From Data Science to Value Creation

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Abstract. Value creation with data science methodologies generates important insights. However, these insights do not systematically provide service value to customers. Therefore, we show a systematic approach to use data science for the process of service design. We develop a structure of data science methodologies in the dimensions of their potential to create service benefit. This enables the mapping of the value contribution of the data science tools on the different perspectives and phases of the service design process. Based on this mapping, a direct link can be established between the outcomes of the data science methodologies and the value drivers for the customer. The resulting new methodology allows the systematic value creation from insights generated by data science.

Keywords: Service science · Data science · Service design · Data product design · Data-driven value creation

1 Introduction

This paper describes a new methodology for creating value from data science. Specifically, the goal is to develop data-based services and products starting with insights generated by data science tools. According to [1] data science tools provide insights which support decision making. However, these insights do not yet make up data products for which user or customers are ready to pay. For new data science-based results the appropriate business applications often are not obvious. In other words, data science tools may provide solutions for which we need to find a suitable application. Therefore, this article describes a way how to systematically design services given data science-based outcomes.

The generic value chain for data-intensive user services is shown in Fig. 1. We assume that we have data available as well as the data science tools to create insight from this data. However, we lack a methodology how to create service value for users out of the insights. The literature provides numerous sources describing how to extract value from data. [1] describes how data science can be used as a driver for analytical engineering and how organisations can incorporate data science in their business strategy. [2] provides an long list of data science applications across various industries and use cases. These sources focus on the generation of insights from data, which represents an essential prerequisite for the creation of value from data. However, it is not clear whether these insights

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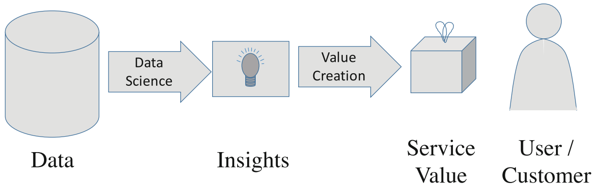

Fig. 1. Creating user value out of data science-based insight

can be considered providing service value from the user's perspective or if there are customers willing to pay.

According to [6] data products are not about data, but about enabling users to do what they want to do. Data products are to deliver results rather than data and data is invisible in the product. [7] points out that data products must always be designed based on the user's objectives in order to create actionable value and not just more data. The so-called drivetrain approach is proposed to find the optimum actionable outcome. Both [6,7] make clear that data products need to be designed to meet the user's objectives and needs.

In order to make sure that the resulting services and products generate value for users, the concepts of service design and service science can be applied, which provide a systematic procedure to create service value for users and customers. The service concepts are based on the assumption that the beneficiary of the service there is always a human being [3]. This holds also for industrial services (e.g., in the Industry 4.0 context), in which human actors are creating value typically supported by technical machines. Services are usually provided in service systems, which are configurations of people, technologies, organisations, and information that create and deliver value to all stakeholders in the system [3,4].

Therefore, we now put the focus on the problem of understanding the user's needs and designing value propositions to meet those needs. When talking about value creation for humans, there are the established tools for service design [11–13]. These tools point out that the value needs to cover both functional as well as emotional user needs (in [11] so-called jobs, pains and gains).

The challenge "How to use data science for service innovation?" is addressed in the literature. In [8] an approach is shown to combining service design with business analytics to improve the service innovation process. However, the approach is focussed on the very specific aspect of identifying patterns of customer behaviour and product usage by customers. The literature [1] discusses the application of data science for business and states that business problems need to be decomposed into sub-problems that can be solved by analytics. The approach is primarily focused on the solution design (the phase "Design of Value Proposition and Processes" in Fig. 3). Also [9,10] apply analytics or artificial intelligence for the segmentation of customers or understanding customer behaviour. Although these approaches highlight important potentials to improve service innovation with the help of data science, there are many additional aspects of the service design process which can leverage the benefits of data science. The literature about service design [11–13] describes the phases of the process for engineering customer-centric services. It becomes clear that in various steps of this process, analytics can help finding better solutions. However, we lack a systematic approach for this support.

According to [4] the application of data's value for smart service systems represents a current research challenge. [5] suggests that the application of advanced technology like smart systems or cognitive computing to advance service is put on the research agenda.

The approach discussed in this paper differs from the approaches in the literature in two ways: First, it considers the application of analytics for the end-to-end service design process, i.e. comprising all phases of Fig. 3. In particular, the phases preceding and following the design of the value proposition are considered. Second, the approach discussed here explicitly takes into account a literature-based structure of data analytics w.r.t. the potential benefits (Fig. 2).

In Sect. 2 we elaborate a structure of data science tools which can be mapped on the structure of the service design process. The latter is discussed in Sect. 3. The mapping scheme of the data science tools to the service design process is presented in Sect. 4. Section 5 provides application examples for the new approach.

2 Structure of Data Science Tools and Their Value Contribution

In this section, we structure the data science-based tools according to their potential contribution to create service value (Fig. 2). The nine boxes in Fig. 2 represent fundamental data mining concepts according to [1]. We use them as basic elements of data science-based insights. They can be combined to larger data science models targeting at value creation for specific service design constellations. Thus, we have a toolbox available for the creation of service value.

The data science concepts can be differentiated into unsupervised and supervised data mining methods (left-hand side of Fig. 2). In case of open, explorative problem statements without a clear goal the unsupervised methods can be applied (e.g., not yet clear how to segment the users or which are the stages of the customer journey). On the other hand, if insights for specific problem statements with specific variables are required, supervised methods are selected (e.g., whether a specific service will be used and paid by customers in a specific situation).

The examples on the right hand side of Fig. 2 are adapted and generalised from [2] and represent an abstract of all potential applications. They suggest elements of potential data products. Figure 2 helps to find elements of services that can be created when we have a specific set of data science-based methodologies available. Therefore, this approach provides a means to find potential data products.

The challenge that we now have to solve is the following: the data science-based outcomes shown in Fig. 2 represent solutions. However, we do not yet

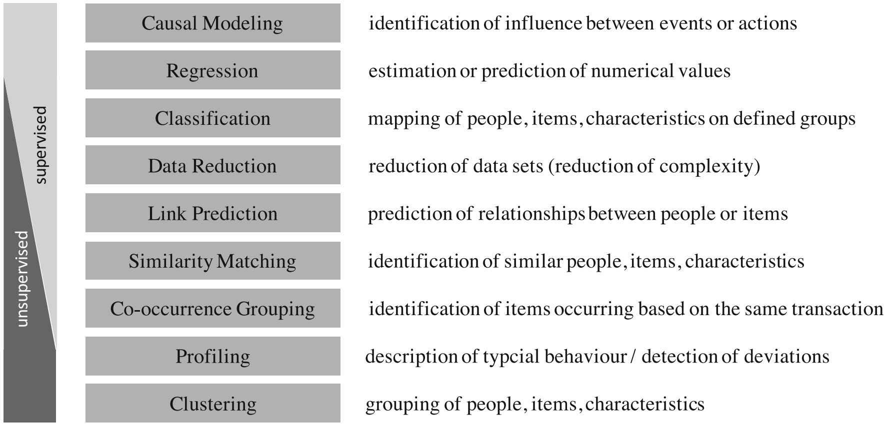

Fig. 2. Structure of data science-based insights with their benefits for services

know for which user this solution may be useful and in which context. I.e., generating data science-based insights provide solutions for yet unknown user needs. Therefore, a process for modelling the user is presented and discussed in Sect. 3.

3 Design of Service Value for Users

Service science and service design provide us with a rich toolbox of methodologies for creating value for users [3,11–13]. There are many variants of the service design process, but they have in common that they generate user insights and an understanding of user needs at a very early stage of the process and then iterate in designing, testing, and improving the value proposition [11–13]. We define here the service design process as shown by the steps in Fig. 3. We differentiate the overarching phases "explore" (for understanding the user and his needs), "create" (for designing the solution), "reflect" (for testing and improving the solution in co-creation with users), and "implement" (for the operational and market deployment of the service).

The process starts with setting the application field describing the situation and context in which the user's challenge is located (e.g., the application field may be "user wants to travel from A to Z"). Next, the phases "Customer Insight Research" and "Customer Profile Modelling" help to understand the user's needs (jobs, pains, gains) in the different contexts and along his user journey. Upon this, in the phase "Design of Value Proposition and Processes" the service and the service processes are designed to fit with the user needs in terms of the jobs, pains and gains. In the phase "Test and Improvement", the service is tested with users (e.g., "Does the value proposition fit the user's needs?", "Do users understand and like the service?", etc.). Note that from this phase the service design process usually jumps back to the previous phases for re-designing the

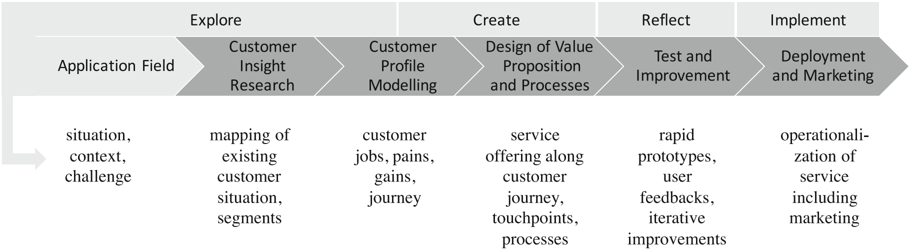

Fig. 3. Phases of the service design process

value proposition, or even for adapting the customer profile. I.e., there are several iterations of "design – test – improve" until the service is found to be ready for deployment. In the last phase of the service design process the service is operationalised and marketed.

In each phase of this process there are design and engineering challenges to be solved. In the phase "Customer Insight Research", for example, the challenge is to capture and quantify the functional and emotional needs and to classify them into segments for the next phase "Customer Profile Modelling", in which the typical customer profiles are described. In the phase "Design of Value Proposition and Processes", the task is to identify service elements which provide relevant value to the user. In the phase "Test and Improvement", the hypothesis for the value proposition needs to be assessed quantitatively. If it is falsified (e.g., the target customer does not sufficiently appreciate the service), a new hypothesis for the value proposition needs to be designed (iteration of "design – test – improve").

4 Identifying the Value Drivers for the Data Tools

In Sect. 2 the fundamental concepts of data science are structured and mapped to potential data products. In Sect. 3 the steps of the service design process and the corresponding design challenges are discussed.

A coupling matrix is now developed bringing the service design phases of Fig. 3 in relation with the data science-based insights discussed in Fig. 2. The approach is now to map the available data science tools to the design phases such that they provide value. The mapping has been developed as follows: for each phase of the service design process of Fig. 3, the typical problem statements as described in Sect. 3 haven been put in relation with the outcomes of the data science tools (Fig. 2). For instance, in the phase "Customer Insight Research", the identification of customer segments with similar needs is one of the most relevant challenges, to which clustering can contribute substantially. In this way, the mapping of the data science tools on the different phases of the service design process has been constructed. The result is shown in Fig. 4. The dots in the matrix show to which phase of the service design process the different data science tools can contribute value. The size of the dots has been assigned qualitatively based on the constructed relationship between the data science tool and the phase of the service design process. It qualitatively indicates the strength of this value contribution (small, medium, large contribution). The empirical validation of this constructed mapping is subject to further studies.

Generic application pattern (dots with numbers 1 to 5 in Fig. 4): In a given business situation in a consumer service context, we may have data available about our customer's past behaviour and how they used various products. This data allows us to cluster customers into groups depending on different attributes (dot 1 in Fig. 4), i.e. to define our customer segments. We can describe a typical customer behaviour using profiling algorithms (dot 2 in Fig. 4). In the value proposition design phase, we may apply almost the full spectrum of data science tools to design our product or service (cluster of dots 3 in Fig. 4): for instance, we may have external data sources about environment conditions (e.g., weather and traffic) allowing us to apply co-occurrence algorithms to analyse in which context the customer is most likely to have which specific problem or pain and design the service features accordingly. Or we may use classification or link prediction to assign service features to specific users or contexts. Additionally, for an early estimation of a business case for our new service, we may have data for regression models indicating the intensity of the service usage and the willingness to pay. In the test phase (dot 4 in Fig. 4), we can apply causal modelling to avoid test insights based on correlations, for example. And, for the go-to-market-phase, we may have data to apply classification for target marketing (dot 5 in Fig. 4).

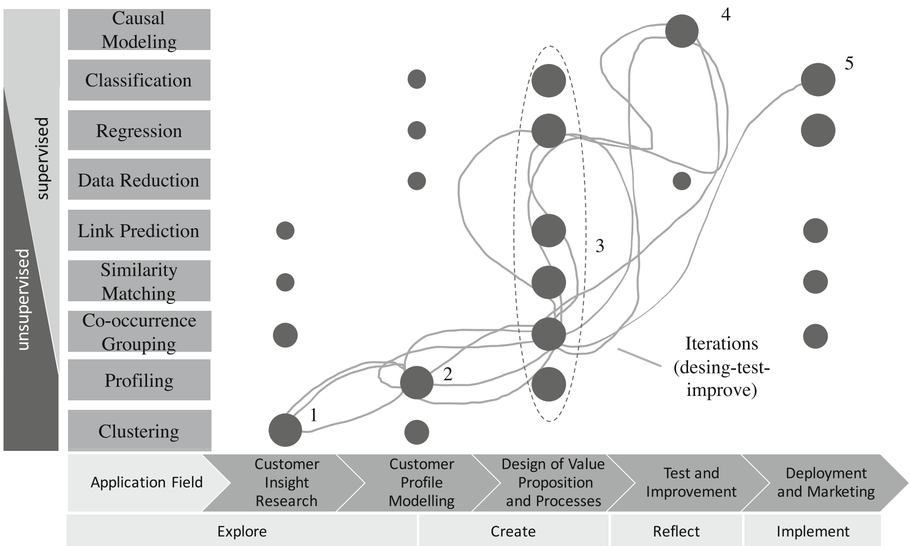

Fig. 4. Mapping the data science-based insights on the service design process

Like the service design process, the procedure to use the data science tools for finding data-driven value propositions is not a linear one. The design process is highly iterative and goes forth and back (again, iterations of "design – test – improve"). These iterations are indicated by the squiggle in Fig. 4.

5 Application Examples

The mapping scheme of Fig. 4 and the generic application pattern of the previous section were applied in first case studies. We discuss two different kinds of cases in this section.

A first case study was conducted with a service provider striving for a new offering in the area of "connected home". Thus, the application field was given, but it was not yet clear which value proposition this service should provide to which customer segments. Various demographic and behaviour data were available. A clustering of customers with different attributes can show whether customers fall into natural groups (e.g., based on the place of residence, patterns of presence and energy consumption etc.). Co-occurrence grouping can be applied to look for customers who already use similar services. The typical behaviour of customers on the company's website can be investigated by profiling. Deviations from these patterns of behaviour may indicate an opportunity for the new service. The value proposition then refers to the customer segments and the customer profile. For example, by a combination of classification and regression, the energy consumption can be predicted for the identification of potential savings. Finally, classification may support personalised marketing campaigns.

In contrast to the previous example for a new service development, many application examples do not follow the service design process in a linear way. For the second example, a case study was investigated in which technical tools for speech-to-text and natural language processing were available and the application field was in the context of customer service representatives (CSRs). The task was then to elaborate how the benefit of these technical tools can be leveraged for the daily work of the CSRs. Thus, considering the CSRs as the customers of the service, the technical tools were considered contributing to the service design phase "Design of Value Proposition and Processes" in Fig. 4. To start, we went back to the phase "Customer Insight Research" to understand the functional and emotional needs of the CSRs and to cluster them into segments. In the case study, this step was partly done using qualitative methods since limited quantitative data was available. Next, the typical journeys and profiles of the CSRs could be described. This allowed us to return to the phase "Design of Value Proposition and Processes" and shape a precise value proposition based on the technical tools (i.e., based on speech-to-text and natural language processing). The value proposition was then focused on the support of the CSR during the dialog with the customer and comprised the following elements: the automatic retrieval of customer data records, the estimation of the customers context situation, the presentation of offers to be made, as well as the recording of the conversation with the customer in a structured way.

6 Conclusions and Further Development

In this paper the question how to get value out of data science-based insights was discussed. First, a structure for the data science principles was shown with their potential contribution to service value creation. Then, the service design process was outlined. The design challenges in the different phases of the service design process were discussed, thus revealing where the data science-based insights can plug in for deploying their value. Finally, the data science and the service science approaches were combined in a new structure which outlines the application of data science along the process of service design.

This new structure has been developed and validated with several practical use cases so far. Complementary research will validate the applicability of the scheme in different industries and different service constellations and adapt it based on the outcomes. Additionally, the constructed mapping scheme of Fig. 4 needs to be verified with more and different empirical application examples. Moreover, the approach discussed in this paper started on the technical side, i.e., the data science-based insight, and then searched for user value contributions fitting to this. Future research will additionally take into account starting on the user side, i.e., the application field and the user's jobs, pains, and gains, and then look for appropriate data science contributions to support the targeted value proposition design.

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