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Implications of Perceived Utility on Individual Choice and Preferences: A New Framework for Designing Recommender System

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ABSTRACT

Consumer psychology and consumer behaviour has constantly been a field of interest for the researchers. Volumes of researches are available in this area, still new theories and concepts keep emerging in response to change in context and environment. Consumer psychology has large cross disciplinary implications. In this paper, a relationship between consumer psychology and recommender system has been explained and how implementing a consumer psychology model can improve recommender system performance.

This paper also gives first level analysis of various filters that can be developed along with the design of recommender system in order to generate a more refined and relevant choice sets. There are attraction effects observed among different items and the attractiveness of a product is co-dependent on attractiveness of other options available in a choice set. In the present paper, we have explored the utility of defender model in the design of recommender systems. Different effects like decoy and asymmetric dominance are also analyzed to achieve better efficiency and effectiveness in the design of recommender system.

Keywords: Decoy, Recommender, Defender Model, Asymmetric Dominance

INTRODUCTION

Recommender systems are the category of information systems which supports searching and suggesting products and services according to user's requirement and preferences (Resnick et al., 1997). The product range may vary from consumer durables such as a book in Amazon or digital goods such as song on *lastfm*. The task of recommending products proactively is performed by recommender systems which work backstage on E-commerce websites. Many recommendation approaches and methods are applied to target internet based consumers. Collaborative filtering was earliest approach to create user to user similarity and then recommend similar products. Recommendation approach was simple. Positively rated items by one set of user were recommended to similar users. However, this 'user to user' correlation lead to scarce data and cold start problems (Ahn, 2008). This problem was targeted by designing an 'item to item' based correlation and this category of algorithms were termed as content based filtering as volume of data available for products was much denser than user data. There were some specialized variations also for example demographic or knowledge based recommender system which includes domain based knowledge to analyze user preference and predict user choices.

As it is evident that recommender system directly interact with consumer and for establishing a better communication it is essential that recommender systems should be intelligent enough to understand consumer's behavioral traits(Pu et al., 2011). Understanding consumer psychology and its phenomenon will actually present meaningful insights to improve recommendations and effectiveness of these systems which in turn can be translated into economical benefits.

The purpose of the recommender system is not only to elicit preference and produce accurate search results but also to improve the decision making in an ecommerce context (Xiao et al., 2007). A good amount of research in the recommender system focuses on developing complex algorithms and software programs which improves the efficiency of recommender systems (Cosley et al., 2003). However, there is a need to identify other significant aspects which attempts to maximize the value derived from a recommender system experience (Xiao et al., 2007). Factors such as trust on online medium (Yaobin et al., 2007) and personal choices (Ho et al., 2008) are often ignored in the design and implementation process. .In the present paper, we propose a conceptual framework based on established theories from the field of consumer psychology. The proposed framework allows the systems designer to incorporate the significance of derived value of a given product/service in order to achieve the single most important objective of any decision behaviour-maximizing utility.

THEORETICAL FOUNDATION

The behaviour regarding choice selection, preference and usage of products is a routine task and everybody at all the time is exposed to these decisions (Bettman, 1986). There are various factors and phenomenon that effect the purchase decision and usage behaviour of consumers. Consumer psychology is a field where we try to explain and understand these factors in order to understand consumers in a better way and can predict the behaviour and choices of consumers.

The consumer psychology majorly has two broad themes of research *Individual decision making and cognizance* and *group and social influences.* The first stream of knowledge deals with exploring personality behaviour, attitude and perception among individuals to determine and capture their preferences and selection patterns. Group and social influences as a knowledge streams contributes in understanding various environmental factors such as peer pressure, social desirability and persuasions. In the current work, we have focused on individual decision making behaviour based on perceived value of the product vis-à-vis its cost.

There are certain behaviour themes like consumer’s prior knowledge and its effect on information processing, prior expectation and cognitive approaches that plays a major role in explaining consumer’s decision behaviour (Loken, 2006). We will discuss few factors briefly in order to understand various factors that determine individual decision making.

Mental Accounting Theory

In the context on internet based business, mental accounting theory is defined as a cognitive process among individuals to code, compare and evaluate products and services based on the value and utility offered (Aimei et al., 2007; Gupta et al., 2010). According to mental accounting theory, individuals evaluate a product/service based on two a two stage process (Thaler, 2008). First, the individual mentally calculates the utility of the product against its cost then he asses the derived value from making purchase decision and finally the value is summarized in order to proceed for the second stage. The second stage or the decision making is concluded by calculating the perceived total value derived from purchasing a product and ensuring maximal value (i.e., maximum total utility). However, previous studies (Aimei et al., 2007; Cheema et al., 2006) have asserted that the perceived maximum utility is subjective to the individual preferences.

Assessment of Co-variation and Risks

This actually means to explain the processes that determine consumer's judgment of a particular event that further explains past event and future contingencies. There were many researches done to extend this concept for price-quality or price-attribute relationships. So if sufficient data is available consumers can accurately assess these relationships. However, this interpretation is subject to fewer biases. This is a relevant phenomenon for designing recommender systems as E-sales platform enable consumers to get access to all sorts of information regarding products and recommended products should be a rational choice as per the price- quality relationship exists.

Consumers perceive some risk associated with every choice they make. This risk can be any uncertainty that may cause unexpected or unpleasant outcomes. They are weighted potential gain and loss that they can make from a particular decision and the selection is made on the basis of value derived. Thus, recommending products that carry high value for customer increases the chance of selection. However, calculating the perceived value of products is a matter of research.

Persuasions and attitudes

As recommender systems are models of virtual persuasion, it is very important to understand how attitudes are formed and how they are translated into behavior. Research has linked attitudes with availability of information and providing favorable information can lead to persuasions. The level of involvement can also lead to motivate the consumers for a particular choice.

Decision behavior can actually be explained through a decision process that depends on various factors and it differs for individuals. According to available literature, decision process can be significantly related to three factors:

- *Effect of task*
- *Effect of context*
- *Accuracy/effort tradeoff*

Where task effort implies alternative available and attributes per alternative to sum up the information. The effect of context refers to some additional set of attributes like similarity which explains comparability or dominance of some of the alternatives. Accuracy/effort tradeoff points that consumers do not put lots of effort in evaluating alternatives completely. This low effort can be further scrutinized and it was observed that applying low effort does not mean that we are sacrificing accuracy in evaluating.

Prior Knowledge, Memory and Mood

Prior knowledge also plays an important role in the decision process. Prior information interferes with understanding of any current information and consumers with existing knowledge are able to absorb more information in shorter time span. Reilly & Conover (1983) in a meta-analysis of seven studies, come up with the result that prior knowledge reduces the external research required for a decision process. Some studies also suggest that memory also interferes with choices as consumers

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tend to forget rejected alternatives, thus any new added alternatives will face comparisons with selected choices.

There are researches that suggest that mood also plays an important role in interpreting information and evaluating alternatives. Mood effects also make an impact on memory as event learned in a particular mood remains in your memory while you tend to lose content in a bad mood state.

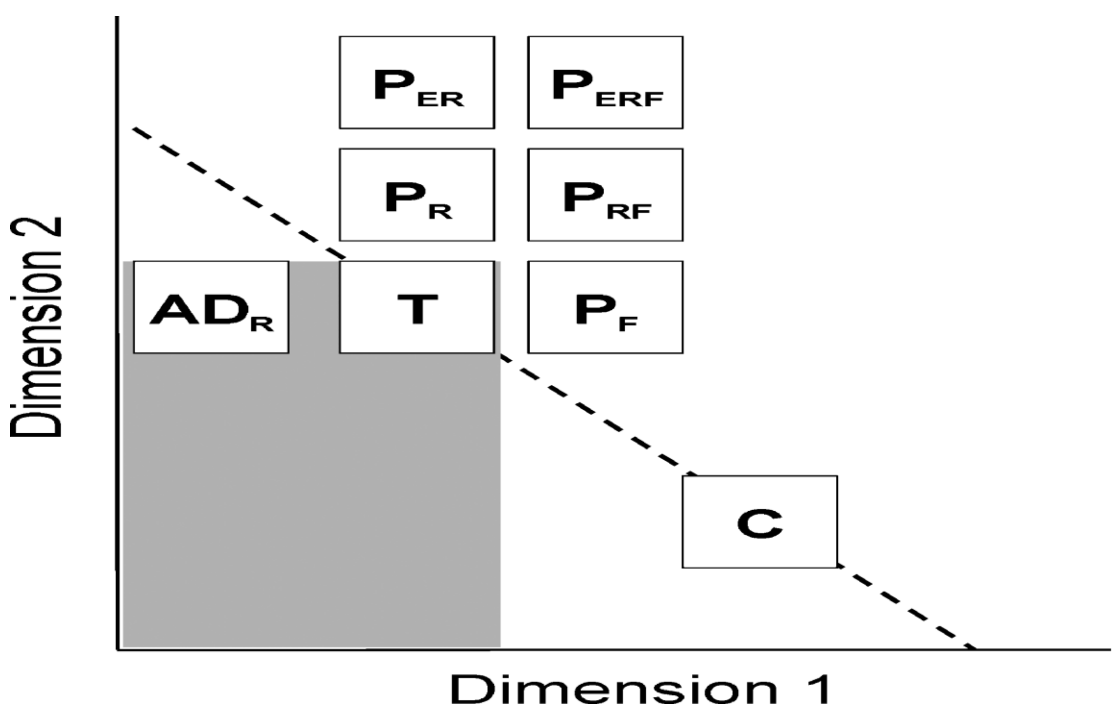
DESIGN CONSTRAINTS FOR RECOMMENDER MODEL

Impact of Decoy on Consumer's Choices

The existence of decoy came when Huber and Puto (1982) explained the concept of attraction effect that states that attractiveness of one alternative may be affected by introducing another alternative in choice set. Decoy effect can be understood by given example.

Figure 1 illustrates locations of several choice alternatives in a two-dimensional space. In this representation, the value of T is superior to C on dimension 2 but not dimension 1. The dotted line represents an equi-preference contour that assumes equal weighting of both dimensions. Because T and C lie on the same contour, each is predicted to be chosen 50% of the time in pairwise choice. The shaded region represents locations in the attribute space of alternatives that are dominated by T. The other labeled alternatives represent possible decoys included in a ternary choice set along with T and C. First consider the standard asymmetrically dominated decoy, designated ADR because it is asymmetrically dominated by T and extends the range downward on T's poorer dimension. Although ADR is rarely chosen, it typically leads to much greater choice of T (Huber et al., 1982).

Figure 1: Illustration of decoy effect (adapted from Huber et al., 1982).



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Decoy and its Impact on Quality of Brand

Implementation of decoy effect involves understanding its impact of various other variables. To understand this Heath and Chatterjee (1995) conducted a study which explains impact of decoy on low and high brands. The major learning from that research was:

- *Decoys will reduce shares of lower-quality competitors more than they will reduce shares of higher-quality competitors.*
- *Decoys will reduce shares of competitors more as they extend the range of the attribute on which the competitor is superior to the target.*
- *Decoys will reduce shares of competitors more in durables than in nondurables.*

These outputs can be extended while recommending products to online consumers and we can design filters according to low/high brand presence in choice sets.

Asymmetric Dominance Effect

The literature in individual decision making suggests that a choice option accrues an incremental value if it dominates another option. Consider products such as computer software, hardware, and many other high-tech products where the benefits derived on purchasing the product depend on how many other consumers use the product (Katz & Shapiro, 1985). In such product categories, marketing a well-designed dominated option can systematically shift sales toward the dominating option and help consumers enjoy the benefits of a larger network of buyers. In this case, the asymmetric dominance effect along with positive network externality may increase consumer willingness to pay for the dominating option, and thereby improve firm’s profit margin as well as sales (Amaldoss et al., 2007).

Simple Dominance Model

To actually design a recommender system that also considers decoy effect for improved recommendation the first practical task is to calculate dominance of products thus finding out decoys. SDM or simple dominance model is an efficient way to calculate perceived dominance of a product item in a given choice set. This method can be well implemented in a recommender system environment. This model assigns a dominance value to every item which signifies that how dominant the given product is with respect to other products in same choice set.

The core elements of SDM are dominance value DV as shown in the formula. After calculating DV a small set represent result set as top items will be recommended to the consumers. However there are some catch holes while implementing SDM and recommending decoy in choice sets. The mathematical representation of the simple dominance model can be written as the equation below.

$$DV_{d \in Items} = \frac{\sum_{i \in \{Items-d\}} \sum_{a \in Attributes} weight_a * \sqrt{\left| \frac{a_d - a_i}{\max_a - \min_a} \right|} * sign(a_d - a_i)}{\#Items - 1}$$

The utility or decoy should not be very low as in some situations decoy can also be the selected product. It violates the basic purpose of a recommender system, recommending good products. We should also understand that SDM can only be implemented on selected item by recommender mechanism; it means the non relevant items are already removed from choice sets.

The parameters of setting dominance to an item should be decided by domain experts or should be based on past statistical data available. However statistical data is very scarce in case of durables where repeat purchase happens after a considerable span of time hence consumer profiling becomes more complex.

Decoy Effect in Designing Recommender System

To design a recommender system based on implementing decoy effect we need to consider various factors while short listing product list or choice list to customer. However, treatment of decoy items is done on second level of short listing.

First, recommender will create a relevant set of items and on those lists filters will work to analyze presence of decoy to process that list for effective choice sets.

In traditional recommender system cycle we add a model based diagnosis system that will take input from specific data reservoir like domain based data, sales data and CRM data. These data sources provide information on different attributes of product presented in recommender system's result and will further find correlation between item to item and item to consumer.

METHODOLOGY

The present paper proposes a conceptual framework which holds value in the field of recommender system designs and implementation. Based on an interdisciplinary synthesis of literature, a well founded concept of defender model is borrowed from the marketing literature. Defender model is then redefined and adapted in order to build a framework which guides the underlying working design of recommender systems. In the next section we will discuss and illustrate the application of defender system which incorporates multidimensional attribute of objects/products evaluated by the recommender system.

PROPOSED CONCEPTUAL FRAMEWORK FOR RECOMMENDER SYSTEM

The key feature of defender model is "per dollar" approach where attribute value is calculated by its utility per dollar spent. However there are various tradeoffs involved in this model. The consumers can tradeoff between attributes and also between price and attribute.

In the present framework, we proposes (1) that each consumer chooses from his evoked set the product which maximizes utility, (2) that utility is linear in the "per dollar" perceptual dimensions, and (3) that consumers vary in their tastes. Linear utility implies straight line indifference curves in perceptual space (Hauser & Gaskin, 1984). We can analyze these tradeoffs by drawing indifference curve which will become planes and angle between them will represent measure of tradeoff between dimensions. However, as the number of dimensions (attributes) increases, plotting the tradeoff curve will become complicated. It is essential that the model is able to successfully determine the key dimension which majorly contributes to the decision making process.

The above illustrated framework can be implemented with various set of attributes named as dimensions. For example a two dimensional defender model may be designed with aesthetics and brand value. Same way a three dimensional defender model considering three attributes will be

Utility of product = (***eff***) + tan α (***ease***) + tan β (***bvalue***)

Where,

eff = effectiveness per dollar of product X

ease= ease of use per dollar of product X

bvalue = brand value per dollar of product X

Figure 2 illustrates step wise process of recommending products to the consumers based on the proposed framework. The process is staged in three consecutive steps where the model progress through elucidating the preference and calculating the recommendation.

Stage 1: Preference Elicitation

This stage enables the recommender system to collate user information based on the previous transactions and record. This information is then utilized to find a portfolio of products or the “choice sets” customized for the individual user. This process will end up in providing a correlated ‘user-product’ list for the next stage.

Stage 2: Result Calculation

The choice sets developed in the stage 1 are further utilized to evaluate the utility of each product as per the user profile and preferences. The defender model is applied to calculate the utility of a product for the selected user. The result calculation then provides a priority list for the selected user based on the estimated utility.

Stage 3: Result Presentation

In the last stage, the priority list obtained in the result calculation stage is presented to the user as per the design of user interface of the recommender system.

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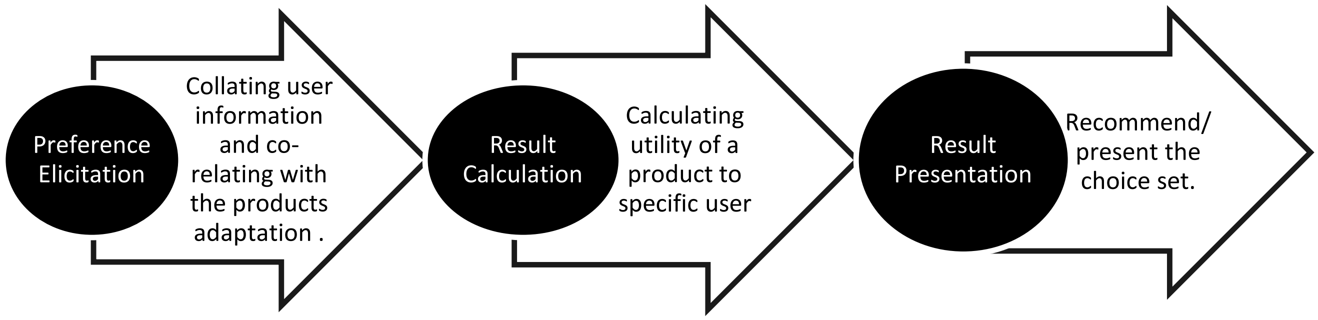
Figure 2: Proposed framework for a typical Recommender system cycle.



IMPLICATIONS FOR RECOMMENDER SYSTEMS

The proposed framework can be implemented in recommenders system to offer or recommend product to customers who possess high perceived value. This will require assigning a utility function to every product and recommending products on the basis of its utility. The basic components (data sets) of this model will be:

Utility of product: This data table will contain utility function for every product. This utility function will be defined category wise and will depend on nature of product and the expectations from consumers.

***Profiles of consumer*:** Profiling of consumers in recommender system is a difficult to achieve goal as it will result in scarce data and cold start problems. We can store customer's information regarding their priority and preference for different attribute. For past consumers maintaining this data will be easy task as we can infer their preference on the basis of past purchased products and the product attributes. The recommender will be based on collaborative filtering and will be recommending items on the basis of utility function.

By incorporating the relationship between preference and perceived utility, recommender systems will provide better decision making experience to the users. Plotting perceived utility against user profile will also help in addressing the scarcity of data by providing initial reference values to the user profiles similar to the available profiles.

CONCLUSION

Recommender systems now are used as agent to persuade customers to buy a product by providing them the choices they might consider. These system can enhance sales and establish better connect with customers by maintaining their web profiles, analyzing their preference by their past purchases and anticipating their needs. Future of recommender system is promising as it can be implemented in various ways and for various items. However to make recommender system more effective understanding consumer behaviour and its implications is very important. This paper deals with borrowing relevant theories and models from psychology and finding their relevance in recommender system. The inferences of this paper can be utilized to design new filters for recommender system algorithms that will further refine the results and make choice sets more attractive for the user.

FUTURE SCOPE AND LIMITATIONS

Recommender system area requires lots of research contribution to evolve and improve. Consumer psychology and its implication on recommender system is not much researched area so further research can be done to identify certain phenomenon that influence the working of recommender system. However the real challenge is implementing the observed effect in recommender system algorithm as scarcity of user data and cold start problem are still the challenges faced by recommender system area. The first stage of the proposed framework works on an assumption of existing prior data. Thus, similar to other recommender design algorithm cold start is a challenge for the proposed framework as well. Another challenge is large size data sets with a number of possible categories. Classifying the large choice sets into manageable categories which offers information on consumer's priority, preference and utility can lead into better future of optimally performing recommender systems design.

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