspectives. Firstly, the requirements gathered in step one can be used to identify if the framework satisfies all relevant needs. Secondly, it can be evaluated towards individual application cases. (7) Finally, the last step, **framework maintenance**, covers the maintenance aspect of the finished framework. Once it is finished it has to be maintained in order to adapt to changes or completely newly arising challenges [12].

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The final step is not part of the conducted work. However, the framework is designed in a way that it is easily adaptable and extendable.

Two iterations of these steps have been carried out. The first iteration identified deductively all relevant aspects of the application of both technologies and machine learning in the area of brick-and-mortar stores. The second iteration is meant to slim down the framework and only keep the classes and connections, which are actually in use. Therefore, use cases have been identified based on another literature review.

3 Theoretical Background

3.1 Retail Analytics

Applying machine learning algorithms to brick-and-mortar stores falls into the field of Retail Analytics. However, Retail Analytics, with a focus not only on e-commerce, i.e. demarcated from web analytics, appears to be a domain that received rather little attention in research yet. [13] discusses the application of data analytics mostly in the context of the apparel industry, with regards to the location data, marketing, and store operations, including labor forecasting, communication, and replenishment. Also focusing on replenishment, [14] presents different ways to forecast the demand of perishable products in order to prevent waste and out-of-stock situations. However, there are only few explicit definitions, explaining what Retail Analytics is. [15] defines Retail Analytics as "any information that allows retailers to make smarter decisions and manage their businesses more effectively". Besides, [16] defines Retail Analytics as "the process of providing analytical data on inventory levels, supply chain movement, consumer demand, sales, etc. that are crucial for making marketing, and procurement decisions". To the best of our knowledge, no scientific paper or scientific book provides an explicit definition of Retail Analytics. As both mentioned definitions are rather high level and imprecise, we derived our own definition of Retail Analytics from a definition of Business Analytics, which appears to be well defined. [17] defines Business Analytics as the "systematic and continuous evaluation of operational data […] to analyze entrepreneurial activity in a past oriented way […] to gain knowledge for future management and […] for future developments" [17]. We use the core of this definition and add the retailers' context and the collection of data through Information and Communication Technology (ICT), as we want to emphasize the potentials, which retailers have due to the advancements in information technology. Consequently, we define that Retail Analytics is the collection, analysis, and use of operational retail data to analyze retailers' and customers' activities to make profound future oriented business decisions both with the help of ICT.

3.2 Data Gathering Technologies

Retail Analytics would not be possible without data to rely on and to utilize. Therefore, different data gathering opportunities have to be inserted into the retail environment. This environment can either encapsulate everything happening within

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the store or accumulate everything happening outside of it. Therefore, the data gathering technologies can be split into *in-store technologies,* capturing events within the stores vicinity, and *out-of-store technologies,* which record events happening outside of stores' parameters. Another typical difference between the two types of data gathering technologies, apart from the location of installation, is the type of deployment. Whereas *in-store technologies* usually require some kind of physical device being introduced into the store (e. g. cameras, transmitter systems, or point of sale (POS) systems) [e. g. 18, 19], *out-of-store technologies* can often be used without the need of additional investments into hardware components (e. g. social media, weather forecasts, or news) [e. g. 20]. However, both types of technologies are used towards the same goal: the acquisition of relevant business data. Once this data is available, it can be processed and analyzed in order to generate a meaningful output, which can then be interpreted and used to improve the relevant business processes.

3.3 Machine Learning

For analyzing the data, different algorithms can be used. These algorithms are utilized by the different applications of machine learning in the context of brick-and-mortar stores and have to be categorized in order to identify similarities as well as differences between differing use cases. Apart from the underlying data, which can occur as discrete or continuous values, the choice of algorithm highly depends on which task needs to be solved. The often-found separation between supervised and unsupervised learning appeared to be a reasonable distinction [21, 22]. On the one hand, supervised learning aims towards accurately *predicting* future values based upon already known data. On the other hand, unsupervised learning tries to *describe* currently unknown sets of data to the user [22]. However, another approach taken is reinforcement learning, which *optimizes actions* by the expected rewards or by following established policies [23]. Therefore, we firstly divided the algorithms into three different categories: *prediction, description, action optimization*. Below these three categories and the differentiation between discrete and continuous values, fifteen classes of methods have been established. Firstly, *artificial neural networks* and *deep learning algorithms*, which are inspired by the structure of brains, are grouped together and can be utilized to predict values as well as structuring data [23, 24]. Solely belonging to the unsupervised algorithms and thus describing previously unknown data are the following: *clustering* algorithms are utilized to recognize patterns within datasets [25]. Outliers and other forms of irregularities can be found by using *anomaly detection* methods [26]. If associations between data points are needed, different *association* methods can provide structure to a large amount of data [27, 28]. Reducing the amount of variables inside the consideration set without using important information is achieved via *dimensionality reductio*n [29-30]. In the area of predicting methods, using some sort of similarity function, *instance based* algorithms base their prediction of specific instances on data instead of relying abstractions [31]. *Decision trees* are used to predict a value of an observation. To this end, a decision tree is constructed in which the nodes along the way represent different criteria towards which the observation is evaluated while the leaves of the tree represent the matching

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classes [32]. *Bayes' Theorem* provides the probability that a certain event will occur based on the events that occurred before. Furthermore, Bayes assumes conditional independence over the provided dataset [33]. [34:137] describes the "goal of *regression and regularization* is to predict the value of one or more continuous target variables t given the value of a D-dimensional vector x of input variables". In order to optimize the next action, reinforcement learning can be divided into three classes. *Model based* agents are given a manual, which guides it through the learning process. This model specifies how the agent should value different outcomes during the decision process [35]. *Policy based* agents are pointed into a pre-defined direction. Thus, is will converge quicker in the defined direction [36]. If no policy or model is given, reinforcement learning can follow a *model and policy free* approach. Here, the agent has to learn without being given a manual [36]. Other options are *image* or *video* recognition algorithms, which try to detect an object on photos or other images. Here, either pixel-based or object-based approaches can be used to classify the desired images [37]. Videos can be seen as an accumulation of images [38] and are therefore handled in a similar fashion to image recognition. If two or more approaches are combined together, the resulting bundle is called a prediction ensemble [39]. Here, different classifiers or predictors vote on the output, which can occur in a weighted or democratic fashion. However, prediction ensembles are not featured here, as they solely represent a combination of the presented models. Dividing the described classes of methods any further was not possible, as the related articles rarely mentioned the explicitly used algorithms. Overall, running machine learning algorithms is no end in itself. It is only a means to acquire a needed output. However, different algorithms yield different outputs.

These outputs can mainly be divided into discrete and continuous. Discrete values offer one single indicator. These can be split into KPIs, targeting a specific business aspect. Clusters of customers or products. Interdependencies between different aspects of the business Probabilities of certain events or purchases. Shopping paths of customers within the store, or planograms depicting the optimal position of items within the shelves. The continuous outputs mainly deal with time series predictions, like sales or turnover predictions.

4 Development of the Framework

4.1 Requirements Analysis

The first part of the framework creation process according to [40] is the establishment of structural and design requirements. Structural requirements (SRQ) are supposed to ensure that every person interacting with the model in our case the framework (designer, expert, user) interacts upon a common understanding. Adding to the structural requirements, design requirements (DRQ) define the appearance of the framework. They are meant to guide the developer in the organization of elements as well as their connections [40]. By combining both structural and design requirements, the resulting framework should be applicable to all important problems arising from

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applying machine learning to brick-and-mortar stores. We raised the following structural and design requirements on the framework:

SRQ 1: The framework must clearly expose those, and only those classes, which are relevant for the application of Retail Analytics in brick-and-mortar stores. This requirement ensures that we consider the full scope of relevant classes in the framework. At the same time, it makes sure that only the relevant classes are part of the framework and no further classes are included that might lead to an unnecessary level of complexity in the classes' interrelations.

SRQ 2: The framework must provide possible specification for each of the identified classes on a level of detail, which allows for implementation. It is not only important to be aware of the full scope of relevant classes, but also of possible specifications in the following called categories for each class. Therefore, a comprehensive set of categories must be delineated for each of the identified relevant classes to guide users seeking to implement Retail Analytics in their store and motivate scholars for purposeful further research efforts.

SRQ 3: The framework must clearly describe the interrelations that exist between the identified classes' possible categories in all relevant directions. Since the possible categories for each of the classes are dependent on the classes of other components, they cannot be dealt with in isolation. Therefore, the framework must consider those interrelations. A good example to get an idea of the importance of that requirement are analysis methods. They are dependent on a specific type and format of input data while their output restricts the space of possible conclusions for business activities.

DRQ 1: The framework must present the relevant components for the implementation of Retail Analytics evident and understandable at a glance. The graphical appearance of the framework provides a first impression to potential users that can decide whether to accept or reject it. Therefore, the components must be presented in an easily recognizable way at first sight. Furthermore, they must be named in a precise way for being plainly understandable.

DRQ 2: The framework must delineate the classes' possible categories in a way that the relation between categories and classes is easily understandable. To ensure the understanding of the affiliation of categories and classes, the framework must unambiguously depict the affinity between categories and their respective superordinate class.

DRQ 3: The framework must visualize the interrelations that exist between the identified classes' possible categories in all relevant directions. The interrelations between the identified classes' possible categories must easily be recognized. They can potentially be multifaceted and complex in the form of many-to-many relations, so that it is difficult to describe them solely textual in an easily understandable way.

4.2 Design of the Framework

The framework was designed within two iterations, taking different approaches and views. Aiming to provide a broad overview over the whole topic of the application of both technologies and machine learning in the area of brick-and-mortar stores, the first iteration took a deductive approach. Therefore, the literature review on

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technologies, machine learning, and applications was taken to provide the different classes of the framework. Secondly, the next iteration took an inductive approach. Thus, multiple single cases of applications were gathered. These were used to fill the existing classes, whilst also omitting classes without any application scenarios. This resulted in the framework being split into five components, as shown in Figure 1. The first component necessary to accumulate the data are the data gathering technologies. These technologies produce outputs of varying kind. Next, the machine learning algorithms use the technology output and calculate a new measure. Lastly, this measure is utilized in different application scenarios.

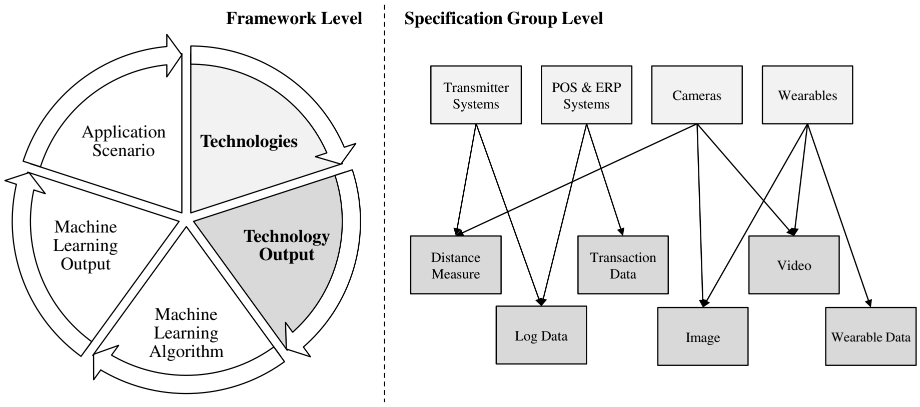

Figure 1. Draft of the Framework

Therefore, the first iteration resulted in the overall structure and the different classes as subordinated layer of the five components (see Figure 2). The five components presented follow the same literature review used to create the draft of the framework, shown in Figure 1 (left side). However, the connections between the categories, as well as classes, as depicted on the right side of Figure 1, could not yet be established. Therefore, the second iteration was used to fill in these blanks.

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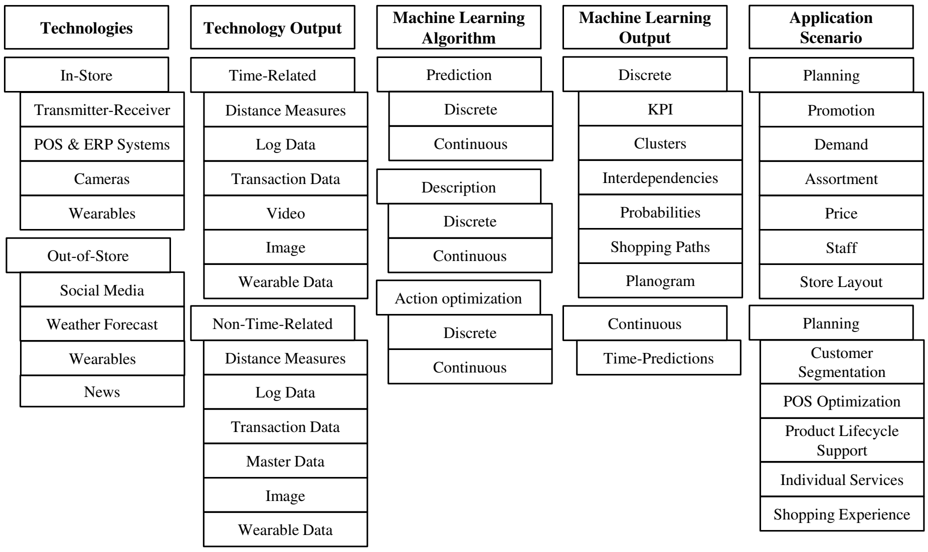

Figure 2. First Draft of Components, Classes, and Categories of the Framework

4.3 Results

The second iteration started with the identification of individual cases based on a structured literature review [11]. The utilized search string was “stationary OR shop OR brick-and-mortar OR brick-and-mortar AND retail OR retailer AND machine learning OR analytics”. Having the resulting publications function as a basis, a backward and forward search was conducted. After discarding publications, which did not fit the concept of applied machine learning in the context of brick-and-mortar stores, this resulted in a total of 78 usable cases. The total of all cases cannot be depicted in this article; however, an extract can be found in the appendix. The extract describes how we have classified the different identified use cases. In the following, we give a rough overview how we have used the cases in order to come up with the final framework.

In the case of the technology category, the first iteration provided eight different categories. During the review of the individual cases it quickly became apparent, that the authors often did not distinguish between POS and ERP systems. Therefore, these categories were grouped together as they also yielded similar datatypes. Furthermore, no cases could be found for the use of weather forecasts, news, or social media. Thus, they could not be featured in the final framework. The most commonly used technologies were transmitter systems (32), POS & ERP systems (29), and cameras (21). Wearables were only used in four single cases.

The utilized technologies offered multiple different outputs. Apart from master data, every other output type gathered during the first iteration could also be found in the individual cases. Here, the most common datatypes were transaction data (32), and log data (17), which were usually collected by the POS & ERP systems. Next, distance measures (16), image (13), and video (9) were collected. Wearable data was only found in two different cases, which also collected image or video data.

The utilized machine learning algorithms offered the largest variety of different applications. Here, every category established within the first iteration was used at least once. The most commonly utilized machine learning algorithms were clustering (15), image processing (12), and associations (9), followed by regression and regularization (8). Least utilized were policy (1) and model and policy free (1) reinforcement learning. However, two cases of cooperative reinforcement learning methods were found, which was therefore introduced to the framework.

The variety in different machine learning algorithms resulted in a large variety of different output types. Again, every output type established in the first iteration could be found at least once within the individual cases. The two most common output types of the algorithms were clusters and shopping paths, which were both featured 23 times. In four instances these two outputs were featured within the same case. Next, interdependencies could be found in 16 cases. The least found output type were time predictions, which only appeared in three different cases.

Lastly, except for product lifecycle support, the application scenarios covered all possibilities established within the first iteration. The application scenarios with the highest usage rate are: store layout (27), customer segmentation (23), demand (19) assortment (17) planning. Least used was staff planning with only one case found.

In order to build the framework, the categories of varying classes have to be connected to one another. Therefore, single cases were put into interrelation matrices between every component of the framework. In total four of those matrices were compiled. An example between the technologies and their respective output can be seen in Table 1. Taking the information of all four matrices into account, the connections between the different categories, as exemplarily seen in Figure 1 for the connection between technologies and their output, can be established as well as quantified. With the quantified categories and edges between them, the framework design is finished.

Technology/ Technology Output	*Dist-ance*	*Log*	*Trans-action*	*Video*	*Image*	*Wear-able*	*Master*
Cameras	3			7	11		
ERP & POS Systems		5	28				
Transmitter Systems	15	11					
Wearables	1			2	2	2	
Social Media							
Weather Data							
News							

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Table 1. Interrelations between Technologies and Technology Output

5 Discussion/Evaluation

After designing the framework, it had to fulfill the requirements raised in section 4.1. Thus, the framework was evaluated towards the established requirements.

SRQ 1 is ensured by the careful analysis of individual cases. A literature base of nearly eighty findings, all following the same identical structure, should ensure that the five components we discovered represent the relevant classes and categories for the implementation of Retail Analytics.

On the framework level, theses five components are easily visible at a glance. Thereby, DRQ1 is also fulfilled. No further information is apparent on that level, which could potentially distract users from the relevant factors. The denotation of the framework level's elements is clear and unambiguous and thus enables an easy understanding of the five relevant components.

SRQ 2 is satisfied through the formation of specification classes. These classes provide information on a level of detail that enables to easily understand possible types of concrete categories and simply understand how the five components could be specified. Without the formation of classes, the amount of concrete categories would be overwhelming and too detailed to understand the contents of the framework without induction and practice.

DRQ 2 is fulfilled by visualizing the hierarchical relation between components, classes and categories. In the complete framework, this relation is noticeable as the elements of the parent layer are always stated next to subordinate layer's elements.

SRQ 3 has been subject to the analysis of interrelations between the categories. It is ensured by the transition matrices we derived for all interrelations we could identify between categories of one component with categories of another component. Since the transitions are not only true in one direction, but also reversed, all possible directions are considered as well. Table 1 for example can be read from the category of technologies towards categories of technology output, but also from categories of technology output towards technologies.

Accordingly, DRQ 3 is ensured by visualizing the interrelations between the specification categories of a component with the specification category of another component in form of nodes for categories and directed edges for interrelations. Although Figure 1 only depicts that for one direction, the complete framework considers all possible directions, i.e. when looking at the specification categories of technology output for example, one would not only see the incoming directed edges from the component of technologies, but also the outgoing edges towards the component of machine learning algorithms.

Adding to the evaluation based on the requirements, a proof of concept is given, in order to show the applicability of the framework. [41] designed a multi-sided platform for brick-and-mortar stores and their customers, called smartmarket[2] [42]. Here, Bluetooth beacons are used to establish a connection with the smartphone of potential customers [43]. Via their API different datatypes are described. As data gathering

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technologies, they utilize beacons as well as a server to collect transactions and user data. This corresponds well to the framework parts of transmitter systems and enterprise resource planning systems & point of sale systems. As stated by [42:4], “based on the RSSI, clients can calculate their distance from the beacons”, which matches up with the distances measurements defined in the technology data output part of the framework. Further is stated that “collected data is analyzed primarily to provide context for customer segmentation; that is, the resulting service enables retailers to create promotions for a single customer or a target group defined by contextual factors, who then receive tailored promotions that fit their interests” [42:5]. Again, a match can be found within the framework. Both customer segmentation and individual services and promotions are part of the application purposes. One possible route taken through the framework would therefore be: (Beacon, ERP & POS System) → (Distance measurements, Transaction data, Log data) → ( ) → (Shopping Paths, Clusters) → (Customer segmentation, Individual Services). The applied algorithms remain unclear while also the algorithm output is not completely defined within these steps. Since the algorithm part is missing it could be inferred by the framework, thus resulting in a complete chain. Namely, the utilized machine learning methods could most likely be clustering, Bayesian, or model based reinforcement learning algorithms. However, this would be inferred under a degree of uncertainty.

6 Conclusion

The established methodology was used to conduct two iterations of the framework creation process. The finished framework consists of five components detailing different aspects of technologies, data types, algorithms, and application scenarios, which are interconnected step by step.

However, there are certain shortcomings users of the framework have to consider. First, the framework could not be evaluated in detail and was only self-evaluated against established requirements as well as tested with an acquired external data source. Furthermore, the current framework could be further extended by including non-scientific resources. As of yet, the framework solely relies on academic publications and does not include state of the art solutions provided by commercial parties. Moreover, the framework currently only exists in analog form. By digitizing the whole components as well as the interconnections between them, interaction could be made possible. This could provide users with an easier way of communication with the framework as well as making it easier to understand and visually attractive.

The framework is meant to provide retailers, who have an interest in acquiring data-driven insight into their business, with a first means of information gathering. They should be able to use the framework to either look for application scenarios they are interested in and then search for the algorithms and technologies, which make this scenario possible. Alternatively, they can utilize the framework the other way around. Therefore, researching, which algorithms can be applied to the data they already have at their disposal and which possibilities are presently available to them. Furthermore,

https://doi.org/10.30844/wi_2020_c2-becker

the framework might encourage retailers, who have not yet encountered machine learning, to explore the topic and consider the possibility of engaging with it further.

Appendix

Author	*Techno-logy Class*	*Data Type Class*	*Machine Learning Method Class*	*Machine Learning Output Class*	*Applica-tion Class*
[…]	[…]	[…]	[…]	[…]	[…]
Akyuz et al. 2017 [44]	EPS	TD	E	TP	D
Chen 2014 [45]	TS	DM, TD	NN	CLS	SX, POSO
Chiou-Wie & Inman 2008 [46]	EPS	TD	R	CLS	A, PPP
Cil, I. 2012 [19]	EPS	TD	AS	IN	A, SL
Cruz et al. 2018 [47]	C	I	I, NN	SPA	SX, POSO
Dawes & Nenycz-Thiel 2014 [48]	EPS	TD	AS	IN	A
Dholakia et al. 2005 [49]	EPS	TD	CL	CLS	D
Epstein et al. 2016 [50]	C	TD, I	R	PR	PPP, D, SP
Frontoni et al. 2017 [51]	TS	LD	IB	P	D
Golderzahi & Pao 2018 [18]	TS	LD	R	PR	CS, D
[…]	[…]	[…]	[…]	[…]	[…]

Table 2. Extract of analyzed literature. Encoded table containing the following items (alphabetical order): A = Assortment, AS = Association, C = Cameras, CL = Clustering, CLS = Clusters, CS = Customer Segmentation, D = Demand, DM = Distance Measures, E = Ensemble, EPS = ERP & POS Systems, I = Image, IB = Instance-based, IN = Interdependencies, LD = Log Data, NN = Neural Networks, P = Planogram, POSO = POS Optimization, PPP = Price & Promotion Planning, PR = Probabilities, R = Regression, SL = Store Layout, SP = Staff Planning, SPA = Shopping Paths, SX = Shopping Experience, TD = Transaction Data, TP = Time Predictions, TS = Transmitter Systems

References

1. Eisert, R., Hohensee, M.: Leere Innenstädte durch Online-Handel?, https://www.wiwo.de/unternehmen/handel/bezos-vision-leere-innenstaedte-durch-online-handel/7805132-4.html
2. Wörrle, J.: Leere Innenstädte: Mythos oder Zukunft?, https://www.deutsche-handwerks-zeitung.de/leere-innenstaedte-mythos-oder-zukunft/150/3092/271064
3. Dierig, C.: Deutschlands Innenstädte drohen zu veröden, https://www.welt.de/wirtschaft/article165248634/Deutschlands-Innenstaedte-drohen-zu-veroeden.html
4. Gerl, M.: Wie das Leben aus Bayerns Innenstädten verschwindet, https://www.sueddeutsche.de/bayern/stadtentwicklung-die-lehre-aus-der-leere-1.3690635
5. Statista: Retail e-commerce sales worldwide from 2014 to 2021
6. Statista: E-commerce share of total global retail sales from 2015 to 2021, https://www.statista.com/statistics/534123/e-commerce-share-of-retail-sales-worldwide/
7. Verhoef, P.C., Kannan, P.K., Inman, J.J.: From Multi-Channel Retailing to Omni-Channel Retailing. Introduction to the Special Issue on Multi-Channel Retailing. J. Retail. 91, 174–181 (2015). doi:10.1016/j.jretai.2015.02.005
8. Devaraj, S., Fan, M., Kohli, R.: Antecedents of B2C channel satisfaction and preference: Validating e-commerce metrics. Inf. Syst. Res. 13, 316–333 (2002). doi:10.1287/isre.13.3.316.77
9. Davenport, T.H.: Competing on analytics, https://sites.google.com/site/dreamznpassions/competing_on_analytics.pdf, (2006)
10. Bollweg, L., Lackes, R., Siepermann, M., Weber, P.: In-Store Customer Analytics - Metriken & Reifegradszenarien zur Erfassung physischer Kundenkontakte im stationären Einzelhandel. In: Lecture Notes in Informatics (LNI), Proceedings - Series of the Gesellschaft fur Informatik (GI). pp. 327–341 (2016)
11. Vom Brocke, J., Simons, A., Niehaves, B., Riemer, K., Plattfaut, R., Cleven, A.: Reconstructing the giant: On the importance of rigour in documenting the literature search process. In: 17th European Conference on Information Systems, ECIS 2009 (2009)
12. Fettke, P.: Eine Methode zur induktiven Entwicklung von Referenzmodellen. In: Multikonferenz Wirtschaftsinformatik. pp. 1034–1047 (2014)
13. Cox, E.: Retail Analytics: The Secret Weapon. Wiley (2011)
14. Sachs, A.-L.: Retail Analytics: Integrated Forecasting and Inventory Management for Perishable Products in Retailing. Springer International Publishing (2015)
15. CollinsDictionary.com: Retail analytics - Definition and Meaning
16. Technologies, H.: What is Retail Analytics?, https://www.hcltech.com/de/node/141578
17. Siepermann, M.: Business Analytics, https://wirtschaftslexikon.gabler.de/definition /business-analytics-54504/version-277533
18. Golderzahi, V., Pao, H.K.: Understanding customers and their grouping via wifi sensing for business revenue forecasting. In: Lecture Notes in Computer Science

(including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics). pp. 56–71 (2018)
19. Cil, I.: Consumption universes based supermarket layout through association rule mining and multidimensional scaling. Expert Syst. Appl. 39, 8611–8625 (2012). doi:10.1016/j.eswa.2012.01.192
20. Zikopoulos, P., Deroos, D., Parasuraman, K., Deutsch, T., Giles, J., Corrigan, D.: Harness the power of big data The IBM big data platform. McGraw Hill Professional (2012)
21. Borana, J.: Applications of Artificial Intelligence & Associated Technologies. Sci. [ETEBMS-2016]. 5, 5–6 (2016). doi:10.1016/s0004-3702(99)00086-7
22. Sathya, R., Abraham, A.: Comparison of Supervised and Unsupervised Learning Algorithms for Pattern Classification. Int. J. Adv. Res. Artif. Intell. 2, (2013). doi:10.14569/ijarai.2013.020206
23. Chang, Z., Lei, L., Zhou, Z., Mao, S., Ristaniemi, T.: Learn to Cache: Machine Learning for Network Edge Caching in the Big Data Era. IEEE Wirel. Commun. 25, 28–35 (2018). doi:10.1109/MWC.2018.1700317
24. Kumari, A., Prasad, U., Bala, P.K.: Retail Forecasting using Neural Network and Data Mining Technique: A Review and Reflection. Int. J. Emerg. Trends Technol. Comput. Sci. 2, 266–269 (2013)
25. Saxena, A., Prasad, M., Gupta, A., Bharill, N., Patel, O.P., Tiwari, A., Er, M.J., Ding, W., Lin, C.T.: A review of clustering techniques and developments. Neurocomputing. 267, 664–681 (2017). doi:10.1016/j.neucom.2017.06.053
26. Chandola, V., Banerjee, A., Kumar, V.: Anomaly detection: A survey. ACM Comput. Surv. 41, 15 (2009)
27. Agrawal, R., Imieliński, T., Swami, A.: Mining Association Rules Between Sets of Items in Large Databases. ACM SIGMOD Rec. 22, 207–216 (1993). doi:10.1145/170036.170072
28. Yabing, J.: Research of an Improved Apriori Algorithm in Data Mining Association Rules. Int. J. Comput. Commun. Eng. 2, 25–27 (2013). doi:10.7763/ijcce.2013.v2.128
29. Jolliffe, I.: Principal component analysis. (2011)
30. Borg, I., Groenen, P.: Modern Multidimensional Scaling : Theory and Applications. J. Educ. Meas. 40, 277–280 (2003)
31. Shao, J., Ahmadi, Z., Kramer, S.: Prototype-based learning on concept-drifting data streams. Proc. ACM SIGKDD Int. Conf. Knowl. Discov. Data Min. 412–421 (2014). doi:10.1145/2623330.2623609
32. Liu, L., Sheridan, D., Tuohy, W., Vasudevan, S.: A technique for test coverage closure using goldmine. IEEE Trans. Comput. Des. Integr. Circuits Syst. 31, 790–803 (2012). doi:10.1109/TCAD.2011.2177461
33. Efron, B.: Bayes ' Theorem in the 21st Century. Science (80-.). 340, 1177–1179 (2013)
34. Bishop, C.M.: Pattern recognition and machine learning. Springer Science+ Business Media (2006)
35. Singh, A.K., Leech, C., Reddy, B.K., Al-Hashimi, B.M., Merrett, G. V.: Learning-based run-Time power and energy management of Multi/Many-Core Systems: Current and future trends. J. Low Power Electron. 13, 310–325 (2017).

doi:10.1166/jolpe.2017.1492
36. Kaelbling, L.P., Littman, M.L., Moore, A.W.: Reinforcement learning: A survey. J. Artif. Intell. Res. 4, 237–285 (1996)
37. Duro, D.C., Franklin, S.E., Dubé, M.G.: A comparison of pixel-based and object-based image analysis with selected machine learning algorithms for the classification of agricultural landscapes using SPOT-5 HRG imagery. Remote Sens. Environ. 118, 259–272 (2012). doi:10.1016/j.rse.2011.11.020
38. Karpathy, A., Toderici, G., Shetty, S., Leung, T., Sukthankar, R., Li, F.F.: Large-scale video classification with convolutional neural networks. In: Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition. pp. 1725–1732 (2014)
39. Brown, G.: Ensemble Learning. Encycl. Mach. Learn. 312–320 (2010)
40. Meise, V.: Ordnungsrahmen zur prozessorientierten Organisationsgestaltung: Modelle für das Management komplexer Reorganisationsprojekte. Kovač (2001)
41. Bartelheimer, C., Betzing, J.H., Berendes, I., Beverungen, D.: Designing multi-sided community platforms for local high street retail. In: 26th European Conference on Information Systems: Beyond Digitization - Facets of Socio-Technical Change, ECIS 2018 (2018)
42. Dahm, C., Beverungen, D.: smartmarket2, https://www.smartmarketsquare.de/
43. Betzing, J.H.: Beacon-based customer tracking across the high street: Perspectives for location-based smart services in retail. In: Americas Conference on Information Systems 2018: Digital Disruption, AMCIS 2018 (2018)
44. Akyuz, A.O., Uysal, M., Bulbul, B.A., Uysal, M.O.: Ensemble approach for time series analysis in demand forecasting: Ensemble learning. Proc. - 2017 IEEE Int. Conf. Innov. Intell. Syst. Appl. INISTA 2017. 7–12 (2017). doi:10.1109/INISTA.2017.8001123
45. Chen, C.C.: RFID-based intelligent shopping environment: a comprehensive evaluation framework with neural computing approach. Neural Comput. Appl. 25, 1685–1697 (2014). doi:10.1007/s00521-014-1652-7
46. Chiou-Wei, S.Z., Inman, J.J.: Do Shoppers Like Electronic Coupons?. A Panel Data Analysis. J. Retail. 84, 297–307 (2008). doi:10.1016/j.jretai.2008.07.003
47. Cruz, E., Orts-Escolano, S., Gomez-Donoso, F., Rizo, C., Rangel, J.C., Mora, H., Cazorla, M.: An augmented reality application for improving shopping experience in large retail stores. Virtual Real. 1–11 (2018)
48. Dawes, J., Nenycz-Thiel, M.: Comparing retailer purchase patterns and brand metrics for in-store and online grocery purchasing. J. Mark. Manag. 30, 364–382 (2014). doi:10.1080/0267257X.2013.813576
49. Dholakia, R.R., Zhao, M., Dholakia, N.: Multichannel retailing: A case study of early experiences. J. Interact. Mark. 19, 63–74 (2005). doi:10.1002/dir.20035
50. Epstein, L.D., Flores, A.A., Goodstein, R.C., Milberg, S.J.: A new approach to measuring retail promotion effectiveness: A case of store traffic. J. Bus. Res. 69, 4394–4402 (2016). doi:10.1016/j.jbusres.2016.03.062
51. Frontoni, E., Marinelli, F., Rosetti, R., Zingaretti, P.: Shelf space re-allocation for out of stock reduction. Comput. Ind. Eng. 106, 32–40 (2017). doi:10.1016/j.cie.2017.01.021

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