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Function recommender system for product planning and design

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ABSTRACT

Functions play a critical role in bridging intangible user needs and physical design parameters. Recommender systems ubiquitously exist in eCommerce to recommend new products to a target user. However, in most cases, the main purpose for users to acquire a product is to gain its functionality rather than owning its physical embodiment. Inspired by existing recommender systems for eCommerce, this paper presents a function recommender system for product planning and design, which represents a revolutionizing paradigm of recommending new functions to a product. A systemic function recommendation process is elaborated, and a case study is presented to showcase practical applications.

1. Introduction

Functions play a critical role in bridging intangible user needs and physical design parameters under constraints [1]. A product's functions are typically represented in the textual form of "verb + object" or as an input–output transformation [2]. To date, many function modeling methods have been developed to model complex products and processes based on their functionalities [3]. A product is not born with any functions. But rather, functions are carefully formulated by designers based on user needs and purposefully assigned to a product as its requirements, hence also called functional requirements [1]. New functions can always be assigned to an existing product. It is imperative for manufacturers to continuously add new functions to a product in order to extend user's excitement. Many once successful products failed market competition due to missing exciting new functions.

Traditionally, new functions are proposed by designers based on solicitation, interpretation, and convergence of user voices via e.g., survey, interview, brainstorming, etc. In practice, functional design is mostly conducted by experienced designers based on their subjective experience, knowledge, and even heuristics. However, such a strategy is often reported to be problematic because, not only the process is time-consuming, but also the result is not always reliable. In the past, it was demonstrated that the massively crowdsourced customer reviews about products can be leveraged to facilitate new concept generation [4]. To date, however, relatively few efforts have been devoted to studying how to process the readily available information about users and products to support functional design.

In eCommerce, recommender systems (RS) are commonly used by online retailers to recommend new products to a target user. Since these RSs are intended to facilitate the business-oriented activities of selling and buying, they are designed to merely consider the user domain and product domain, without functions in the big picture. As a result, manufacturers have gained little value from the prosperity of RSs. However, in most cases, a user's true purpose of acquiring a product is to gain its functions rather than owning its physical embodiment. Based on relevant studies about RSs for eCommerce, this paper presents a Function Recommender System (FRS) for product planning and design.

2. Applicability of recommender systems for product design

Recommender systems (RS) ubiquitously exist in eCommerce. It is not exaggerated to state that RS is one of the cornerstones that founded today's prosperous eCommerce sector. RSs are designed to address the basic problem of how to estimate a user's "rating" for a new item that the user has not seen, purchased or used before [5]. To date, many RSs have been developed to recommend a wide range of items (e.g., product, movie, book, restaurant, service, etc.). There are three commonly used recommendation approaches: collaborative approach (CA), content based approach (CbA), and hybrid approach (HA) [5]. First, CA leverages the "collaboration" among similar users to make recommendations. A user will be recommended a product highly rated by other users who are similar to the target user. Secondly, CbA employs the commonalities among those previously preferred products to make recommendations. A user will be recommended a new product that is similar to those products that he/she had highly rated in the past. Lastly, HA combines CA and CbA in different ways to address the inborn shortcomings of using either approach alone. From the perspective of design, a limitation of these approaches is that they all have ignored the critical role played by functions in impacting a user's rating for a product. After all, a customer need is directly satisfied by means of a functional requirement instead of a design parameter [1].

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In essence, RS is a particular information filtering system. The popularity of RSs in eCommerce can be largely attributed to the long tail phenomenon [6]. Because online retailers offer a significantly larger variety of products than the physical stores, users often feel overwhelmed by the information overload caused by too many choices. Hence, it became necessary to filter information via RSs for users to make informed purchase decisions. Product design now faces a similar challenge or opportunity that can be explained by combining the long tail model [6] and the Kano Model [7], as shown in Fig. 1. Against the sweeping trend of product personalization [8], manufacturers need to shift their focus from a few popular product features in the head of the curve to a huge amount of unique product features in the tail of the curve. Nowadays, it is increasingly difficult to keep users excited purely based on a few popular features because popular features will be quickly made well-known by various social networking services. As a result, most of the popular features will soon lose their basis of triggering excitements – the surprising effect, and thereafter become performance features. Ever more often, a user's true excitement is stimulated by those "unpopular" features tailored to his/her unique need and preference. However, unlike the few popular features that can be relatively easily identified by benchmarking, the unpopular exciting features are hidden deeply within the wide spectrum of the long tail and they must be uniquely personalized. Moreover, due to the information explosion, manufacturers must process a huge amount of information coming from diversified channels to make informed decisions.

Inspired by various RSs developed for eCommerce to address the long tail phenomenon and information overload, a function recommender system (FRS) is proposed for product design and planning. It should be noted that FRS represents a new paradigm of recommending new functions to a target product, which is profoundly different from the present paradigm of existing RSs in eCommerce (i.e., recommending new products to a target user).

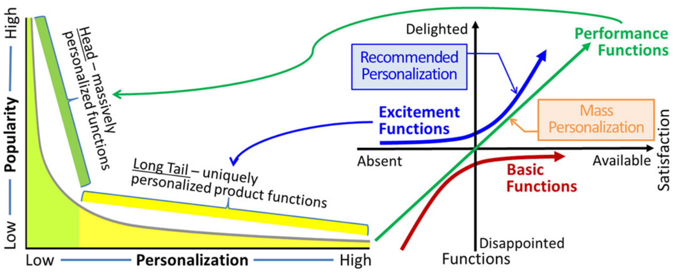

Fig. 1. Combination of long-tail model and Kano customer model.

3. Function recommender system

3.1. Theoretical formulation of FRS

The proposed FRS is designed to address the problem of how to estimate the unknown rating of a candidate function f for a target product p, formally $R(p, f)$. Among the three commonly used recommendation approaches, the hybrid approach is chosen because it is proven to be more effective of addressing those common issues for RSs (e.g., cold start, overspecialization, limited content, etc. [5]). FRS is largely based on the collaborative approach with some characteristics of content-based approach integrated mainly to identify peer products. Specifically, a candidate function f is abstracted from a peer product p' that is similar to the target product p, and $R(p, f)$ is estimated based on the similarity of p' to p as well as the rating of f for p'.

Furthermore, FRS is characterized by the hybrid of user's rating and designer's rating. Any product, as an artifact, is a man-made thing. Functions are purposefully assigned to a product by designers based on user needs, instead of chosen by the product itself. In other words, a product cannot directly rate its functions. But rather, the ratings have to be indirectly supplied by relevant human stakeholders. An unknown $R(p, f)$ is estimated based on known information supplied by both users and designers. On one hand, it depends on how much a function is desirable on a product, which is best known by users. On the other hand, it is also affected by the difficulty of integrating the function to a product in light of the product's existing functions, parameters, and structure which is best known by designers. The interplay between user's rating and designer's rating jointly determines $R(p,f)$. That being said, FRS is also related to customer involvement. For example, lead users can be involved to provide the initial ratings [9], which is a commonly used strategy to cope with the cold start problem for RSs [10].

3.2. Process of recommending new functions to a target product

As illustrated in Fig. 2, a complete function recommendation process consists of 5 steps: (1) identify peer products; (2) calculate similarity of peer products to the target product; (3) rate candidate functions by users and designers; (4) aggregate user's and designer's ratings; (5) rank-order candidate functions.

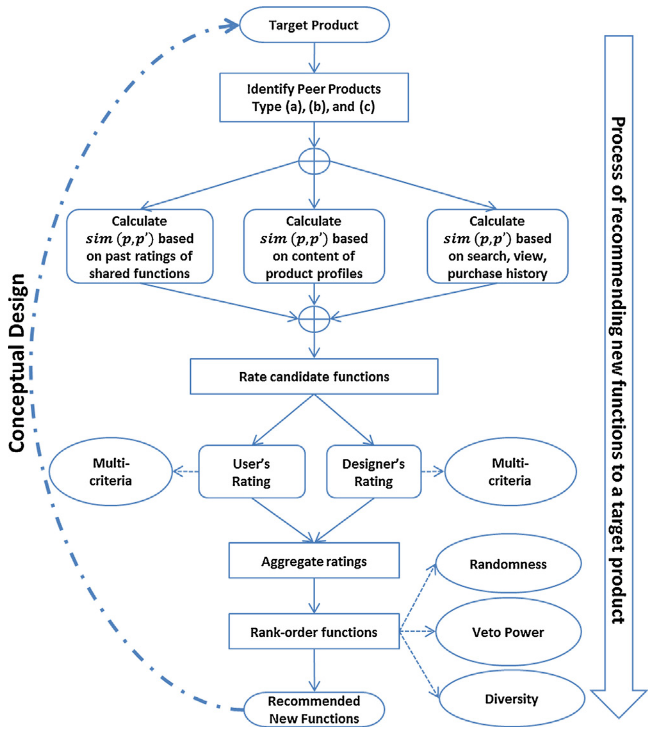

Fig. 2. Process of recommending new functions to a target product.

A wide range of explicit and implicit data can be utilized as the input of FRS. Explicit data can be collected by directly soliciting inputs from users, e.g., by asking them to rate multiple functions in numerical scale or propose a list of most preferred functions on a product, etc. Implicit data can be collected based on eCommerce or social platforms, e.g., by counting how often a certain function is mentioned or discussed within user reviews, how often two products are purchased together, etc. With the Internet of Things, implicit data can also be collected from "smart products" in terms of when, where, and how often a function is activated. The input data will be used in different steps of the process.

Step 1 (identify peer products): given a target product, the first step is to find its peer products. FRS considers three types of peer products. In practice, it is possible that different types of peer products may overlap. Peer products can be hand-picked by designers or automatically searched by deploying web crawlers.

Type (a): products that carry the same set of highly rated functions with the target product before. In practice, they often mean the directly competing products. If a competitor's product is