

A METHOD AND A SYSTEM FOR RECOMMENDING LIMITED CHOICES WHICH ARE PERSONALIZED AND RELEVANT TO A CUSTOMER

FIELD OF THE INVENTION:

This invention relates to the domain of recommender systems. In specific, the invention relates to a method and system for recommending limited choices which are personalized and relevant to the customer in real-time.

BACKGROUND OF THE INVENTION:

A few decades ago, the defining problem of the internet age was how to find the information needed. This gave birth to search engines for finding information by organizing the world's information. Now, an inflection point has reached, and the defining problem is no longer just a search for information. The biggest challenge faced by most users/customers is the explosion of choices due to more and varied sources of information, higher number of devices, increase in real-time data, higher transparency and the rise of social sites for influence on user behavior.

The book titled 'The Paradox of Choice' by Dr. Barry Schwartz, Swarthmore College (<http://wp.vcu.edu/univ200spencer/wp-content/uploads/sites/4941/2014/08/Paradox-of-Choice.pdf>) puts it: too many choices have led to decision paralysis, postponed moments of reckoning, increased expectations and decreased satisfaction in life. In other words, more choices is more confusion and leads to the decision paralysis.

In order to discover the relevant choices for the user, many methods are used, and they have significantly evolved in the recent times. The penetration of internet and usage of web resulted in the explosion of web data and machine generated data and started influencing the way enterprise data is getting interpreted. The sheer volume and variety of these data sets created the need for automatic recommendation systems. The social curation of user decisions in both enterprise context and consumer context resulted in the adoption of algorithm driven social recommender systems in online commerce segment. This opinion driven commerce is the result of consumption driven society, and the discovery of choices in this new world became a big challenge.

The domain of recommender systems covers the steps of prediction and recommendation and leverages different mathematical methods to solve the problems of finding similarity and ranking in the choices presented to the user. The usage of these recommended choices by the user is driven by both the objective methods (usefulness) and subjective perception (desirability).

The efficiency of the objective methods is based on the algorithms used to determine the choices for the user, and there are two main methods to drive recommendations to the user.

The first method is called Collaborative Filtering where usage of the ratings or actions of the other users similar to the user under focus drives the choices. Hence, it is driven by the assumption that if the user exhibits similar behavior like others for other items, the similarity measure determines the list of choices for the current item based on the others ratings for the current item. This is called User to User method for collaborative filtering. A variation of this is called Item to Item method for collaborative filtering where the similarity of the items is computed by leveraging the user ratings.

The second method is called content based filtering where the attributes of the items under consideration are used to derive the similarity and drive the recommendation to the user.

The history of collaborative filtering dates back to early 90s where there were solutions for recommending articles to read, music to listen to or jokes to hear. Products like Grundy, Tapestry, Grouplens, Ringo and Jester are good examples of these solutions. In late 90s and early 2000's, the popular examples are from online book stores like Amazon and online movie rental firms like Netflix. They have used a mix of purchase history, browsing history and current context to predict the possible choices for their online customers. These are the earliest examples of recommender systems in action for online e-commerce segment.

The below mentioned list is a representative list of some of the technical literature which explains the foundational layers of the concepts mentioned above.

- The non-patent literature titled 'collaborative filtering recommender systems' by Ekstrand et al. (<http://files.grouplens.org/papers/FnT%20CF%20Recsys%20Survey.pdf>);
- The non-patent literature titled 'An algorithmic framework for performing collaborative filtering' by Herlocker et al. (<http://files.grouplens.org/papers/algs.pdf>);
- United States Patent no. 8095432 by Berman et al discloses 'a system and method for generating a recommendation list for an item for purchase in a social network based on the order defined by the ranking';
- United States Publication no. 20120278310 by Laksmono et al discloses 'a system and method for providing a user a recommendation, with respect to objects, based on the social and spatial information for the user associated with a spatial-aware social graph'; and
- United States Publication no. 20130041862 by Yang et al discloses 'a method for providing recommendations in a social network by utilizing the conditional probability distribution to capture the similarity between the users using Bayesian inference'.

In the online world, the item to item collaborative filtering is gaining traction as it is often the case where the number of users exceeds the number of items under consideration. It is a challenge to compute the similarity measures of the users when the user base becomes a very large number. It is also noted that the item to item similarity does not change that often and hence it can be pre-computed and stored to drive the recommend process.

While the aforesaid approaches have their advantages, they have got certain disadvantages as well.

- They cannot be effectively used to deliver cross-category recommendations, i.e., by knowing a user's preferences in movies, the algorithms cannot deliver recommendations, for example, books;
- There is a cold-start problem here, i.e., they need a substantial information about the user before they can start delivering recommendations;
- They cannot be used to configure delivery of recommendations by understanding the taste of users holistically, i.e., they cannot be trained to increase serendipity, remove biases of location, etc.; and
- They cannot be setup for delivery of recommendations by combining a user's taste, context and behavior, i.e., they cannot be used to deliver choices by combining a user's location, social media likes, feedback, credit card spends, etc.

Hence, it is clear that there exists a need for an improved method and system for recommending limited choices which are personalized and relevant to a user, while keeping the value of serendipity and novelty.

SUMMARY OF THE INVENTION:

Before the present methods, systems, apparatuses and hardware enablement are described, it is to be understood that this invention is not limited to the particular methodologies, systems, and apparatuses described, as these may vary. It is also to be understood that the terminology used in the description is for the purpose of describing the particular versions or embodiments only, and is not intended to limit the scope of the present invention which will be limited only by the appended claims.

The present invention provides a method and system for recommending limited choices which are personalized and relevant to the customer in real-time to solve the problems mentioned in the art.

According to one embodiment of the invention, a method is provided for recommending limited choices which are personalized and relevant to a customer in real-time, in which steps thereof are implemented by a computer, the method comprising: receiving data across different categories of

products; configuring a taste graph based on the received data; calculating a net affinity between any two products in the taste graph and exporting them as taste scores to a taste table; understanding the customer based on context and behavior from different customer information sets; generating scores for the different customer information sets; determining different weightages for each score to calculate a net score associated with each product for the customer; and recommending the limited choices which are personalized and relevant to the customer in real-time based on the descending order of the value of the net score associated with the product.

According to another embodiment, a system is provided for recommending limited choices which are personalized and relevant to a customer in real-time comprising: at least one net affinity calculator adapted to calculate a net affinity between any two products in the taste graph and export them as taste scores to a taste table; at least one choice configurator adapted to understand the customer based on context and behavior from different customer information sets, to generate scores for the different customer information sets and to determine different weightages for each score to calculate a net score associated with each product for the customer; and at least one choice engine adapted to recommend the limited choices which are personalized and relevant to the customer in real-time based on the descending order of the value of the net score associated with the product.

BRIEF DESCRIPTION OF THE DRAWINGS:

The summary, as well as the following detailed description of preferred embodiments, is better understood when read in conjunction with the appended drawings. For the purpose of illustrating the invention, there is shown in the drawings example constructions of the invention; however, the invention is not limited to the specific methods, apparatuses and systems disclosed. In the drawings:

Figure 1 shows an exemplary system with which the methods according to the present invention may be implemented.

Figure 2 shows the overall system according to one exemplary embodiment of the invention.

Figure 3 shows the configuration of a taste graph by the configurator as shown in Figure 2.

Figure 4 shows an example of the taste graph according to one exemplary embodiment of the invention.

Figure 5 shows the taste graph according to another exemplary embodiment of the invention.

Figures 6 and 7 show how the net affinity calculator calculates net affinity according to various exemplary embodiments of the invention.

Figure 8 illustrates how the scores for different user information are calculated according to one exemplary embodiment of the invention.

Figure 9 shows how the configurator (as shown in Figure 2) calculates net score for each product.

Figure 10 shows how the choice engine (as shown in Figure 2) recommends choices to the customer.

Figure 11 illustrates the working example of the present invention.

DETAILED DESCRIPTION OF THE INVENTION:

Many of the functional units described in this specification have been labeled as means, in order to more particularly emphasize their implementation independence. For example, means may be implemented in software for execution by various types of processors. An identified means of executable code may, for instance, comprise one or more physical or logical blocks of computer instructions which may, for instance, be organized as an object, procedure, or function. Nevertheless, the executables of an identified means need not be physically located together, but may comprise disparate instructions stored in different locations which, when joined logically together, comprise the module and achieve the stated purpose for the means.

Indeed, a means of executable code may be a single instruction or many instructions, and may even be distributed over several different code segments, among different programs, and across several memory devices. Similarly, operational data may be identified and illustrated herein within means, and may be embodied in any suitable form and organized within any suitable type of data structure. The operational data may be collected as a single data-set, or may be distributed over different locations including over different storage devices, and may exist, at least partially, merely as electronic signals on a system or network.

Reference throughout this specification to 'one embodiment', 'one exemplary embodiment', 'another embodiment' or similar language means that a particular feature, structure, or characteristic described in connection with the embodiment is included in at least one embodiment of the present invention. Thus, appearances of the phrases 'one embodiment', 'one exemplary embodiment', 'another embodiment' or similar language throughout this specification may, but do not necessarily, all refer to the same embodiment.

Reference to a non-transitory computer readable medium may take any form capable of generating a signal, causing a signal to be generated, or causing the execution of a program of machine-readable instructions on a digital processing apparatus. A non-transitory computer readable medium may be embodied by a transmission line, a compact disk, digital-video disk, a magnetic tape, a Bernoulli drive, a magnetic disk, a punch card, flash memory, integrated circuits, or other digital processing apparatus memory device.

Furthermore, the described features, structures, or characteristics of the invention may be combined in any suitable manner in one or more embodiments. In the following description, numerous specific details are provided, such as an example of programming, program code and computer program product to provide a thorough understanding of embodiments of the invention. One skilled in the relevant art will recognize, however that the invention may be practiced without one or more of the specific details, or with other methods, components, materials, and so forth. In other instances, well-known structures, materials, or operations are not shown or described in detail to avoid obscuring aspects of the invention.

The present invention will be described with respect to particular embodiments and with reference to certain drawings, but the invention is not limited thereto but only by the Claims. Any reference signs in the Claims shall not be construed as limiting the scope. The drawings described are only schematic and are non-hinting. In the drawings, the size of scope of the elements may be exaggerated and not drawn on a scale for illustrative purposes. Where the term "comprising" is used in the present description and Claims, it does not exclude other elements or steps. Where an indefinite or definite article is used when referring to a singular noun e.g. "a" or "an", "the", this includes a plural of that noun unless something else is specifically stated.

Furthermore, the terms first, second, third, initially, next step, finally and the like in the description and in the claims, are used for distinguishing between similar steps and not necessarily for describing a sequential or chronological order. It is to be understood that the terms so used are interchangeable under appropriate circumstances and that the embodiments of the invention described herein are capable of operation in other sequences than described or illustrated herein.

The present invention provides a method and system for recommending limited choices which are personalized and relevant to the customer in real-time to solve the problems mentioned in the art. By way of explanation and example, the present invention will be described in detail below using following methods, apparatuses, and systems:

Figure 1 shows an exemplary system **100** with which, the methods according to the present invention may be implemented. The system **100** comprises of a processing device **110**, a memory **120**, a storage device **130**, a customer input device **140** and an output device **150**.

According to one aspect of the invention, the processing device **110** comprises of any one of the following: processor, microprocessor, controller, computer, central processing unit (CPU) or combination of these hardware based on the requirements.

In another aspect, the processing device **110** may be connected with one or more other processing devices (not shown) to form a network of processing devices via a communication network, wherein the other processing devices may be processor, microprocessor, controller, computer, central processing unit (CPU) or combination of these hardware, etc based on the requirements. In one exemplary aspect, the communication network may be wired or wireless communication network. In a preferred aspect, the communication network is an internet.

In one aspect, the memory **120** may be coupled to the processing device **110**, wherein the memory comprises of RAM, ROM, or any other storage memory known in the art, based on the requirements of the computing system **100**. The memory **120** may be used for storing

- i. program instructions executable by the processing device **110** for executing the methods according to the present invention; or
- ii. input received from a customer via the customer input device **140**; or
- iii. output received from the processing device **110**.

In one aspect, the storage device **130** may be coupled to the processing device **110**, wherein the storage device **130** comprises of RAM, ROM, or any other storage device known in the art based on the requirements of the computing system **100**. The storage device **130** may be used for storing

- i. program instructions executable by the processing device **110** for executing the methods according to the present invention;
- ii. input received from the customer via the customer input device **140**; and
- iii. output received from the processing device **110**.

In another aspect, the storage device **130** may be an optional device and for providing additional storage space in the computing system **100**.

In one aspect, the customer input device **140** may be coupled to the processing device **110**, wherein the customer input device **140** may be a mobile phone. In another exemplary aspect, customer input device **140** may be any one of the followings such as tablet, computer, and

wearable sensors, etc. In another exemplary aspect, the customer may enter the required inputs via the customer input device **140** such as keyboard and mouse.

In one aspect, the output device **150** may be coupled to the processing device **110**, wherein the output device **150** may be a display device which can show the output of the processing device **110** in any format comprising text, audio, video, or a combination of these, etc.

In another aspect, the methods according to the present invention may be implemented by using the processing device **110**, memory **120**, storage device **130**, customer input device **140**, and output device **150** connected to the processing device **110**. The method of recommending limited choices which are personalized and relevant to the customer in real-time carried out in the above said system according to the methods of the present invention.

For example, in an exemplary aspect, the customer may log on a mobile application (mobile app) and may enter the required inputs, that the customer is looking for a movie. In addition, the customer may enter additional details, examples of which can be that the customer is with a spouse, what restaurants the customer likes, and age and gender of the customer.

In the first step of the method, upon receiving the above said details, the processing device **110** may retrieve raw data such as different categories of the products via a recommendation application resident in the memory **120**, wherein the different categories of products comprises of books, movies, restaurants, hotels, music, shopping, television (TV) shows and events and deals, etc. According to one aspect, the raw data may be stored in a product database (not shown) which is stored in the memory **120** or in the storage device **130**. In another aspect, the data may be stored in the non-transitory computer readable medium which may be inserted into the processing device **110** (such as computer, laptop, tablet and notebook, etc) to retrieve the data. In another aspect, the data may be stored in a server, and the processing device **110** may retrieve the data from the server (not shown) using the recommendation application via the communication means such as internet.

In one aspect, the data may be received by the processing device **110** in the following formats such as {customer-product-review} tuples, product metadata, user information and review details, etc or combinations thereof based on the requirements. In one exemplary aspect, the product metadata comprises of the movie name, actors, directors, genre, year of release, popularity and critic rating for the movie, etc, or combinations thereof. In another exemplary aspect, the user information comprises of reviewer type and location, etc, or combinations thereof. In another exemplary aspect, the review details comprise of rating and exact review, etc, or combinations thereof.

In the next step, a taste graph may be configured by the processing device 110 using the recommendation application based on the retrieved data and the customer inputs. The context of the taste mentioned above as well as throughout the specification should be considered as the preference or likeliness of the customer for different products like food, movies, books, TV shows, shopping, and hotels, etc.

In one aspect, the taste graph may be configured in such a way that it enables all possible forms of pruning and shaping of the graph flow. For example, if the customer likes the movie 'Pulp Fiction' and then, firstly, it can indicate that the customer may like movies such as 'Snatch' and 'Red Dragon' which are most connected to the movie 'Pulp Fiction'. Secondly, it can indicate that the customer may like movies such as 'Night of the Twisters' and 'Miller's Crossing' which are most connected niche movies in respect of the movie 'Pulp Fiction'. Thirdly, it can indicate that the customer may like movies such as 'Kill Bill' and 'Face Off' with same director 'Tarantino'. Further, it can also indicate that the customer may like books such as 'The Maltese Falcon' and 'The Black Dahilla' which are most connected with the movie 'Pulp Fiction', etc. Therefore, the taste graph may be configured in a such a way that it may contain only top n connections from any product to any product, top movies where actor/director/genre is same, niche movies even if the niche movies has lower affinity and book connections where the genre with the movie is same etc. Further, the proper pruning of configuration of taste graph will enable a much better modeling of customer's taste.

As shown in Figure 3, the processing device 110 may take configuration file (TBD) and the retrieved data across different categories of products as input using the recommendation application and may utilize at least one filter to output the taste graph. In one exemplary aspect the filter may use the following formula while considering various parameters such as from node, to node and affinity between the nodes to configure the taste graph:

Select

((FromNode.type = "Movie") AND (ToNode.type = "Movie") AND (Vertex.Strength in Top 2)

) UNION

((FromNode.type = "Movie") AND (ToNode.type = "Movie") AND (FromNode.Director = ToNode.Director) AND (Vertex.Strength in Top 2)

) UNION

((FromNode.type = "Movie") AND (ToNode.type = "Movie") AND (ToNode.Likes < 100) AND

(ToNode.rating>8) AND (Vertex.Strength in Top 2)).

In the above said manner, the taste graph may be configured and developed by the processing device 110.

In another exemplary aspect, the processing device **110** may configure and develop the taste graph as shown in Figure 4, using multiple taste attributes and different categories of products using the recommendation application. In one exemplary aspect, the processing device **110** starts with (Product-Customer-Taste as) tuples, and builds 6 sets of connections based on these tuples and domains:

1. Calculate affinity strengths between products using co-occurrence of reviews. The co-occurrence may be identified using explicit indications in the structured data or unstated indications like sentiment analysis

Example: Movie “Pulp Fiction” may be connected to Movies “Snatch” and “Red Dragon”.

2. Derive niche choices using heuristic-scaling of the ratings. The processing device **110** may be used to:
 - Recommend niche products in the consumers’ taste that would generally be left out of the popular rating based recommendation engines

Example: “Pulp Fiction” may be connected to “Night of the Twisters” and “Miller’s Crossing”, both of which are non-blockbusters (unlike “Pulp Fiction”)

3. Calculate equivalent affinity between products with multiple hops in the graph. The processing device **110** may be used to:
 - Deliver serendipitous choices which would otherwise not be usually selected by the consumer
 - Cater to sparse taste matrices, and this may be done by using a Thevenin’s theorem known in the art.

Example: Movie “Pulp Fiction” may be connected to Movies “Snatch” and “Red Dragon”, which in-turn could be connected to “Ocean’s Thirteen” and “Silence of the Lambs”.

4. Develop attribute-led taste discovery using domain-led heuristics. The processing device **110** may be used to:
 - Map the attributes of the product (like director, actor, and genres in the movies) to the taste of the person

Example: “Pulp Fiction” may be connected to other ‘Tarantino’ movies like “Kill Bill” or other John Travolta movies like “Face Off”.

5. Develop higher-level abstraction of the attributes. This processing device **110** may be used to:

- Map the underlying unstated-attributes of the product to the taste of the person

Example: “Pulp Fiction” would be construed as Film Noir, and other movies in the same Genre (like “The Big Sleep” and “Night and the City”) would be linked to it

6. Derive cross-category linkages. The processing device **110** may be used to:

- Understand the preferences of a person beyond single-categories, to develop a holistic picture of the taste of the person

Example: “Pulp Fiction” could be linked to the books “The Maltese Falcon” and “The Black Dahlia”.

In the above said manner, taste of the customer may be understood by the processing device **110** to configure and develop the taste graph. For example, if the customer likes the movie ‘Pulp Fiction’ and then, firstly, the customer may like movies such as ‘Snatch’ and ‘Red Dragon’ which are most connected to the movie ‘Pulp Fiction’. Secondly, the customer may like movies such as ‘Night of the Twisters’ and ‘Miller’s Crossing’ which are most connected niche movies in respect of the movie ‘Pulp Fiction’. Thirdly, the customer may like movies such as ‘Ocean’s Thirteen’ and ‘Silence of the Lambs’ which are connected to ‘Snatch’ and ‘Red Dragon’, respectively which in turn connected to the movie ‘Pulp Fiction’. Fourthly, the customer may like movies such as ‘Kill Bill’ and ‘Face Off’ which are most connected movies with same director ‘Tarantino’. Fifthly, the customer may like movies such as ‘The Big Sleep’ and ‘Night and the City’ which are most connected movies based on the higher level of abstraction of attributes with the movie ‘Pulp Fiction’. Finally, the customer may like books such as ‘The Maltese Falcon’ and ‘The Black Dahilla’ which are most connected with the movie ‘Pulp Fiction’.

In the next step, as shown in Figure 5, a graph can be developed using all the affinities from the previous step. Subsequently, net affinity between any two products in the taste graph may be calculated, and those net affinities may be exported as taste scores to a taste table by the processing device **110**. In one exemplary aspect, the taste scores may be represented in a 3 column-table represented by the following structure:

Product 1 – Product 2 – Taste score

In one exemplary aspect, the net affinity between any two products in the taste graph may be heuristically calculated by the processing device 110 using a graph traversing methodology and corresponding formulae as shown in Figures 6 and 7.

For example, the product may be any one of the followings such as books, movies, restaurants, hotels, music, shopping, television (TV) shows, and events and deals, etc. Let us consider the product is a movie and then the net affinity between any two movies may be calculated as follows:

As shown in Figure 6, in the taste graph, nodes are represented by the movies and the connections between the nodes are represented by the affinity values, respectively. If the affinity value between 'Movie A' and 'Movie B' is 'x' and the affinity value between the 'Movie B' and 'Movie C' is 'y' then the affinity value between the Movies 'A' and 'C' may be calculated using the following formula:

$$\text{Net Affinity} = xy / (x+y)$$

Any other formula utilizing the affinity values of 'x' and 'y' may also be used to calculate net affinity between the movies 'A' and 'C' based on the requirements.

In another example, the taste graph may contain various nodes 'P₁', 'P₂', 'P_n', 'P_p' and 'P_q' and nodes 'P₁' and 'P₂' are connected with each other directly, via the node 'P_n', via the node 'P_p' and via the node 'P_q'. The nodes 'P₁', 'P₂', 'P_n', 'P_p' and 'P_q' may represent the product and the connections between any two nodes may represent the affinity value, respectively. For example, the product may be any one of the followings such as books, movies, restaurants, hotels, music, shopping, television (TV) shows, and events and deals, etc. Let us consider the product is a movie and then the net affinity between the two movies i.e. nodes 'P₁' and 'P₂' may be calculated with various degrees of depth as follows:

The net affinity between the nodes 'P₁' and 'P₂' (which are connected to each other directly i.e. a first degree of depth) may be calculated using the following formula, as shown in Figure 7:

$$\text{NetAffinit } y_{P_1, P_2} = \text{Affinity }_{P_1, P_2}$$

The net affinity between the nodes 'P₁' and 'P₂' (which are connected via node 'P_n' i.e. a second degree of depth) may be calculated using the following formula, as shown in Figure 7:

$$\text{NetAffinit } y_{P_1, P_2} = \text{Affinity }_{P_1, P_2} + \sum_n \frac{1}{(1/\text{Affinit } y_{P_1, P_n}) + (1/\text{Affinit } y_{P_n, P_2})}$$

, wherein n represents the number of nodes present in the taste graph and 'P_n' represents nth node in the taste graph.

The net affinity between the nodes 'P₁' and 'P₂' (which are connected via the node 'P_n' and a node 'P_p' i.e. a third degree of depth) may be calculated using the following formula, as shown in Figure 7:

$$\text{NetAffinit } y_{P_1, P_2} = \text{Affinity } y_{P_1, P_2} + \sum_n \frac{1}{(1/\text{Affinit } y_{P_1, P_n}) + (1/\text{Affinit } y_{P_n, P_2})} + \sum_{n,p} \frac{1}{(1/\text{Affinit } y_{P_1, P_n}) + (1/\text{Affinit } y_{P_n, P_p}) + (1/\text{Affinit } y_{P_p, P_2})}$$

, wherein 'P_p' represents a first intermediate node.

The net affinity between the nodes 'P₁' and 'P₂' (which are connected via the node 'P_n', the node 'P_p' and a node 'P_q' i.e. a fourth degree of depth) may be calculated using the following formula, as shown in Figure 7:

$$\text{NetAffinity } y_{P_1, P_2} = \text{Affinity } y_{P_1, P_2} + \sum_n \frac{1}{(1/\text{Affinity } y_{P_1, P_n}) + (1/\text{Affinity } y_{P_n, P_2})} + \sum_{n,p} \frac{1}{(1/\text{Affinity } y_{P_1, P_n}) + (1/\text{Affinity } y_{P_n, P_p}) + (1/\text{Affinity } y_{P_p, P_2})} + \sum_{n,p,q} \frac{1}{(1/\text{Affinity } y_{P_1, P_n}) + (1/\text{Affinity } y_{P_n, P_p}) + (1/\text{Affinity } y_{P_p, P_q}) + (1/\text{Affinity } y_{P_q, P_2})}$$

, wherein 'P_q' represents a second intermediate node.

In the next step, the processing device **110** may understand the customer based on context and behavior of the customer from different customer information sets. In an exemplary aspect, the information sets may relate to the context of the customer comprises of what is the location, what is the date/time, what the weather is and who is the customer accompanied by, etc. In another exemplary aspect, the information sets may relate to the behavior of the customer comprises of what are the transactions of the customer, what are the social media likes of the customer, what are the stated preferences of the customer, what attributes does the customer like and what the customer feedback to the choices is already provided, etc.

In addition to the customer inputs, in an exemplary aspect, the customer input device **140** may identify location, time, date, weather and activity the customer indulges in. In another exemplary aspect, the customer input device **140** may track the digital trail the customer leaves behind including every site the customer visits, every click the customer makes. Increasingly, with the proliferation of cameras, customer input device **140** may even capture every gesture or face the customer makes to understand the behavior and the current context of the customer. Further, the customer input device **140** may ask for customer's age and gender as an input from the customer to understand the behavior and the current context of the customer. The customer input device

140 may also read the customer's likes from the social networking sites such as Facebook, Twitter and also understand the feedback on choice earlier sent to the customer.

In the next step, the scores may be generated by the processing device **110** as shown in Figure 8, for the different customer information sets. In one exemplary aspect, the scores for the different customer information sets may be generated based on heuristics models and the taste graph, wherein the scores for the different customer information sets comprises of accompany score, weather score, location score, data/time score, preference score, social media like score, segment score and feedback score, etc. In an exemplary aspect, the scores may relate to the context of the customer comprises of accompany score, weather score, location score and data/time score, etc. In an exemplary aspect, the scores may relate to the behavior of the customer comprises of preference score, social media like score, segment score, and feedback score, etc.

In one exemplary aspect, the location score may be derived by the processing device **110** using the following formula:

Customer location-> Customer lat/ long -> distance of all restaurants from the Customer
-> normalized distance score.

As an example, the normalized distance score may be calculated as a constant number divided by the distance for the customer for each restaurant

In another exemplary aspect, the social media like score of the customer may be derived by the processing device **110** using the following formula:

Customer social media data -> Customer likes -> Likes scores from the taste table.

As an example, the social media score for each product may be the sum of affinities for that product, based on the products liked by the customer in Facebook.

In another exemplary aspect, the preference score of the customer may be derived by the processing device **110** using the following formula:

Customer preferences -> Product attributes that the Customer likes -> Attribute scores for each product.

As an example, attribute score for each product may be a constant number (greater than 1) when it contains the attributes liked by the customer and 1 otherwise.

Similarly, other scores may be derived by the processing device **110** using various formulas, which will be heuristically derived, depending on the situation

In the next step, different weightages for each score may be determined as shown in Figure 9, to calculate a net score associated with each product for the customer. In one exemplary aspect, depending on the situation/client/use-case, different weightages for each score may be determined to calculate the “net score” for the customer for each product.

As an example, the net score may be:

Attribute score * (Preference score + Social media score + Feedback score) * Location score

This will indicate that, to deliver choices:

- the algorithm looks for stated preferences and/or likes in social media and/or feedback on some products from the customer;
- the algorithm then weighs the score by attributes that the customer has indicated that the customer likes; and
- the algorithm then weighs the score by the location score, thereby giving higher weightages to products that are available nearby.

In the final step of the method, as shown in Figure 10, limited choices which are personalized and relevant to the customer may be recommended by the processing device **110** in real-time based on the descending order of the value of the net score associated with the product. Preferably, the limited choices vary from 2-6 choices.

In addition to the above, at least one feedback about the choices from the customer may be received to utilize the same in feedback score of the customer by the processing device **110** for improving the recommendation of limited choices which are personalized and relevant to the customer.

According to another embodiment of the invention, a system is provided for recommending limited choices which are personalized and relevant choices to the customer in real-time. As shown in Figure 2, the system **200** comprises of a taste configurator **205**, a net affinity calculator **210**, a choice configurator **215**, a choice engine **220**, a customer input device **225**, a memory **230** (not shown), an output device **235** (not shown) and a product database (not shown), etc. The method of recommending limited choices which are personalized and relevant to the customer in real-time carried out in the above said system according to the methods of the present invention.

In one aspect, the taste configurator **205**, the net affinity calculator **210**, the choice configurator **215** and the choice engine **220** comprises of any one of the followings such as processor, microprocessor, controller, central processing unit (CPU) or combination of these hardware, etc based on the requirements. The taste configurator **205**, the net affinity calculator **210**, the choice configurator **215** and the choice engine **220** may be located either together in the server (not shown) or remotely located in various servers (not shown) and logically connected together to perform the required task.

Initially, the customer may enter the requirements via the customer input device **225** which is similar to the customer input device **140** as depicted in Figure 1.

Upon receiving the customer inputs in the customer input device **225**, the taste configurator **205** may retrieve raw data such as different categories of products from the product database as discussed above with respect to Figure 1. The taste configurator **205** may also configure a taste graph based on the retrieved data and the customer inputs as discussed above with respect to Figure 1.

In another aspect, the net affinity calculator **210** may calculate a net affinity between any two products in the taste graph and export them as taste scores to a taste table as discussed above with respect to Figure 1.

In another aspect, the choice configurator **215** may understand the customer based on context and behavior from different customer information sets as discussed above with respect to Figure 1.

In another aspect, the choice configurator **215** may generate scores for the different customer information sets as discussed above with respect to Figure 1.

In another aspect, the choice configurator **215** may determine different weightages for each score to calculate a net score associated with each product for the customer as discussed above with respect to Figure 1.

In another aspect, the choice engine **220** may recommend limited choices which are personalized and relevant to the customer in real-time based on the descending order of the value of the net score associated with the product as discussed above with respect to Figure 1.

In another aspect, the choice configurator **215** may also receive at least one feedback about the choices from the customer to utilize the same in feedback score of the customer in order to improve the recommendation of the limited choices which are personalized and relevant to the customer.

According to another embodiment of the invention, an apparatus is provided for recommending limited choices which are personalized and relevant to a customer in real-time, comprising: means for receiving data across different categories of products; means for configuring a taste graph based on the received data; means for calculating a net affinity between any two products in the taste graph and exporting them as taste scores to a taste table; means for understanding the customer based on context and behavior from different customer information sets; means for generating scores for the different customer information sets; means for determining different weightages for each score to calculate a net score associated with each product for the customer; and means for recommending the limited choices which are personalized and relevant to the customer in real-time based on the descending order of the value of the net score associated with the product.

According to another embodiment of the invention, a non-transitory computer readable medium is provided for recommending limited choices which are personalized and relevant to a customer in real-time, including program instructions executable by a computer for: receiving data across different categories of products; configuring a taste graph based on the received data; calculating a net affinity between any two products in the taste graph and exporting them as taste scores to a taste table; understanding the customer based on context and behavior from different customer information sets; generating scores for the different customer information sets; determining different weightages for each score to calculate a net score associated with each product for the customer; and recommending the limited choices which are personalized and relevant to the customer in real-time based on the descending order of the value of the net score associated with the product.

According to another embodiment of the invention, a computer program is provided, comprising program code stored in a non-transitory computer readable medium, the program code executable by a computer to carry out the above mentioned method of the present invention.

According to another embodiment of the invention, a computer program is provided, comprising program code stored in a non-transitory computer readable medium, the program code executable by a computer to carry out the above mentioned method of the present invention, the program code arranged for being integrated in or added to a computer application for joint execution of said computer program and said computer application by said computer.

According to another embodiment of the invention, a computer program product is provided, comprising program code stored on a non-transitory computer readable medium, the program code readable by a computer, which operates to carry out the above mentioned method of the present invention, when said program code is executed by said computer.

According to another embodiment of the invention, a computer program product is provided, comprising program code stored on a non-transitory computer readable medium, the program code readable by a computer, which is operable to carry out the above mentioned method of the present invention, and further comprising integrating said program code into a computer application for joint execution of said program code and said computer application by said computer.

The invention is described in the example given below which is provided only to illustrate the invention and therefore should not be construed to limit the scope of the invention.

Consider a typical decision – Zara has just arrived in a new city after 6 hours of flight, it's 6.30pm and she wants to get a decent vegetarian meal. What does she do? She fires up Google, searches for good restaurants in that city, and filters them by type, price, location, etc. She searches the review sites and blogs, both international and local for reviews and ratings on what might be a decent choice. She asks the hotel concierge or asks some friends on Facebook, email or SMS for ideas. She whips out her mobile phone and looks for stuff that is 'nearby'. A good 30-60 minutes later, tired and weighed down by information overload, she does what most would in the coffee shop of the hotel she is staying at, or even order room service. The good meal she planned will have to wait till tomorrow. The challenge she faces is not lack of information. The challenge is to filter the right information, for her, the decision-maker. To do so, she needs to spend a huge amount of effort and time to navigate the choices. But the one thing she does not have enough is time.

To solve the above mentioned problem of filtering too many misery choices and to provide the most relevant and personalized choice to the Zara, the present invention provides a recommendation application which is connected to the mobile application (mobile app) of the Zara's mobile.

As shown in Figure 11, she logs on the mobile app and enters her requirements i.e. she is looking for restaurants nearby area which is suitable for her. The recommendation application knows she is a vegetarian that she doesn't like spicy food. The sensors of the mobile identify her location. Upon processing the inputs received from her and other relevant information, the recommendation application configures and processes the taste graph to calculate the taste scores which link all restaurants with other restaurants with an affinity score. Further, the recommendation application understands the current context and behavior of the Zara using various scores related to the context and behavior of the Zara along with the taste score to generate 4 most relevant and personalized choices and displays the same on the display of the Zara's mobile. Now, she looks at the screen and there are 4 choices of restaurants that serve vegetarian food – one recommended by a friend of hers who has been there recently, one reviewed well in her favorite newspaper, another that has rave reviews from other vegetarians,

and a fourth that is really close by and affordable. She clicks on two of them to get to know more, and after 5 minutes, she's made her choice. In this way, the recommendation application of the present invention helps to choose the best choices of restaurants in an easy, simple, quick and really useful way.

It will be appreciated that the above description for clarity has described embodiments of the invention with reference to different functional units and processors. However, it will be apparent that any suitable distribution of functionality between different functional units or processors/computers may be used without detracting from the invention. For example, functionality illustrated to be performed by separate processors or controllers may be performed by the same processor or controllers. Hence, references to specific functional units are only to be seen as references to suitable means for providing the described functionality rather than indicative of a strict logical or physical structure or organization.

The invention can be implemented in any suitable form including hardware, software, firmware or any combination of these. The invention may optionally be implemented at least partly as computer software running on one or more data processors and/or digital signal processors. The elements and components of an embodiment of the invention may be physically, functionally and logically implemented in any suitable way. Indeed the functionality may be implemented in a single unit, in a plurality of units or as part of other functional units. As such, the invention may be implemented in a single unit or may be physically and functionally distributed between different units and processors.

Although the present invention has been described in connection with some embodiments, it is not intended to be limited to a specific form set forth herein. Rather, the scope of the present invention is limited only by the accompanying claims. Additionally, although a feature may appear to be described in connection with particular embodiments, one skilled in the art would recognize that various features of the described embodiments may be combined in accordance with the invention. In the claims, the term comprising does not exclude the presence of other elements or steps.

Furthermore, although individually listed, a plurality of means, elements or method steps may be implemented by e.g. a single unit or processor. Additionally, although individual features may be included in different claims, these may possibly be advantageously combined, and the inclusion in different claims does not imply that a combination of features is not feasible and/or advantageous. Also, the inclusion of a feature in one category of claims does not imply a limitation to this category but rather indicates that the feature is equally applicable to other claim categories as appropriate. Furthermore, the order of features in the claims do not imply any specific order in which the features must be worked and in particular the order of individual steps

in a method claim does not imply that the steps must be performed in this order. Rather, the steps may be performed in any suitable order.

INDUSTRIAL APPLICABILITY:

The methods, systems and apparatuses of the proposed invention can be used in multiple industries, including Banking industry to deliver right offers that the customer could use the bank credit card, Retail industry to recommend the right products that the customer could buy, Hotel industry to help the customer with concierge services, and Telecom industry to provide the customer with personal content guide, etc. The methods, systems and apparatuses of the proposed invention can also be used in other industries as applicable.

ADVANTAGES OF THE INVENTION:

The methods, systems and apparatuses of the proposed invention can be used for

- Recommending limited choices which are personalized and relevant to the customer in order to make the customer feel more confident in their decisions and be happier with their choices;
- Helping the customer to choose the best choices in an easy, simple, quick and really useful way; and
- Helping industries to reach out to their customers with the most relevant and personalized recommendation of products/services, thereby resulting in higher sales and higher customer engagement.

We Claim:

1. A method of recommending limited choices which are personalized and relevant to a customer in real-time, in which steps thereof are implemented by a computer, the method comprising:
 - receiving data across different categories of products;
 - configuring a taste graph based on the received data;
 - calculating a net affinity between any two products in the taste graph and exporting them as taste scores to a taste table;
 - understanding the customer based on context and behavior from different customer information sets;
 - generating scores for the different customer information sets;
 - determining different weightages for each score to calculate a net score associated with each product for the customer; and
 - recommending the limited choices which are personalized and relevant to the customer in real-time based on the descending order of the value of the net score associated with the product.
2. The method as claimed in claim 1, further comprising receiving at least one feedback about the choices from the customer and improving the recommendation of the personalized and relevant choices utilizing the feedback.
3. The method as claimed in claim 1, wherein the net affinity between any two products is calculated using a graph traversing methodology.
4. The method as claimed in claim 1, wherein the scores for the different customer information sets are generated based on heuristics models and the taste graph.
5. The method as claimed in claim 1, wherein the different categories of products comprises of books, movies, restaurants, hotels, music, shopping, television (TV) shows or events and deals.
6. The method as claimed in claim 1, wherein the data may be received in a format comprises of tuples, product metadata, user information or review details.
7. The method as claimed in claim 1, wherein the information sets relate to the context of the customer comprises of what is the location, what is the date/time, what the weather is or who is the customer accompanied by.
8. The method as claimed in claim 1, wherein the information sets relate to the behavior of the customer comprises of what are the transactions of the customer, what are the social media

likes of the customer, what are the stated preferences of the customer, what attributes does the customer like or what the customer feedback to the choices is already provided.

9. The method as claimed in claim 1, wherein the scores for the different customer information sets comprises of accompany score, weather score, location score, data/time score, preference score, social media like score, segment score or feedback score.

10. The method as claimed in claim 1, wherein the limited choices may vary from 2-6 choices.

11. A system for recommending limited choices which are personalized and relevant to a customer in real-time comprising:

- at least one taste configurator adapted to receive data across different categories of products and to configure a taste graph based on the received data;

- at least one net affinity calculator adapted to calculate a net affinity between any two products in the taste graph and export them as taste scores to a taste table;

- at least one choice configurator adapted to understand the customer based on context and behavior from different customer information sets, to generate scores for the different customer information sets and to determine different weightages for each score to calculate a net score associated with each product for the customer; and

- at least one choice engine adapted to recommend the limited choices which are personalized and relevant to the customer in real-time based on the descending order of the value of the net score associated with the product.

12. The system as claimed in claim 11, wherein the at least one choice configurator is adapted to receive at least one feedback about the choices from the customer and to improve the recommendation of the personalized and relevant choices utilizing the feedback.

13. The system as claimed in claim 11, wherein the at least one net affinity calculator is adapted to calculate the net affinity between any two products using a graph traversing methodology.

14. The system as claimed in claim 11, wherein the at least one choice configurator is adapted to generate the scores for the different customer information sets based on heuristics models and the taste graph.

15. The system as claimed in claim 11, wherein the different categories of products comprises of books, movies, restaurants, hotels, music, shopping, television (TV) shows or events and deals.

16. The system as claimed in claim 11, wherein the data may be received in a format comprises of tuples, product metadata, user information or review details.
17. The system as claimed in claim 11, wherein the information sets relate to the context of the customer comprises of what is the location, what is the date/time, what the weather is or who is the customer accompanied by.
18. The system as claimed in claim 11, wherein the information sets relate to the behavior of the customer comprises of what are the transactions of the customer, what are the social media likes of the customer, what are the stated preferences of the customer, what attributes does the customer like or what the customer feedback to the choices is already provided.
19. The system as claimed in claim 11, wherein the scores for the different customer information sets comprises of accompany score, weather score, location score, data/time score, preference score, social media like score, segment score or feedback score.
20. The system as claimed in claim 11, wherein the limited choices may vary from 2-6 choices.
21. A non-transitory computer readable medium for recommending limited choices which are personalized and relevant to a customer in real-time, including program instructions executable by a computer for:
- receiving data across different categories of products;
 - configuring a taste graph based on the received data;
 - calculating a net affinity between any two products in the taste graph and exporting them as taste scores to a taste table;
 - understanding the customer based on context and behavior from different customer information sets;
 - generating scores for the different customer information sets;
 - determining different weightages for each score to calculate a net score associated with each product for the customer; and
 - recommending the limited choices which are personalized and relevant to the customer in real-time based on the descending order of the value of the net score associated with the product.