Recommender Systems for Variant Management in the Automotive Industry

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Abstract

This paper transfers some state-of-the-art methods of recommender systems for an application in the product development process of variant rich products in the automotive industry. Therefore, an introduction into the characteristics of the rule-based description of variant-rich products is given, followed by a presentation of three selected recommendation approaches, namely Collaborative Filtering, Association Rule Mining and Bayesian Networks. The presented approaches are then evaluated against the background of the variant-rich product configuration. Advantages and disadvantages of the methods in regard of this special use-case are highlighted and possible applications and limitations are discussed. In conclusion, further research needs for future implementation are identified.

Keywords

recommender systems, variant-rich product description, automotive industry

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1. Introduction

This paper deals with variant management in the automotive industry. The product development process, in particular in the German automotive industry, is characterized by the challenges of the highly variant products and the resulting requirements [1-5]. In the early phase, assumptions, estimates and historical data from direct predecessor vehicles are used for planning. Historical vehicle orders can be used as a basis for forward sourcing, but do not provide flexibility in scenario planning of new options, and in optimizing the offering program and packaging for variant reduction. To make this possible, an analysis of historical data for trends and frequently jointly sold equipment is being sought. In this context, historical data refers to existing vehicle orders since the start of production. Due to the many configuration options, almost every vehicle is unique. However, the individual features can be handled as an item list for the examination.

Therefore, the approach of recommendation systems is investigated, and different methods are examined with the objective of using knowledge about customer behavior for the planning and development process in the automotive industry.

This paper starts by explaining the challenges with using recommender systems for highly variant products followed by three derived research objectives and one research question. Moreover, three state-of-the-art methods are selected and the methodology is presented. Subsequently, the general approach of recommender systems is introduced. Hereafter, the use case of a rule-based variance scheme for encryption of the diversity of variants in automotive manufacturing is explained in detail followed by a description of the selected approaches and an evaluation to which degree the respective approach can be exploited for the use case in the automotive industry. In a conclusion, future research needs and limitations are identified as well as which methods can be used best for which field of application.

2. Research Problem & Question

In saturated markets, offering customer-oriented products and services creates a unique selling proposition and competitive advantage. With this mass customization approach, the German automotive industry, especially the premium segment, represents an exceptional role model for variant management and will serve as the environment for consideration in this paper. As a result, manufacturers are faced with the problem of controlling and managing the enormous number of variants, while customers face the problem of navigating through the complex configuration process, in order to obtain the vehicle with the desired options considering given restrictions. For this reason, there is a need to support the process at several stages. First of all, the offer on the manufacturer's side must be optimized. Furthermore, the variant-related restrictions must already be taken into account during the planning phase. Finally, the offered product range has to be presented to the customer in an appropriate and prepared form.

Three research objectives can be derived to help supporting this process: First, utilizing the implicit knowledge from historical data to package feature-values and optimize the manufacturer's offering program. Second, considering dependencies extracted from existing projects for planning and forward sourcing of follow-up projects. Third, making recommendations in the original sense during the configuration process at the customer site (‘customers who bought this feature also bought...’).

Considering the research objectives, this leads to the following research question, among others:

- To what extend can existing concepts of recommender systems be applied to the constraint-based variant description in the German automotive industry and what are their respective advantages and disadvantages regarding this use case?

3. Methods & Use Case

To answer the research question, the general approach of recommendation systems is investigated, and different methods are examined with the objective of using knowledge about customer behavior for the planning and development process in the automotive industry.

In order to achieve this, it is first examined which methods are successfully used in the field of recommender systems and the typically available User/Item relations, which they need to work properly. Starting point of this research are the much-cited papers by Agrawal et al. [6] and Sarwar et al. [7], which consider the use of Collaborative Filtering and Association Rule Mining to recommend items from User/Item relations. Furthermore, Bayesian Networks are proposed to perform the model building process [7]. For this reason, this paper deals with these three methods. Other methods such as neural network approaches are not covered in this paper, since they suffer explainability, which is crucial for the application in the development process. In addition, the currently used product description in the German automotive industry is presented as an example of a rule-based variant description and examined for its particularities such as the User/Feature-Value relations.

Subsequently this paper aims to transfer these state-of-the-art methods of recommender systems for an application in the product development process of variant rich products in the automotive industry. Therefore, the translation of the User/Feature-Value relations into a machine-readable form is described, followed by an analysis of requirements of the automotive industry towards a customer-behavior-analysis on the opposite side.

The presented approaches are then evaluated against the background of the variant-rich product configuration and are to be applied according to their advantages and disadvantages to help solving their respective research objective. By answering the research question, a knowledge transfer from existing methods to a product development use case is achieved and planned for usage in sales to the customer.

4. Related Work & Preliminaries

4.1. Recommender Systems

Since the mid-1990s, recommender systems (RSs) as a subfield of data mining have been a discipline of Knowledge Discovery in Databases [8, 9]. The goal of RSs is to provide item recommendation to users, which will match their interests and preferences. There are several approaches to achieving this aim. A systematic overview is given in Adomavicius, Tuzhilin and others [8, 10, 11].

The distinction of recommendation approaches is made in four categories: Collaborative-based, content-based, knowledge/constraint-based and hybrids [11, 12]. The approaches are classified primarily according to the data used to calculate the recommendations.

The idea behind Collaborative Filtering (CF) is to give item recommendations to users based on their previous choices and choices of other like-minded users [7]. Therefore, CF methods use the purchase data or preference data of many users (collaborating). CF approaches can again be divided into the two classes memory-based and model-based [7].

The memory-based approach uses the statistical nearest neighbor method. The approach is simple but has one major drawback. For a new recommendation, the whole database has to be evaluated and therefore loaded in system memory [13]. Hence, it suffers scalability.

The model-based approach, on the other hand, calculates a probabilistic model, which can be build using machine learning algorithms such as Bayesian Networks, clustering, and rule-based approaches [7]. Recommendations are then calculated by using reference mechanism into the model [13]. As such, model-based approaches have the advantage that they are less computationally intensive, and recommendations can be calculated at runtime.

Content-based approaches use historical data of the target user as well as attributes of the considered items. Since the available data in the presented use case doesn't fit these requirements (customers do not buy new cars on a frequent basis and often own only one car at a time [14]), these approaches are not explored further in the following.

The distinction between knowledge-based approaches and content-based approaches is not always explicit [15]. For this paper, the definition from Burke is used, who describes the capability of knowledge-based approaches to use additional domain knowledge and therefore model more complex relationships such as constraints between feature-values [15]. For the automotive sector, these approaches are important due to the Boolean constraint formulation described in the following section. To make use of the respective advantages of these systems, hybrid methods of for example collaborative and content-based methods are being investigated by Burke [15] or de Campos et al. [16] and others.

4.2. Automobile Industry

The automobile is defined by its features, where the feature-values are chosen by a customer. For a simple example of a product with 50 different features to choose from and the simplifying assumption of three feature-values (e.g., ‘1,4l TDI’, ‘2.0l TDI’, ‘3.0l TDI’) per feature (e.g., ‘Engine’), this leads to a total of $3^{50} \approx 7{,}18 * 10^{23}$ unique variants. In reality, the number of actually occurring variants can be even larger (at Daimler: $\approx 10^{27}$ [3]). If $|end\ product\ variants| \gg |part\ variants|$, the end-product is called multi-variant, which therefore applies especially to the European automotive manufacturers. Additionally, the complete variance space is restricted by a set of rules which specifically exclude or prescribe individual combinations of feature-values. The reasons for the various constraints can be of a technical, legal or sales nature. In the literature, this problem is known as a Constraint Satisfaction Problem [17]. For a further understanding of the product encryption and development implications see Herlyn, Stich, Zagel, Holtze and Frischen et al. [1-5]. For a further study into the challenges of product personalization based on modular product families see Kuhl et al. [18].

For the analysis of customer behavior and investigation of the selected recommendation methods, valid historical vehicle orders are available. In addition, first approaches already exist to generate a set of vehicle orders synthetically by using algorithms. These synthetic "item sets" fulfill the satisfiability against the constraints [19]. In the following, m vehicle orders are assigned to U_i users. The vehicle orders consist of a discrete set of n feature-values F_j that can be chosen from a set of feature-values M. M contains all feature-values $F_A, \dots, F_n$ as elements. To be able to analyze them in the context of RSs, they can be encrypted in a User-Feature-Value matrix stored in a binary Allocation Matrix $AM(U_i, F_j)$, where (1) states a selected feature-value and (0) an unselected feature-value. Within a feature, the feature-values are in the “Exclusive-Or” (XOR), which extends the set of rules presented so far. The associated Boolean constraints are formulated in the Conjunctive Normal Form (CNF) and shown in Figure 1. The entire set of rules in this case is given as a minimal logical expression in one term.

$User\ U_i$
$with\ i = 1, \dots, m\ \in\ \mathbb{N}$

$Feature - Value\ F_j\ \in\ M$
$with\ j = A, B, C, \dots, n$
$M = \{F_A, F_B, F_C, \dots, F_n\}$

	F_A	F_B	F_C	F_D	F_E	…	F_n
U_1	1	0	1	0	1	…	0
U_2	1	0	1	1	0	…	1
U_3	1	1	0	1	0	…	0
⋮	⋮	⋮	⋮	⋮	⋮	⋱	⋮
U_m	1	1	0	1	0	…	1

$Constraints\ formulated\ in$
$Conjunctive\ Normal\ Form\ (CNF)$

$$F_A \land \\ (F_B \lor F_C) \land \\ (\neg F_B \lor \neg F_C) \land \\ (\neg F_D \lor \neg F_E) \land \\ (\neg F_B \lor F_D) \land \\ (\neg F_C \lor F_D \lor F_E)$$

$$Allocation\ Matrix\ AM(U_i, F_j) = \begin{cases} 1, & if\ F_j\ is\ choosen\ for\ U_i, \\ 0, & if\ F_j\ is\ not\ choosen\ for\ U_i. \end{cases}$$

Figure 1: Historical Allocation Matrix $AM(U_i, F_j)$ and associated Boolean constraints

5. Results & Discussion

Collaborative filtering methods use a User-Item matrix as the input for the calculation, where rows represent users and columns represent items. An entry in the matrix links a user to an item. For the use case in the automotive industry, the usage of the User-Feature-Value matrix is proposed instead, described in the section above. A User-Item matrix could not be evaluated appropriately because customers usually only buy one vehicle and use it for multiples of the time as most products of everyday use. Furthermore, in the context of variant configuration, the relationships between the feature-values and the users (customers) are of importance.

In the following, the three selected methods of RSs and their possible application considering the research objectives are described.

5.1. Collaborative Filtering

CF approaches can be divided by their procedures into the two categories user-based filtering und item-based filtering. The main idea of user-based filtering is to first calculate a user group with users from the database, which showed similar preferences as the target user. Subsequently, it is determined what users of this user group rated high or bought in order to predict what else the target customer might like. In contrast, item-based filtering looks for relationships between items by calculating an Item-Item matrix. Thereafter recommendations are given to a target user by searching the matrix for items closely related to those the target user bought or was interested in in the past. To calculate the similarity between users and between items respectively, distance metrics like cosine similarity or Pearson correlation coefficients can be used.

The proximity measure cosine similarity calculates the cosine of the angle between two vectors. In the case of user-based filtering the two vectors represent two customers a and b in the n-dimension item space, see Formula 1 [7].

Cosine Similarity: $$Similarity\ (a,b) = \cos\left(\vec{a},\vec{b}\right) = \frac{\vec{a}\cdot\vec{b}}{\|\vec{a}\|_2 * \|\vec{b}\|_2} \qquad (1)$$

In the case of item-based filtering the same proximity measure can be used, with the difference that the two vectors represent two items in the m-dimensional user space. To consider the difference in the rating scales of users some adjustments can be made, described by Sarwar et al. [7]. The proximity measure Pearson correlation for two customers a and b can be calculated based on their respective ratings r_{ai} and r_{bi} for item i in Formula 2 as follows:

Pearson Correlation: $$Correlation\ (a,b) = \frac{\sum_{i=1}^{n}(r_{ai}-\overline{r_a})*(r_{bi}-\overline{r_b})}{\sqrt{\sum_{i=1}^{n}(r_{ai}-\overline{r_a})^2 * \sum_{i=1}^{n}(r_{bi}-\overline{r_b})^2}} \qquad (2)$$

Differences in the ordinal scaled rating scale of different users are taken into account by subtracting the user average ratings $\overline{r_a}$ and $\overline{r_b}$ from the respective user ratings. The Pearson correlation can be used for item-based filtering respectively with item-ratings [7].

In the application within e-commerce, the user-based filtering approach has its limits [7]. The process of neighborhood formation is a performance bottleneck if recommendations are sought in real-time. Item-based filtering has the major advantage that the similarity calculation between items can be calculated beforehand, given the preliminary that the set of items is more stable than the set of users. Furthermore, they can be stored in a reduced manner considering only the k-most similar items to each item, as only a subset of the similar items is relevant for the recommendation calculation [7].

The general approach of CF is applicable to the automotive industry, but it suffers some major downsides. The database in the automotive industry is systematically smaller than for everyday products because, first, they are purchased less frequently and usually only one product is owned at a time [14]. Since the Item-Feature-Value matrix is nominal scaled and comes down to a simple counting of common feature-values (Hamming metric) due to its binary notation, it is not suitable for a comprehensive description of a customer in this case. User rating data is not available for this study and generally hard to obtain. In automotive manufacturing, CF has so far only been applied in peripheral areas such as ergonomic design based on image-based CF [20]. The general approach is not designed to satisfy additional constraints applied to the set of items. In the presented use case, this will result in vehicle orders which are not feasible and therefore not applicable for planning. An often-mentioned general problem of RS is the “Cold Start” problem [16]. The Cold Start or New item/new customer problem refers to missing data on a new and not yet evaluated item or user [8]. Since the proposed approach relies on the use of historical data and not only feature-values but also constraints change over time, these approaches face the Cold Start problem in the form of new feature-values and new constraints if applied within the development process. While CF approaches offer limited possibilities for planning, they can be used to make recommendations to customers during the configuration process based on the calculated similarity to other customers who configurated a similar car. As a particularity, it should be remembered that the recommended configuration needs to continue to satisfy the given constraints.

5.2. Association Rule Mining

Association Rule Mining (ARM) is a data mining technique aiming to find association rules as $X \rightarrow Y;\ X, Y \subseteq M;\ X \cap Y = \emptyset$ which state that if set X is chosen, then set Y has to be chosen as well and both X and Y are subsets of M. A common model for the mining process is the support-confidence framework established by Agrawal et al. [6]. In this model, the two quality measures support and confidence are calculated, where support refers to frequencies of occurring patterns (see Formula 3) and confidence to the strength of the implication (see Formula 4) [6, 21, 22].

Support: $$supp\ (X \rightarrow Y) = \frac{\text{number of transactions X} \cup \text{Y}}{\text{number of transactions}} = Support\ (X\ \cup\ Y) \qquad (3)$$

Confidence: $$conf\ (X \rightarrow Y) = \frac{\text{number of transactions X} \cup \text{Y}}{\text{number of transactions X}} = \frac{Support\ (X \rightarrow Y)}{Support\ (X)} \qquad (4)$$

Minimum values for support and confidence have to be set manually defining when to consider an association rule (user-specified threshold). To tackle the task of calculating frequent item sets the Apriori algorithm is the most famous one. For an overview of existing algorithms for ARM see [23, 24]. Considering the described use case, many of the found association rules will represent existing constraints and their transitive relations. A method for mining association rules containing attributes to satisfy one or multiple given Boolean constraints is described in [25] as “Constraint-based Rule Mining”.

There are multiple advantages in using ARM within the planning process. The recommendations are interpretable and make explanation possible to name the first. Furthermore, association rules that are found can be modelled in the same way as the constraints that exist because of technical, legal or sales restrictions described in the preliminaries. As such, they can be used directly for modelling purposes without any adaption.

For the given use case and the specified historical User-Feature-Value matrix (see $Allocation\ Matrix\ AM$, Figure 1) support and confidence for an exemplary association $F_A \rightarrow\ F_B$ can be calculated in Formula 5 and 6 as follows:

$$supp\ (F_A \rightarrow F_B) = \frac{\sum_{i=1}^{m} x_i}{m} \quad with\ x_i = \begin{cases} 1, & AM(U_i, F_A) = 1\ and\ AM(U_i, F_B) = 1 \\ 0, & else \end{cases} \tag{5}$$

$$conf\ (F_A \rightarrow F_B) = \frac{\sum_{i=1}^{m} x_i}{\sum_{i=1}^{m} y_i} \quad with\ x_i = \begin{cases} 1, & AM(U_i, F_A) = 1\ and\ AM(U_i, F_B) = 1 \\ 0, & else \end{cases} \tag{6}$$

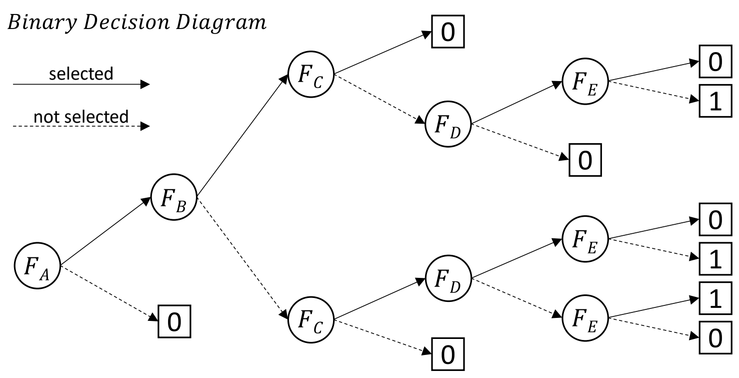
$$and\ y_i = \begin{cases} 1, & AM(U_i, F_A) = 1 \\ 0, & else \end{cases}$$

After the association rules are mined against a user-specified threshold, they need to be checked whether they satisfy and are not transitive relations of the given Boolean constraints. In this way, associations of subsets of feature-values, for example $X_1 \rightarrow Y_1$ with $X_1 = \{F_A, F_B\}$ and $Y_1 = \{F_C, \ldots, F_n\}$ can be explored and discovered as well. Using this combination of feature-values to subsets, possible candidates of packaging can be investigated and recommended to a product manager in the early phase of the development process.

5.3. Bayesian Networks

A Bayesian Network (BN) is a directed acyclic graph, in which each variable is represented by a node and each conditional probability is represented as a directed edge [26]. The conditional probability to each variable is given under the condition of the occurrence of its parents [26]. Two variables A and B are called conditionally independent if $P(A,B|C) = P(A|C) * P(B|C)$ [13]. For the generation of a BN, it is necessary to have the structure of the network itself, which is derived from the causality of the use case, and the corresponding Conditional Probability Table (CPT) [26]. To represent the probability table in recommendation approaches, BNs use a decision tree structure to indicate the dependencies in a graphical and compact notation [28].

Revankar and Haribhakta categorize BN-Model alongside cluster models as model-based collaborating filtering approach [29]. Model-based BN approaches base their recommendation not only on item attributes (such as gender, age, salary), but also on contextual knowledge and domain knowledge [11]. Typically, the structure of the BN is created by the experience of an expert. Since the structure of the BN is generated from the available constraints in the presented use case, it is considered a constraint-based/knowledge-based approach. According to the available Boolean constraints, dependencies are mapped and provided with conditional probabilities derived from the historical vehicle orders. The following Figure 2 shows a simplified Binary Decision Diagram (BDD) representing the rule-based dependencies and the corresponding CPT for F_D and F_E calculated with the available historic data AM and the given Boolean constraints (see Figure 1).



$CPT\ for\ F_D\ and\ F_E$

F_A	F_B	F_C	F_D	F_E
1	0	0	0	0
1	1	0	$P(F_D|F_B)$	0
1	0	1	$P(F_D|F_C)$	$P(F_E|F_C)$
1	1	1	0	0

$Bayes'\ Theorem$

$$P(F_D|F_B) = \frac{P(F_B|F_D) * P(F_D)}{P(F_B)}$$

Figure 2: BDD and corresponding CPT for given Boolean constraints

One major advantage of BNs is that the used constraints can be directly considered in the model and this approach provides explainable and interpretable results with probability of occurrence at the same time. Since the probability of occurrence is formulated as a conditional probability, the calculation is very similar to the approach of calculating support and confidence in ARM (see above Formula 3 and 4) and offers a promising approach for improving the results in the generation of synthetic data for planning [19].

An existing problem is the new item problem for a new feature-value for which there is no historical data. In addition, the huge amount of data necessary to calculate a stable CPT is directly dependent on the depth of the BN itself. After each decision for a feature-value, only historical data with this feature-value will continue to be used. Another issue is the effect of the order of decisions on which all further decisions are conditionally dependent. In particular, the choice of the first nodes has an immense impact on the structure of the BN and can be chosen differently with the available constraints. Thus, the approach is partially applicable for the consideration of dependencies extracted from existing projects and can support the forward sourcing of follow up projects. Up to a limited depth of the BN, the approach can be used with BDD and must then be combined with other methods for finding solutions in order to obtain usable results. One example of such an additional method is described in Demke et al. [19].

6. Conclusion & Future Research

On the one hand, analysis of the studied literature points out that the selected methods of RS have already been described and studied sufficiently and in depth. On the other hand, a lack of application of the presented methods for the transfer of knowledge to the use case of the automotive industry was determined. To the best of our knowledge, previous research of RSs in automotive industry has only referred to e. g. the use of "software multi-agent systems" [12] or was limited to identifying target customers based on combining user-attribute and item-attribute matrix and applying an ARM and CF approach [14]. Since the use case has special requirements due to the underlying variance scheme and the explicitly required explainability of the results for planning processes, the identified advantages and disadvantages of the considered approaches to the use case as well as the proposed application to solve the formulated research objectives are listed in the following Table 1 below:

Table 1: Comparison of the considered approaches regarding the specified use case

Method	Advantages	Disadvantages	Proposed Application
Memory-based Collaborative Filtering (CF)	Generally applicable because of low sparsity in item/feature-lists Works without explicit knowledge of given constraints	Bad scalability No possibility to include constraints Low explainability Focus on target-user Cold Start problem (especially new user)	Making recommendations during the configuration process
Model-based Association Rule Mining (ARM)	High interpretability of the results Same representation as existing constraints Additional constraint check possible (constraint-based-rule-mining)	Long runtime for dynamic models User-specified threshold Cold Start problem (new items and constraints)	Deriving new constraints Packaging and optimizing offering program
Model-based/ Knowledge/ Constraints-based Bayesian Networks (BN)	Works with the constraints model description High explainable and interpretable decisions because of BDD Independent of knowledge engineer (Expert)	Amount of data necessary to calculate a stable CPT Dependent on sequence of decisions Cold Start problem (new items and constraints)	Extract dependencies for creating synthetic vehicle orders for forward sourcing

In conclusion, the application of the presented methods for the described use-case is feasible and desirable. CF is generally suitable for recommendations to users based on User-Item matrixes, feature-value lists and user ratings. The results are poorly explainable and do not work with additional constraints. Since the ordinally scaled customer ratings are hard to obtain, the approach is only of limited use for the application of recommendations in the configuration process working with the available customer data. ARM can be applied for finding new explainable constraints to include in the offering program with the goal to reduce the variance. The results must be checked afterwards whether they are not transitive relations of the given constraints and if they still satisfy them. The approach is promising to support the product development in the early phase with data-driven recommendations and to use customer associations from the past to make the product portfolio of the future more competitive. BNs are suitable to represent and simulate customer configuration processes and provide explainable analysis. They offer the possibility to find and visualize dependencies and model customer behavior based on conditional probabilites given previous choices. At the same time, this approach is the most demanding in terms of required data.

All three investigated methods suffer the Cold Start problem in different forms. This specially refers to changes in feature-values and constraints over time, which challenges the analysis beyond the Cold Start in the original sense. Therefore, all the investigated approaches are under the limitation of the variability of the variance scheme over time, which will be part of future research in the domain of planning based on probabilistic models.

References

[1] Herlyn, Wilmjakob: Zur Problematik der Abbildung variantenreicher Erzeugnisse in der Automobilindustrie. Düsseldorf: VDI Verlag, 1990.

[2] Stich, Volker; Quick, Jerome; Cuber, Stefan: Konfiguration logistischer Netzwerke. In: Günther Schuh und Volker Stich (Hrsg.): Logistikmanagement. Berlin, Heidelberg: Springer Berlin Heidelberg, 2013, S. 35–75.

[3] Zagel, Mathias: Übergreifendes Konzept zur Strukturierung variantenreicher Produkte und Vorgehensweise zur iterativen Produktstruktur-Optimierung. 2. Aufl. Kaiserslautern: Techn. Univ. Kaiserslautern, Schriftenreihe VPE, Band 1, 2006.

[4] Holtze, Peter: Data Mining in der Bedarfsprognose von Komponenten und Teilen. Neue Ansätze zur Planung einer variantenreichen Serienfertigung. Aachen: Shaker, Innovationen der Fabrikplanung und -organisation, Band 2, 2000.

[5] Frischen, Christian et al.: Durchgängige Variantensteuerung mit Hilfe der regelbasierten Komplexstückliste. In: Krause, Dieter; Paetzold, Kristin; Wartzack, Sandro (Hrsg.): DFX 2019: Proceedings of the 30th Symposium Design for X, Jesteburg, Germany. 18th-19th September 2019: The Design Society, 2019, S. 13-24.

[6] Agrawal, Rakesh; Imieliński, Tomasz; Swami, Arun: Mining Association Rules Between Sets of Items in Large Databases. In: ACM SIGMOD Record 22 (2), 1993, pp. 207–216.

[7] Sarwar, Badrul et al.: Item-based Collaborative Filtering Recommendation Algorithms. In: Vincent Y. Shen, Nobuo Saito, Michael R. Lyu and Mary Ellen Zurko (eds.): Proceedings of the 10th International Conference on World Wide Web - WWW '01. The 10th International Conference. Hong Kong, Hong Kong, 01.05.2001 - 05.05.2001. New York, New York, USA: ACM Press, 2001, pp. 285–295.

[8] Adomavicius, Gediminas; Tuzhilin, Alexander: Toward the Next Generation of Recommender Systems: A Survey of the State-of-the-Art and Possible Extensions. In: IEEE Transactions on Knowledge and Data Engineering. 17 (6), 2005, pp. 734–749.

[9] Goldberg, David et al.: Using Collaborative Filtering to Weave an Information Tapestry. In: Communications of the ACM 35 (12), 1992, pp. 61–70.

[10] Almonte, Lissette et al.: Recommender Systems in Model-driven Engineering: A Systematic Mapping Review. In: Software and Systems Modeling 21 (1), 2022, pp. 249–280.

[11] Felfernig, Alexander; Burke, Robin: Constraint-based Recommender Systems: Technologies and Research Issues. In: Dieter Fensel and Hannes Werthner (eds.): Proceedings of the 10th International Conference on Electronic Commerce - ICEC '08. The 10th International Conference. Innsbruck, Austria, 19.08.2008 - 22.08.2008. New York, New York, USA: ACM Press, 2008, pp. 17–26.

[12] Mavridou, Efthimia et al.: Mining Affective Needs of Automotive Industry Customers for Building a Mass-Customization Recommender System. In: Journal of Intelligent Manufacturing 24 (2), 2013, pp. 251–265.

[13] Thi Do, Minh-Phung; van Nguyen, Dung; Nguyen, Loc: Model-based approach for Collaborative Filtering. University of Information Technology. In: The 6th International Conference on Information Technology for Education (IT@EDU2010), 2010.

[14] Yao, Liming et al.: Synergies Between Association Rules and Collaborative Filtering in Recommender System: An Application to Auto Industry. In: Fausto Pedro García Márquez and Benjamin Lev (eds.): Data Science and Digital Business. Cham: Springer International Publishing, 2019, pp. 65–80.

[15] Burke, Robin: Hybrid Recommender Systems: Survey and Experiments. User Model User-Adap Inter. In: User Modeling and User-Adapted Interaction 12 (4), 2002, pp. 331–370.

[16] De Campos, Luis M. et al.: Combining Content-based and Collaborative Recommendations: A Hybrid Approach based on Bayesian networks. In: International Journal of Approximate Reasoning 51 (7), 2010, pp. 785–799.

[17] Astesana, Jean-Marc; Cosserat, Laurent; Fargier, Helene: Constraint-based Vehicle Configuration: A Case Study. In: 2010 22nd IEEE International Conference on Tools with Artificial Intelligence (ICTAI). Arras, France, 27.10.2010 - 29.10.2010: IEEE, 2010, pp. 68–75.

[18] Kuhl, Juliane; Üreten, Selin; Krause, Dieter: Challenges of Modular Product Families and Product Personalization - An Interview Study. In: IEEE International Conference on Industrial Engineering & Engineering Management, Singapore, 2021, pp. 447-451.

[19] Demke, Niels et al.: Derivation of probability-based configurations for early feasibility statements in the development of products with high variance. Helmut Schmidt University, Hamburg, 2021.

[20] Jung, Ho-Ill et al.: Ergonomics Automotive Design Recommendation Using Image Based Collaborative Filtering. In: 2012 International Conference on Information Science and Applications. 2012 International Conference on Information Science and Applications (ICISA). Suwon, Korea (South), 23.05.2012 - 25.05.2012: IEEE, 2012, pp. 1–6.

[21] Zhang, Chengqi; Zhang, Shichao: Association Rule Mining. Models and Algorithms. Berlin-Heidelberg: Springer Nature, 2002, pp. 25–39.

[22] Beierle, Christoph; Kern-Isberner, Gabriele: Maschinelles Lernen. In: Beierle, Christoph; Kern-Isberner, Gabriele: Methoden wissensbasierter Systeme: Grundlagen, Algorithmen, Anwendungen: Vieweg+Teubner, 2008, S. 147–157.

[23] Kumbhare, Trupti A.; Chobe, Santosh V.: An Overview of Association Rule Mining Algorithms. In: International Journal of Computer Science and Information Technologies (IJCSIT) 5 (1), 2014, pp. 927–930.

[24] Kaushik, Minakshi et al.: A Systematic Assessment of Numerical Association Rule Mining Methods. In: SN COMPUTER SCIENCE 2 (5), 2021, pp. 348.

[25] Adamo, Jean-Marc: Constraint-Based Rule Mining. In: Data Mining for Association Rules and Sequential Patterns; Sequential and Parallel Algorithms. New York, Berlin, Heidelberg: Springer, 2001, pp. 67–78.

[26] Ertel, Wolfgang: Maschinelles Lernen und Data Mining. In: Wolfgang Ertel (Hrsg.): Grundkurs künstliche Intelligenz. Computational Intelligence. Wiesbaden: Springer Fachmedien Wiesbaden, 2016, S. 191–264.

[27] Getoor, Lise; Sahami, Mehran: Using Probabilistic Relational Models for Collaborative Filtering. In: In Workshop on Web Usage Analysis and User Profiling (WEBKDD'99), 1999.

[28] Hameed, Mohd Abdul; Jadaan, Omar Al; Ramachandram, Sirandas: Collaborative Filtering Based Recommendation System: A survey. In: International Journal on Computer Science and Engineering (IJCSE) 4 (5), 2012, pp. 859–876.

[29] Revankar, Omkar S.; Haribhakta, Yashodhara V.: Survey on Collaborative Filtering Technique in Recommendation System. In: International Journal of Application or Innovation in Engineering & Management (IJAIEM) 4 (3), 2015, pp. 85–91.