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Do we need to believe Data/Tangible or Emotional/Intuition?

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Abstract:

Now Data are clearly prevailing in all domains like a new black gold for companies and the rules in business decision-making are called into question. In this context, we think that Data Analytics combined with collaborative decision processes promotes a rational decision-making.

However best practices show that more and more executives and managers, the famous HiPPO (Highest Paid Person's Opinion), now frequently use their intuition for strategic decision-making. Moreover a lot of empirical surveys also show how important is the emotion in the intuitive decision-making processes.

We will try to explain how we can interpret differently data coming from big data using the most recent scientific advances in the field of psycho-cognitive sciences, in the goal to improve decision support systems and to take into account emotion in the decision-making processes. Finally we hope this could provide some elements to answer to the question: Do we need to believe Data/Tangible or Emotional/Intuition?

Keywords: decision-making, intuitive decision-making, emotion, e-commerce, recommender systems.

1. Introduction

With the advent of the reign of the datum, the new "black gold" of companies, it is all the modalities of business decision-making that is questioned. In this context, we could think that the analysis of data combined with a process of collaborative judgment promotes rational decision-making.

However, the observation of real practices shows that a growing number of executives and managers, also called "HiPPO" (Highest Paid Person's Opinion), use frequently their intuition in strategic decision-making.

Many empirical studies have helped to clarify the conditions of elaboration of the intuitive decision-making and the role of emotion in this process. It would seem that the decision-making results from a complex mechanism mixing closely the analysis of the facts, the possible options and their consequences with the activation of the emotional memory.

Consequently, the question that arises is: Do we need to believe Data/Tangible or Emotional/Intuition?

2. Rational decision-making versus intuitive decision-making

Illustrated by the theory of games [1], the Rational Decision-Making (RDM) presupposes the rationality of the decision-maker in all circumstances and the selection of an optimal solution among the possible choices based on reason and facts.

In a RDM process, an individual will often employ a series of analytical steps to review relevant facts, observations and possible outcomes before making a decision. Simon [2] and Kahneman [3] two psychologists - Nobel Prize in Economics, have contributed to discredit the myth of the rational decision-making.

Table 1: Rational decision-making versus intuitive decision-making [4, 5, 6, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18]

Rational decision-making	***Intuitive decision-making***
• Based on a conscious and extensive cognitive process • Based on abstract and explicit knowledge • Sequential process based on causal relationships • Does not take into account the emotion	• Mainly based on non-conscious processes • Based on past experience • Holistic process that is based on free associations • Essentially based on emotion

The observation of actual practices shows that a large number of executives and managers, also called "HiPPO" (Highest Paid Person's Opinion) often use their intuition when making a strategic decision [4,5].

The Intuitive Decision-Making (IDM) is an intangible and hard to define phenomenon. Simon [6] was one of the first researchers to study the IDP. There are many definitions of IDM [4, 7, 8, 9]. A single and unified definition of IDM is still slow to emerge.

However, we can define IDP as a cognitive process based on past experiences and emotional data from decision maker [4]. This definition has the advantage of highlighting the role of emotion in IDP.

3. Decision making and emotions

There are currently several theoretical approaches to emotion (physiological theory, Darwinian theory, cognitive theory, social constructivist theory). Most researchers agree on one point: An emotion is an affective state characterized by:

- A physiological reaction [19, 20];
- A behavioral expression [21, 22, 23] ;
- A subjective manifestation [24, 25, 26].

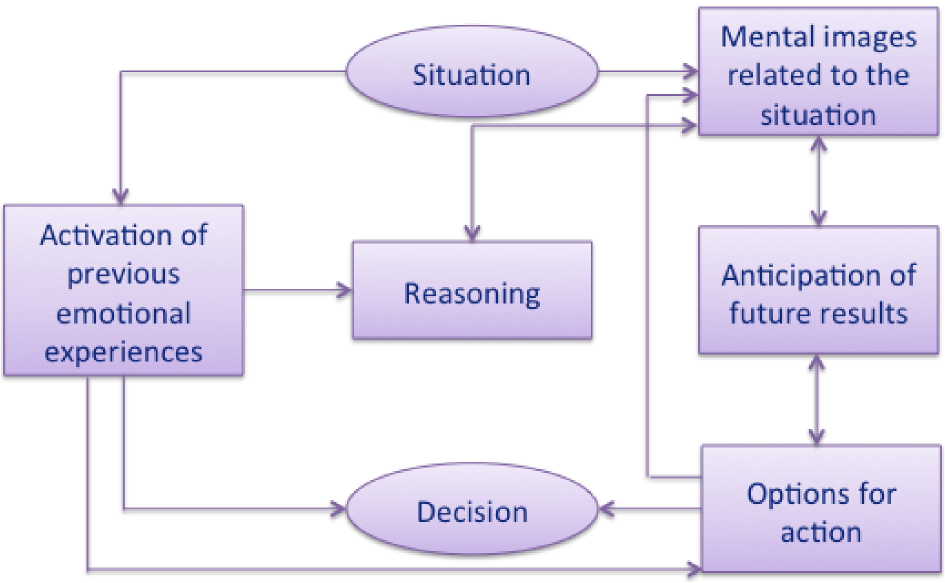
Our emotions reflect an appraisal of things that surround us. They are positive or negative and produce attraction or rejection.

Recent studies have shown that emotion is still the first factor of decision [27]. A positive or negative emotional state influences the way people judge the outside world: Like a heuristic, they refer on their present feelings to guide their judgment and make decisions in complex situations [28, 29].

People in a positive emotional state are more risk averse than those with a negative or neutral mood [30]. A positive emotional state facilitates complex decision-making by reducing confusion and increasing the ability to assimilate information [31, 32]. Mood affects the content of the decision-making [33].

The following illustration shows that emotion participates in decision-making by reducing the opportunities offered by the reason. In other words, it simplifies its work by limiting its choices.

Impact of emotion over reason



4. Emotion and e-commerce

Emotion-oriented E-commerce is a new and fascinating research field that poses many opportunities to understanding the purchasing behavior of online consumers [34]. For the online consumer, it's very important not just buy a product / service, but to feel emotions related to the act of buying and owning a product / service [35].

The irresistible urge to buy a product /service that sometimes feels suddenly a consumer on an e-commerce site can be explained by the anticipation of emotions or feelings associated with the consumption of the product /service coming [36]. Brands and Emotion are really the Future of E-Commerce [37].

5. E-commerce and recommender systems

Since the first introduction into e-commerce in 1990s [38], recommender system has been widely used in all kinds of online shopping environment. Due to its ability to assist the consumer to find desired products, it is playing an increasingly important role in the e-commerce operation. Recently, almost all of the e-commerce websites use recommender in their website, and many of them use more than one type of recommender to develop a recommender system.

A recent report by Netflix shows that more than half of the new order is coming from recommendation. More cases can be found in other B2C websites and this is not occasional. Recommender system add value to consumer in the following perspectives: [39]

a) **Reduce the time and complexity of search.** Modern e-commerce websites display a huge variety of products. If a consumer doesn't know the exact information of the product she wants, it may take her five or more steps to find it. A performing recommender system, however, simplify this process based on the matching of the potential product features to the customer preference, making it easier for consumer to find her desired product.

b) **Clarify an ambiguous and ineffable needs.** In many cases, consumer is not able to describe her needs with explicit keywords. While search engines is not capable of this, a recommender works. By deep-mining the historical behavior, some recommenders can help consumer clarify her needs and recommend relevant items for her [40]. This create a level of trust, and make the consumer dependent on the system, leading to a higher-level of customer loyalty.

c) **Identify unconscious needs.** By detecting the consumer's "center of interest" and matching it with the product's "characteristics" (attributes tag), some recommenders are able to amaze the consumer with products which is greatly appealing to her unconscious needs.[41] Such serendipity effect is unexpected (or unplanned) but relevant. It can greatly improve the consumer's level of satisfaction, and creating an exciting online shopping experience for her.

The e-commerce websites, on the other hand, enjoy great benefits of a recommender system as well.

a) **Serve as an automated shopping guide.** In modern e-commerce websites, consumer see hundreds of products in the same time. For those who are not familiar with information system, it's very inefficient and tedious to find the product she wants. As a recommender knows both the consumer preference and the website structure/catalog, it serves as an intermediary to facilitate the "communication" of buyer and seller by guiding and matching the consumer needs to the website offers. [42,43]

b) **Optimize the web server capacity.** A good recommender system helps consumer find what she wants with less queries to the server. The side effect is that the server workload is reduced, enabling the server to deal with more important computation tasks [44].

c) **Increase the quantity of items sold.** Consumers sometimes give up browsing because they feel impatient for inefficient searching. A recent data analysis by Taobao [1]shows that most of the consumers only browse through 3 pages of search result on PC, 2.6 pages on tablet and only 1.3 pages on smart phone. With recommenders, e-commerce website increase sales volume by giving to consumer what she want in an acceptable timeframe. [44]

d) **Increase the diversity and variety of items sold.** Recommender is an efficient tool for up-selling and cross-selling. Item-based collaborative filtering provides consumer with more choices in the same product category; user-based collaborative filtering propose serendipitous items to consumer leading to unplanned purchase.[73]

e) **Maintain a high level of consumer fidelity.** Being efficient in finding the "desired" products for the consumers, recommenders gain certain level of trust from their users. As such trust becomes dependency, consumers will visit the e-commerce site more often and consume more. [45,46] Relying on such trust, recommender system provides online retailers with an ideal platform to use labeling (by provider, retailer, or consumer) in order to enhance consumer confidence in the recommended items. [47,48]

f) **Optimize profitability.** Recommenders can pair the consumers' needs and wants with the low-moving stocks or high-margin products of e-commerce websites. Recent technology allows e-commerce websites to tag each item in the product catalog, making the pairing process automatic and real-time. [49]

g) **Identify consumer preference.** E-commerce recommender is a powerful tool to identify consumer preference. [50] Through the measurement and analysis of the consumer's interaction with the recommend result, retailers will have a better knowledge about their consumers (not only the consumed items, but also the interested items), compared with the technique used by Walmart in 1990s[2] .

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[1] Taobao (www.taobao.com) is one of the biggest B2C and C2C e-commerce platform, with over 200 million user and its annual sales revenue is 2 trillion yuan.

[2] Walmart analyzes consumers' shopping receipt to identify their preference. Such knowledge are used for personalized recommendation and cross-selling (direct mailing).

To summarize, both the consumers and the e-commerce websites benefit from a recommender. Consumer get better online shopping experience with recommender, and for e-commerce websites, recommender is a powerful tool to improve profitability, efficiency and customer knowledge. The following table shows the benefits and their inter-relationship.

Summary of the Benefits of Recommender System

For consumer	For e-commerce website
Reduce time and complexity for search	Serve as an automated shopping guide.
	Optimize the web server capacity
Clarify ambiguous and ineffable needs	Increase the quantity of items sold
Identify unconscious needs	Increase the diversity and variety of items sold.
	Maintain a high level of consumer fidelity.
	Optimize profitability
	Identify consumer preference

6. How do e-commerce recommenders work?

To make a recommendation, a classic recommender needs two components to function: the data and the algorithm.

Data can be classified by two main dimensions. Consumer data describes consumer's preference with a large amount of explicit and implicit parameters; Item data describe the attributes of every item on the e-commerce website. Data can be collected before, during and after the consumer's online shopping activities. [39]

Algorithm identifies and proposes items that consumers want. Recently, several approaches work on this challenge:

a) ***Collaborative filtering*** is based on the theory of transferrable similarity. Similarity matrix with scores is the key of this approach, who has two major branches. [51,52] ***"User-based correlation"*** measures the preference similarity, and propose items to a consumer based on the choice of other people who have the similar "taste". ***"Item-based correlation"*** measures the similarity between items, and proposes something "similar" to a consumer's previous choice [53].

b) ***Content-based approach*** correlate consumer's needs to the attributes of an item [54]. A preference profile is built for every consumer, indicating what kinds of items she possibly like. Meanwhile, keywords are used to describe the attributes of each item. [55] Content based recommenders are designed to find the items whose attributes match the consumer's preference. [56,57]

c) ***Statistical approach*** mainly focus on the most popular items. Popularity can be defined by items which are most searched, clicked, viewed, liked, ordered, bought, reviewed, or referred by consumers. The hypothesis is that consumers like to follow the trends.

d) ***Demographic approach*** assume that people with similar demographic profile have some behaviors, preferences and activities in common. In e-commerce, demographic criteria are widely used to constitute consumer groups. Favorite items of a certain group will be recommended to its group members. [58]

e) ***Knowledge-based approach*** deals with situations when consumer have a clear needs of some product but have no idea about a series of key parameters of the product, as well as the implication to change these parameters. These recommenders analyze consumer preference, adjust parameters and propose a specific product specification that suits most to the consumer's needs. [59,60] Good example is the third party online air-ticket recommender who analyze consumer preference, and then compares all available offers from different airlines and make recommendation.

f) Thanks to the recent rise of social networks, people start to share their shopping experience and their comments online. ***Community-based approach*** takes into account the comments and choices of the consumer's friends, believing that friends are more trustworthy than a stranger who looks "similar" to the consumer. [61,62]

While each of the approach has its strength and competence, they also have limits and disadvantages, making it impossible for a single approach to dominate the world of e-commerce recommenders.

Disadvantage of Different Recommender Systems

Approach	Disadvantages
Collaborative filtering: item based	Data sparsity (insufficient for correlation); cold start (new item with little rating or buying records); limited diversity and variety of result;
Collaborative filtering: user based	Data sparsity (insufficient for correlation); cold start (new user, inactive user); frequent calculation due to user profile update; "hot" items only;
Content-based	Highly dependent on the good definition of key words; difficult to deal with non-text objects (e.g. image, video, music etc.);
Statistics	Not personalized recommendation
Demographic	Difficulty in acquiring demographic data for new users; difficulty in making the right demographic group (criteria); recommendation result not personalized or less correlated;
Knowledge-based	Limited diversity (only for one type of product) and flexibility (standardized and comparable specifications);
Community-based	Consumer privacy; Relevance (friends are not necessarily similar, they can be very different in taste);

Due to the above disadvantages, the ***hybrid system*** aims to leverage the benefits of different approaches and minimize their disadvantage. [63,64,65] Depending on the objective, e-commerce websites can choose from the following hybrid techniques.

a) ***context*** technique choose the most suitable algorithms for the context;

b) ***weighted*** technique re-rank the results of different algorithms based on a pre-defined weight;

c) ***mixed*** technique display different types of results in the same time;

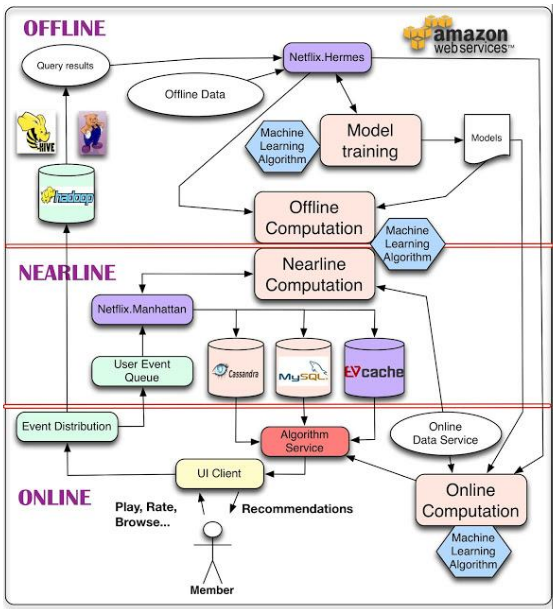
d) ***cascade*** technique uses several different algorithms to calculate and filter the result one by another;

e) ***feature augmentation*** technique prepares different parts of information with different algorithms, and use an algorithm to calculate the result;

f) ***condition*** technique incorporate factors (location, weather, purpose) to make the result more relevant;

In terms of deployment and application in e-commerce website, "online-nearline-offline" system is one of the good examples. [66] The online module has a cache of pre-calculated correlation matrix to deal with most of the frequent user queries. In the same time, algorithms with high efficiency and acceptable accuracy are also deployed in the online system to respond to some special queries (no match in the cache). If the online algorithm result is not satisfactory (low score), nearline system will make a query to the offline system, who is equipped with high accuracy algorithms (usually it takes longer to get a better result). If the offline system make a better recommendation, nearline system will upload it onto the online cache.

System Example for Personalization and Recommendation[3]



In business world, most of the major e-commerce websites develop their recommender system based on a hybrid approach. The following table provides a snapshot of the recommender system used by the world's famous e-commerce websites.

[3] Xavier Amatriain, Justin Basilico (2013). System Architecture for Personalization and Recommendation. Netflix techblog (http://techblog.netflix.com/2013/03/system-architectures-for.html)

Recommender in the Major E-commerce Website [4]

Approach	Amazon	Taobao	Ebay	Fnac	Decitre
Collaborative filtering: item based	Y	Y	Y	Y	Y
Collaborative filtering: user based	Y	Y	Y	N	N
Content-based	Y	Y	Y	N	N
Statistics	Y	Y	Y	Y	Y
Demographic	Unknown	Y	N	N	N
Knowledge-based	Y	Y	Unknown	Y	N
Community-based	N	N	N	N	N

***Notes**: Y – Deployed; N – Not Deployed; Unknown – Information not available*

7. What's the challenge of e-commerce recommenders?

E-commerce recommender system strives to propose items which can be accepted by the consumers. An effective recommender system aims for a sustainable and high level of consumer acceptance in e-commerce environment. [39]

To achieve and maintain effectiveness, e-commerce made great efforts to improve their algorithm and methodology. In the past decades, several innovative theories and hundreds of new methods are proposed and put into use to suit different e-commerce situations. Through years of field tests, it is widely believed that a hybrid approach, which incorporate several different types of theories and methodologies, performs better than a single solution. These efforts have successfully made the new recommenders system more efficient and intelligent than their ancestors. Recently, algorithm accuracy is still the hottest research area in the domain of e-commerce recommender effectiveness.

But is this sufficient? Maybe not. [67] Offline shopping experience shows that consumer accept a recommendation not only based on the proposed item, but also other rational and emotional considerations such as the presentation skill of a shopping guide, the ambience of the shopping environment, level of trust, and the state of mind for shopping on that very moment. Similar phenomena are also observable in the online shopping situation, where consumers prefer to browse e-commerce websites with a user-friendly information structure (presentation) [68], with pleasant page layout and colour theme (ambience), with better track record of quality and service (trust) [69].

[4] Source: Website analysis (www.amazon.com, www.taobao.com, www.ebay.com, www.fnac.fr, www.decitre.fr)

Mismanagement of these factors will have direct impact on the effectiveness of the recommender. A good presentation is indispensable and essential to the success of an e-commerce recommender. [70] If an e-commerce website choose to use pop-up window to present their recommendation, it will probably see very poor click-through results. Most of the consumers consider pop-up window annoying. A poor presentation kills good recommender algorithm.

We know in theory that "right" recommendation proposed in the "right" time by the "right" way is more likely to be accepted by consumers. But if a recommendation is rejected, is it because of the "right thing", the "right way", the "right time"? This question is fundamental because it shows us the direction of improvement. Unfortunately, very few recent researches can provide an answer.

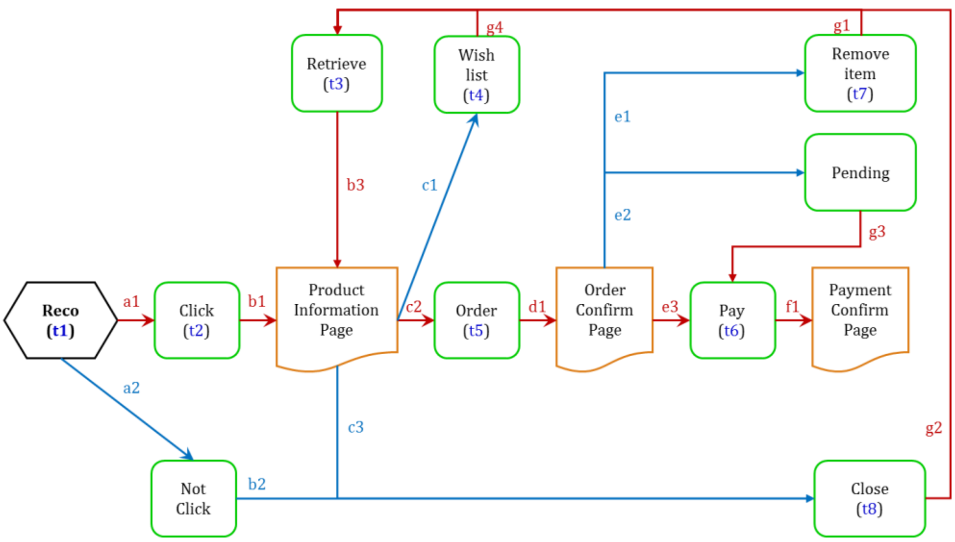
A multi-recommender system brings diversified choices to consumers, but the effectiveness of a multi-recommender system is not the sum of each recommender's effectiveness. Because of cannibalization, complementarity and limited page space, e-commerce website need to select different recommenders which can achieve highest total effectiveness when working together. Recently, researchers made little advancements in this domain.

In summary, the effectiveness study of e-commerce recommender is far from mature and comprehensive. Recently, most researches are focus on the effectiveness of the algorithm. In reality, consumer-centric factors (e.g. user-friendly interface design, consumer perception and communication) and systematical factors (multi-recommender system effectiveness) are not well considered and analyzed yet.

8. A new framework of consumer behavior analysis

Online consumer behavior research has been popular in the past decades. Thanks to the recent technology, websites can capture hundred thousands of consumers' behavior data in a more comprehensive and detail manner, enabling them to analyze e-commerce recommender's effectiveness from new perspectives.

Consumer Behavioral Model and Data in E-commerce Recommender



Various studies have suggested that algorithm is not the only one to be blamed when a recommender doesn't work [71,72,74,75]. The importance is to identify the other significant factors and manage them. In the following consumer behavioral model, the author try to identify the factors which are critical to the recommender system effectiveness.

When provided with a recommendation, consumer makes quite a few decisions based on various key factors.

Key decisions of consumers when receiving a recommendation

Decision	Description	Critical Factors Related to Recommender
Click	Click on the recommended item	• Attractiveness of the item (conscious, unconscious needs) • The type of information presented • The place where the recommendation is presented • The layout/design of the recommendation interface • The consumer's state of mind • Consumer's trust in the recommender system
Browse	Browse the item page in detail	• Waiting time for the page to be fully loaded to the browser • Attractiveness of the item (conscious, unconscious needs) • The consumer's state of mind
Wish list (Favorite)	Keep the item into a wish list	• Attractiveness of the item (conscious, unconscious needs) • The consumer's state of mind
Order / Remove	Put the item into the shopping cart	• Attractiveness of the item (conscious, unconscious needs) • Other consumer's reviews • Cost of the item • Comparison with other recommended items (same category)
Purchase / Cancel	Pay for the item	• Attractiveness of the item (conscious, unconscious needs) • Cost of the item • Cost of delivery • Ease of payment • Comparison with other recommended items (same category)
Retrieve	Retrieve the item recommended	• Attractiveness of the item (conscious, unconscious needs) • Recommender system function

While the attractiveness of item (decided by the algorithm) is still playing a key role, other factors are also important. To achieve the full functionality of a recommender system, it is imperative to evaluate all the factors and identify the improvement areas. The benefits of this approach are obvious:

a) **Integrity.** This method extended the scope of effectiveness from algorithm to the entire system, making it possible to assess and complete the system (instead of the algorithm/method only) in a more comprehensive manner.

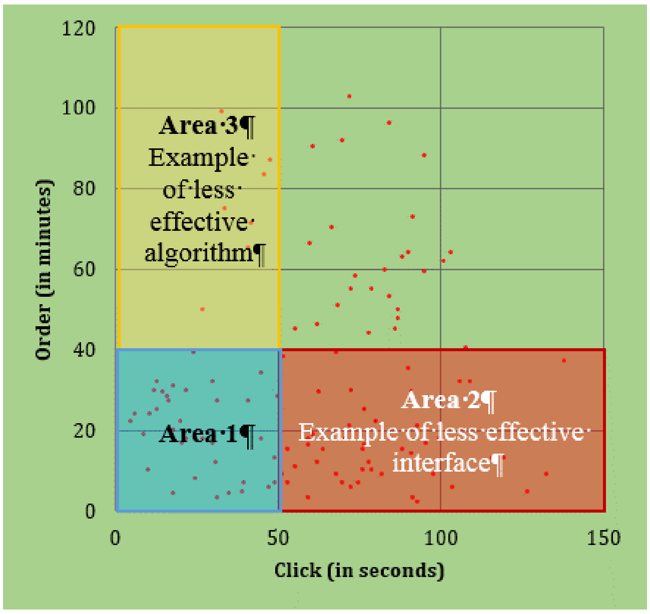
b) **Objectivity.** Unlike consumer surveys who evaluate consumer's subjective feelings about online shopping experience, this approach focus on the courses of actions. By measuring these data, we will be able to understand consumers' preference and attitude towards recommender system without interrupting or interrogating them.

c) **Credibility**. This approach can work on the data of hundred thousands of consumers of an e-commerce website in the same time, and use these objective observations to evaluate the effectiveness of a recommender system.

The next step is to define all the data points related to the mentioned behavior, and use the data to develop metrics system to make diagnose of the recommender. Here are some conceptual examples explaining the principle of behavioral analysis.

Example 1 illustrates the value to map and analyze the consumer's online buying behavior. This matrix describes some fundamental browsing and buying behavior of consumers. Axis X measures the time elapse between items being proposed and then clicked; axis Y measures the time elapse between items being clicked and then ordered.

Consumer Behavioral Matrix for E-commerce Recommender



The best case is that most observations are plotted in Area 1. Consumers quickly click and buy the recommended item. However, things can be different in real business world:

• If most observations are plotted in Area 2 (buy quickly but click slowly), the effectiveness of the recommender interface is in question: either the time to recommend is wrong (e.g. consumers are busy shopping/browsing), or the recommender interface failed to attract consumers' attention (poor interface or interaction).

• If most recommendations are quickly clicked but not bought, and the remaining clicked and bought items are mostly plotted in Area 3, we may conclude that the recommender has a good interface to attract consumer's attention, but the algorithm needs to be improved to propose more relevant items.

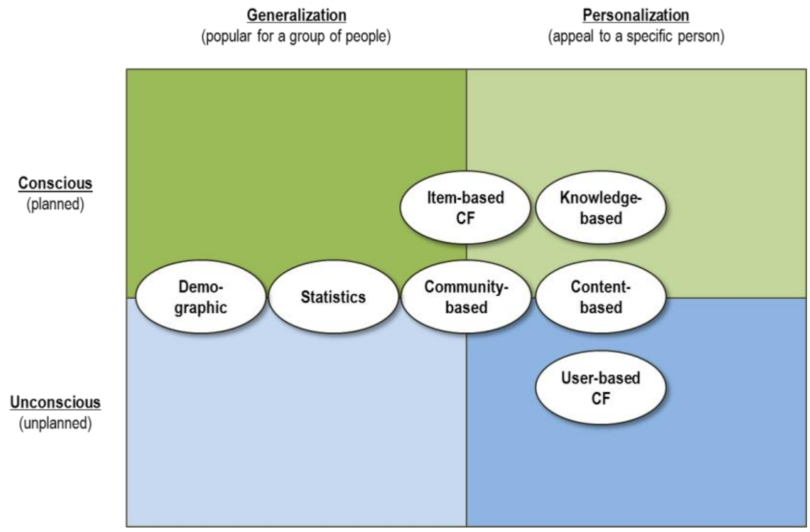
Example 2 examines how often consumer buy recommended items without clicking the recommendation link, but using a validation process (e.g. search for key words) by herself. Frequent occurrence of such cases indicates a crisis of the credibility of a recommender system. Several years ago, one major e-commerce website was accused of price fraud in their recommender system. The trick was discovered by some regular customers who searched for recommended items and saw two prices (webpages) for the same product. Although the online retailer claimed that it was just a "technical problem", it cost the company quite a lot to resolve the legal case, and to reassure the customer.

Example 3 shows how a misplacement of improper recommender system lead to unnecessary lost sales:

- Item-based recommenders are proficient in finding similar items based on a consumer's query, enabling the consumer to have more choices before making a buying decision. However, if it is misplaced in an order confirmation page (where consumer has made her buying decision), it adds no value to the close of the deal but makes the consumer hesitant and unsure about her own choice.

- User-based recommenders are good at proposing unconsciously interesting items. But if it is displayed when a consumer is very busy with her conscious needs, the click-through-rate can be very low (even if the algorithm is very relevant). E-commerce websites need to analyze the consumer behavioral data to find out where can be the best places to display such kinds of recommenders.

A New Taxonomy for Recommendation Methodology



9. Possibility to capture behavioral data from e-commerce and analyze the effectiveness of recommenders

Recommenders system is playing an increasingly important role in the e-commerce system, but we are still in the early stage to assess its effectiveness. Thanks to the Web 2.0 and big data, it's now possible for researchers to capture a larger variety and quantity of consumer behavioral data in order to assess the recommender effectiveness in a more comprehensive and detail manner. With new research techniques and tools, it is imperative for the researchers to work on the following subjects:

a) *Effectiveness of a recommender system* – the importance of system interface need to be quantified to achieve a personalized interface that will best suit the consumer's preference and taste; the relationship between consumer's state of mind and the level of acceptance to recommendations need to be studied, so that future e-commerce websites will be able to actively predict, or even create the "right moment" for consumers to accept a recommendation.

b) *Relationship between different types of recommender systems.* The total effectiveness of a multi-recommender system might not be necessarily the sum of each. Two item-based recommenders (one for upselling, one for diversity) might not be as effective as one item-based system plus one content-based system. It will also be interesting to know if such effectiveness will be different when the demographic profile (e.g. age, sex) or preference of consumer changes. Such knowledge will help e-commerce websites to provide the system that most suits the target consumer.

Recommender system is a cross-disciplinary subject which incorporates marketing, information technology, mathematics, psychology and economics. While IT and mathematics lay the foundation of an e-commerce recommender, marketing, psychology and economics help to make it more effective. With the new breakthrough in the algorithm, system interface and user's state of mind, it is sure that the future recommender will be smarter.

10. The contribution of search'XPR™

The technology developed by Search'XPR™ (named Oorace™) can generate impulse buying by suggesting to the Internet user or mobile user a product / service that the emotional, experiential and symbolic potential is perfectly in line with its expectations and desires. In order to do that, Oorace™ need to:

- Identify the non-conscious centers of interests of a user on an e-commerce site;
- Recognize the wandering phase of this user on the e-commerce site;
- Detect the emotional state of this user at a given time and in a given situation.

11. Conclusion

When you do not have enough elements to make a decision, intuition is your most valuable asset. It's a cognitive process by which we come to a conclusion without realizing all the logical steps leading to it. In this process, emotion plays an important role.
So, in conclusion, trust your emotions while leaving the control to your cortex.

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