A Conceptual Framework for Enhancing Product Search with Product Information from Reviews

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Research-in-Progress

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Abstract

Product search today is limited, as users can only search and filter for a restricted set of product features, e.g. 15" and 1TB hard disk when searching for a laptop. The often decision-critical aspects of a product are however hidden in user reviews ("noisy fan" or "bright display") and are not available until a product has been found. This paper proposes a conceptual framework for the integration of product aspects, that have been mined and derived from consumer reviews, into the product search. The framework structures the challenges that arise in four major fields and gives an overview of existing research for each one of them: Data challenges, user experience challenges, purchase process challenges and business challenges. It may inform researchers from various disciplines to perform target-oriented research as well as practitioners what to consider when building up such an enriched product search.

Keywords: User-generated content, product search, product feature extraction

Introduction

The search functionalities offered in today's web shops are limited. As an example, a user searches for a laptop with the following requirements – the size should be 15", have at least 8GB RAM, but most of all the screen should be bright, as the laptop is intended for work outside. In the web shop, the user can select the size of the laptop and RAM, but the search functionalities do not allow to search for a bright screen. For all laptops that match the criteria of size and RAM, the user has to go through all the reviews to get an idea of which laptops have a bright display.

Current search functionalities allow users to search and filter for a limited but objective set of product features, such as screen size. All other aspects, among them decision-critical ones as depicted in the example, are not accessible in the product search. Therefore, a mismatch exists of what users write about in reviews, and what they can search for. The information that users write down in reviews depicts what matters to them, and there is strong indication that this information will also be decision-critical to other users (Cao et al. 2011; Chevalier and Mayzlin 2006), not only *after* they found a product they consider buying, but already during search (Huang et al. 2012).

The number of product reviews increased enormously in the last decade, and ecommerce customers now have a rich source of information at hand to gain insights into the products they consider buying. As the amount of reviews grows constantly, is becomes more important to organize and rearrange reviews (Hu and Liu 2004). As a result, both a problem and an opportunity arise: The emerging problem is that users often feel overcharged with information as they can hardly consume all the reviews (Chen et al. 2009; Furner et al. 2015; Park et al. 2006). The emerging opportunity is that the amount of reviews, sometimes a few hundreds or thousands for a single product, possibly allows to infer from opinions and user experiences to commonly agreed product aspects (e.g. most people stated a "long-lasting battery" or a "noisy fan",). Commonly agreed product aspects (or product features, whereat the term "aspect" is more neutral than "feature", as not only positive aspects are mentioned) first of all can help to provide a condensed view on user experiences, in order to provide a quick overview over the product. Even more, such inferred product aspects could be used in the product search process to provide a richer search functionality (e.g. search for laptops with a "bright display"). Thus, we investigate on the question whether the existence of a high amount of product reviews empowers business innovation in product search, solving both the information overload problem and the lacking possibility to express the keywords that really matter to users in the search process.

Whereas a lot of research has been done on the technical side on how to extract product aspects from user reviews, little is known about how to integrate inferred product aspects into a product search. Hence, we ask: **How can a product search be designed that is enriched with product aspects mined from social media content?**

As open research questions cover a wide field, we see a vital need for a universally valid, flexible, and structuring framework that provides the basis for target-oriented research. As a cohesive approach, such a framework may not only provide a guideline for researchers, but also bring a sustainable understanding of the challenges and opportunities of an enriched product search into practice. For this reason, we construct a conceptual framework that covers several challenge areas: (1) Data challenges, (2) user experience challenges, (3) purchase process challenges and (4) business challenges. For each category, we carve out the challenges and research relevant for this field.

A Conceptual Framework

In this section, we construct an in-progress version of a conceptual framework which may serve as a basis for researchers, but also for innovative teams that want to tailor solutions considering the integration of derived product aspects into the product search process.

Methodology. The development of a conceptual framework requires an iterative design process, that is ideally backed by design science methods and pursues a number of continuous cycles of adjusting and evaluating design alternatives. We opted for the informed argument method of Hevner et al. (2004) and iteratively applied it throughout the design process. As a basic setup, we used the knowledge of our research domain and experiences we have made with implementing prototypes of such a solution, including knowledge from product feature mining, opinion mining, sentiment analysis, information quality theory, user expectations, cost-benefit-analyses and theory about purchase processes. We critically reflected on our own practical experiences with building prototypes as well as recent literature during analytical reflection sessions and built up a first draft of the framework. Over several months we improved the framework stepwise generating alternatives and using the informed argument method (see Figure 1). After each generation-evaluation-cycle, we managed to homogenize different framework alternatives into one coherent framework in reflection sessions. Each cycle advanced the framework leading to the final one as presented in the remainder of this section.

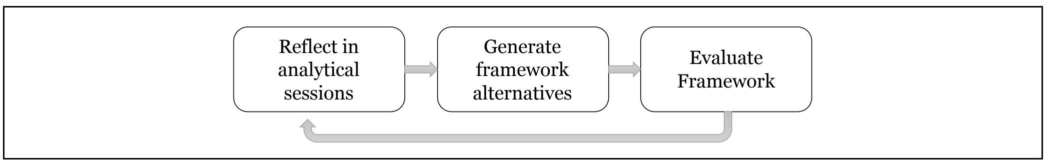

Figure 1. The Generation-Evaluation-Lifecycle using the Informed Argument Method

Figure 2 contains the conceptual framework as a synopsis of four challenge areas that we elicited: Data challenges, User Experience challenges, Purchase Process challenges and Business challenges. The four challenge areas represent the result of the iterative development of conceptual frameworks. The basis for our framework is a four-field matrix with two orthogonal dimensions: In one dimension, it separates set-up time challenges from runtime challenges (vertical axis in Figure 2). We chose this dimension as it structures the approach in a time-related perspective. The other dimension distinguishes the innovative tool from its context and environment (horizontal axis in Figure 2). The distinction between tool and environment has already been proven useful to set up frameworks, e.g., it has been used by Amberg et al. (2003) to measure the acceptance of innovative technologies. Given that one dimension is related to time and the other to the scope, the two dimensions are supposed to be orthogonal. In the preliminary final version of the framework, we filled the four fields with the following application specific challenges: a) Data challenges (tool design / setup time), b) User Experience challenges (tool design / runtime), c) Purchase process challenges (tool environmental / runtime), and d) Business challenges (tool environmental / setup time). The attribution to the four fields can be reasoned as follows: The tool design in the set-up time perspective mainly involves *data* challenges, i.e. the mining of product features; in the runtime perspective it however mainly involves challenges considering the *user experience*. In the environmental perspective we subsume effects outside of the tool itself, which include the effects on the *purchase process* (at runtime) and on *business in general* (setup time). In the following subsections we present the four challenge areas in detail.

Data Challenges

A lot of research has been made on the technical perspective. Several approaches exist on how to extract product aspects from user reviews. In general, information from consumer reviews has to be processed in three steps for the derivation of product aspects: 1. Identification of product aspects in full texts, 2. Analysis of sentiments, and 3. Aggregation of sentiments per product aspect over all reviews.

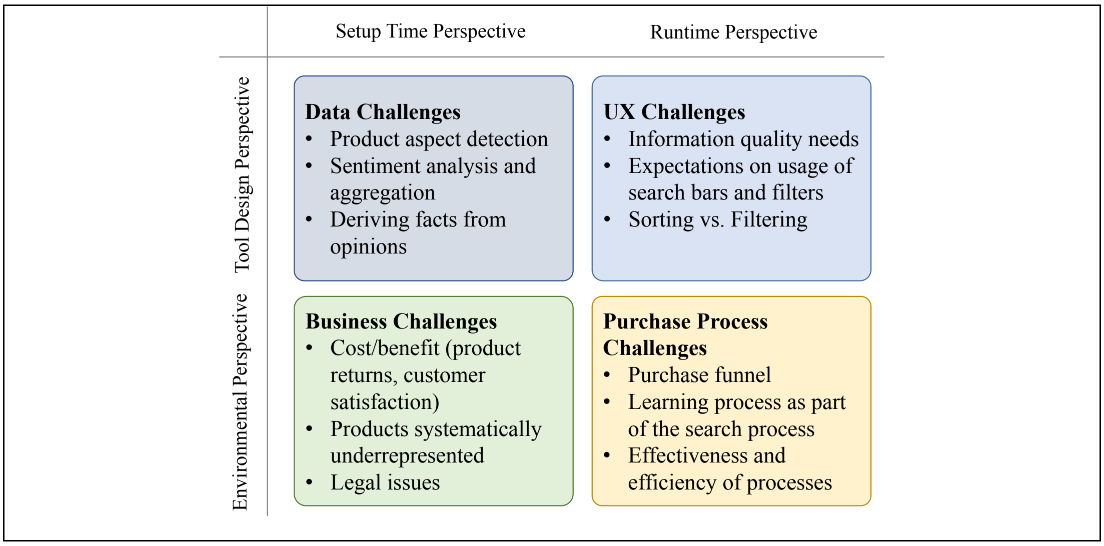

Figure 2. Conceptual framework for a product search enriched with mined product aspects

Product aspect extraction. A lot of research has been done on information extraction, usually with the help of natural language processing (NLP) and domain knowledge in the form of ontologies. We focus on research with particular focus on product aspect identification only.

Huang et al. (2012) proposed an approach to search for restaurants with features extracted from reviews. Similarly, Feuerbach et al. (2017) constructed a system to integrate hotel features mined from reviews into the search process. Dave et al. (2003) proposed a classifier that draws on information-retrieval techniques for feature extraction and scoring in order to generate a list of product attributes (e.g., quality, features, etc.) and aggregate opinions about each of them. Social business intelligence (BI) approaches (Francia et al. 2014) make up an interdisciplinary research area and combine data-mining technologies, natural language processing, and other promising techniques to identify product aspects. Gallinucci et al. (2013) proposed a way to aggregate topics for social BI, and Hu and Liu (2004) proposed an approach to mine and summarize customer product reviews, focusing on product features only and generating feature-based summaries. Further, Popescu and Etzioni (2005) constructed an unsupervised information-extraction system, which mines reviews in order to build a model of important product features. Yang et al. (2016) proposed a combined approach, which integrates local context information and global context information to extract and rank features based on feature score and frequency. Finding a new way of combining supervised and unsupervised learning techniques, Wang et al. (2014) propose two novel semi-supervised models for product aspect extraction. Quan and Ren (2014) propose a method of unsupervised product aspect extraction for feature-oriented opinion determination, where domain-specific features are extracted by measuring the similarity distance of domain vectors. Wei et al. (2009) propose a semantic-based product feature extraction technique that exploits a list of predefined positive and negative adjectives to recognize opinion words semantically and subsequently extract product features expressed in consumer reviews.

Sentiment analysis and aggregation. After product aspects have been detected and sentiments have been assigned, they need to be aggregated across all reviews per product aspect. While sentiment analysis is a well understood research area, less research has been done on the aggregation of sentiments, as this is not a straight forward task and subject to many subjective issues. As aggregating subjective opinions is a challenge, it still leads to more intersubjective information, referred to as objectivity by averaging (Parameswaran and Whinston 2007). Approaches for aggregating sentiments using ontologies have been proposed by Mukherjee and Joshi (2013, also see 2014) and Grandi et al. (2014). As some users might have had a positive experience while others might have had a bad experience, representing the experiences with a location parameter like average or median would lose important information. Research on the distribution of star ratings on reviews has found that reviews typically show a J-shaped (Hu et al. 2009) or U-shaped distribution. Without loss of generality we can assume that this also holds for single product aspects mentioned in the reviews. Therefore, it seems more adequate to describe the distribution of sentiments per product aspect with additional dispersion parameters like variance or a discussed factor. Open research questions on how to aggregate sentiments on a product level include if reviews should be associated with different weights according to age of the review, indications that the reviewer is an expert, or credibility of the review.

Deriving facts from opinions. At the point when sentiments have been aggregated on product aspect level across all reviews for a product, we may try to infer facts from opinions. That is, trying to map a world of opinions to a world of truth. For product aspects with a high variance in the opinion space, this is clearly not meaningful. But if a product aspect is mostly mentioned in a positive way, customers would probably agree that the aspect is truly positive. Derived product aspects share some special characteristics. Some might be highly discussed, whereas in other aspects user might totally agree on a product aspect. Some might have a very strong support because hundreds of reviews have been written about the particular product aspect, others might have just been mentioned a few times. Whereas there exists a mechanism to gain intersubjectivity by stabilizing subjectivity with a lot of opinions, also called objectivity by averaging (Parameswaran and Whinston 2007), a lot of information quality problems in the original product review (e.g. poor description, wrong words, …) are also reflected in the mined product aspects. Further IQ problems might be caused by the information extraction and sentiment analysis techniques, e.g. associations to wrong concepts or sentiments.

User Experience Challenges

Incorporating product aspects, that can only be derived with a certain probability and therefore are subject to uncertainty, into a search functionality poses severe challenges for the interaction design. It is both important to know which information quality needs users have when searching for products, as well as which interaction designs are suitable to support expectations on the quality of search results.

Information quality (IQ) needs throughout the product search. In existing product search applications, we usually find high quality data behind search or filter options. In such contexts, the IQ needs of users never had to be elicited. In cases of somehow uncertain information however, such as information from product reviews, the question arises which information quality needs are most important to users. Information about which IQ dimensions users prefer in a specific purchase-process stage may distinguish a value-adding product aspect extraction from a useless one. A recent study on information quality needs in such a context found that most important IQ dimensions were accuracy and believability, whereas timeliness, completeness and amount of data was assessed least important from users (Hirschmeier et al. 2016). The study also found that these IQ needs are stable throughout the purchase process. The findings allow suggestions on how to implement a search based on derived product aspects. As the distribution of reviews implies that there is some information with high accuracy but also a lot of information with low accuracy, the tradeoff between presenting a lot of data with low accuracy and only few data with high accuracy should be decided in favor of high accuracy. In this regard, less can be more when derived product aspects should be used in search applications.

Expectations on search and filter results. Users have expectations when they use search functionalities like search bars or filters. For example, when a user filters for laptops with 16GB, he is used to get the complete set of laptops with 16GB, and no laptops that have 8GB. These expectations are coined by previous searches and experiences. For a search bar on ebay for example, these expectations are somehow different. Users know that if their search string does not match the words the vendors used in their product description, they would not find all matching products and therefore obtain an incomplete result list, i.e. not all the products that match their interest. These two examples should motivate that is vital to study the expectations of users for different search functionalities, and then elicit which search functionality might best fit for derived product aspects and its characteristics. Interaction mechanisms have to be found that a) leverage the strength of derived product aspects, i.e. to support the user with distinctive and decision-critical content during the filter process and b) cope with the weaknesses of derived product aspects, which among others is, that this valuable product aspect information is sparse and incomplete. Open research questions should aim at understanding what are the expectations of ecommerce users when using such mechanisms, and if the IQ of derived product aspects could meet these expectations: Which result set quality do ecommerce customers expect when using filters or search bars? Beneath standard interaction mechanisms, it should be elicited if anticipatory search control (Liu et al. 2016) helps support the expectation of consumers.

Sorting vs. filtering. Depending on the expectations of customers, possibly both filters and search bars would lead to a confusing customer experience for derived product aspects. In this case, sorting options might be taken into consideration as an alternative. Derived product features would then not be used for explicit filtering out products, but for prioritizing products in the result set. The user can select which product aspects are important to him/her, and the result set will be sorted accordingly. As an alternative, instead of showing single product features, also frequently mentioned product feature sets could be presented to the user.

Purchase Process Challenges

Apart from user interaction challenges, underlying processes have to be analyzed and how a product search that comprehends derived product features may affect these processes. Apart from the search process in general for which we use the purchase funnel model, we shed light on the learning process that consumers go through when reading reviews.

Purchase funnel. The product search process can be described by the customer purchase funnel model, also called consumer purchase funnel, sales funnel, conversion funnel or purchase funnel (Court et al. 2009; Evans 2008; Jansen and Schuster 2011; Jobber 1995; Li et al. 2015). The purchase funnel is widely used in practice, especially in marketing, sales, and customer relationship management, and exists in dozens of different versions, ranging from three to seven steps. The purchase funnel goes back to the AIDA model (Coolsen 1947), an acronym which stands for awareness, interest, desire and action. The AIDA model maps a customer journey from the moment a product attracts a customer to the point of purchase. The funnel is mostly distinguished into five steps: Awareness, interest, consideration, preference and purchase (Figure 3). In the status quo, the first steps are only supported by marketer-generated content (MGC), whereas the latter steps are also supported by UGC. Whereas these five steps depict a positively directed one-way process, the real process has some loops. Especially the consideration set is a dynamic set. Customers might delete products from their consideration set again after they read the product reviews. They might also add more products by performing more searches.

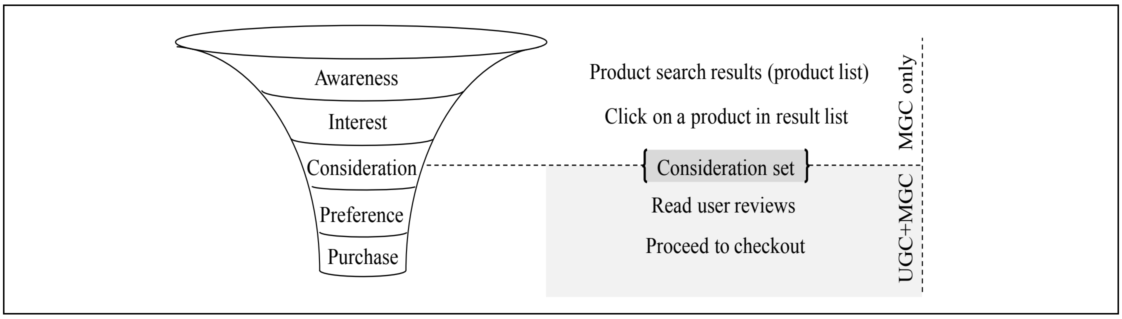

Figure 3. The purchase funnel and the corresponding steps in the context of a product search

Learning process. Reading reviews involves a learning process than can be described by diverse learning theories (Askalidis and Malthouse 2016; Jang et al. 2012; Lu et al. 2014; Tong and Zhong

2009; Wu et al. 2015; Zhao et al. 2013). Before reading, most readers do not even know which product features matter to them. They find out while reading: "I also don't want to buy a headphone whose plastic breaks after 6 months". After they get awareness of new product aspects (learning by exploring), the question arises if this is a single opinion or if more people report something alike. While reading other reviews, seeking for confirmation, they get aware of other decision-critical aspects about the product as well (learning by confirming). Therefore, the process of reading user reviews is an interplay of updating beliefs (by confirming suspicions they got aware of) and creating new beliefs (by getting aware of more suspicious aspects).

Effectiveness and efficiency of processes. It is still an open question if this learning process could be performed more efficiently or effectively when all the product aspects would be available to the user in the product search already, e.g. in the form of filter options. The learning process might be more efficient, if the number of supporting reviews, i.e. how many people mentioned a certain aspect, would be displayed to the user directly, as confirmation loops might be skipped. Stigler points out that customers stop searching when the value of the expected insights are smaller than the expected search costs (Stigler 1961). If the awareness about product aspects and their support by reviewers can be transported in almost one step, users might significantly shorten the learning process. Research has to show, if the learning process can be reduced or if users want to undergo the complete learning process. It also must be elicited, if users still want to read the reviews to get a proof of the mined product aspects.

Business Challenges

Apart from the fact that from a technical perspective, it is possible to extract product aspects, and challenges concerning user experience and processes, questions have to be raised on the business side.

Systematic underrepresentation of certain products. With derived product aspects incorporated into the product search, some products with bad reviews might be systematically underrepresented, while others might be overrepresented. Similar concerns were raised when reviews were introduced years ago, but it is still an open question if the integration into the product search would catalyze this effect.

Cost-benefit analyses. From an ecommerce platform provider's point of view, the question of cost effectiveness has to be raised. Why should anyone build a product search enhanced with derived product aspects? When consumer reviews had been introduced on ecommerce platforms years ago, studies had been made on cost and benefit of reviews, and studies could show that sales increases with the amount of reviews (Lin 2014). So similarly, a better user experience with reviews might increase sales once again. The reason for ecommerce platforms to build up a solution might therefore be to gain a competitive advantage and to channel more traffic through their site.

Legal issues. From a legal standpoint, it has to be clearly separated and made clear to the customer which information is user-generated and which information is marketer-generated. If both are confused with each other, the vendor might face some risks: As the correctness of derived product aspects cannot be guaranteed, an increase of product returns might result as a consequence. Even worse, customers might sue for compensation when it is not clear which information becomes part of the contract and which information is just user-generated content. At last, the reputation of the ecommerce platform might be affected. Whereas technically, it would make sense to join reviews from several ecommerce platforms, from a legal perspective, platform providers should check if they own the rights to process user-generated content and derive product aspects from it.

Conclusion and Outlook

This paper's main contribution is the development of a conceptual framework for the integration of product aspects that have been derived from user reviews into the product search process. Companies should get aware of the fact that even though information is created by customers, i.e. actors *outside* of the company, and also consumed by customers – again *outside* actors –, in between producing and consuming customers the company should act as a *manager of the knowledge*. As of today, the producer-consumer mechanism takes place without much involvement of the company, somehow neglecting the fact that the information is a valuable asset that still can be leveraged.

The conceptual framework provided illustrates the building blocks of an innovative search for derived product aspects from user-generated content. It enables researchers and practitioners to perform further contributions and evaluations effectively and target-oriented. The framework allows researchers from various disciplines to position their contributions. Considering design science, the framework may help to identify meta-requirements and lead to the development of more artifacts that pursue a holistic approach to integrating mined product features into the product search process.

Still, the framework leaves space for a lot of research in at least three of the four challenge areas. While the data challenges are quite well understood (product feature extraction and sentiment analysis), a lot of open questions remain how to optimally design the user interface and the user experience for a product search enriched with product features derived from user-generated content. Also, open questions remain in which way to step into the learning and purchase process, including the implications on the business side. First startups have launched prototypes with the possibility to search for aspects derived from reviews. We are eager to see if and how such solutions find their way into the market and how challenges will be mastered along the way.

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