General Framework factorization for Context-Aware Recommendation of E-Commerce on Automotives

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Abstract

The twenty-first century is a battle for automotive industry. Many Companies emerged as the bones for the Horseless carriages. E-commerce rejuvenates major services to global market. There is high impact of automotives on the Consumers and they are bound to utilize automotives in their daily life. E-Commerce brings various options to products and services on various choices and the study of variants perceptively. The global market places high end recommendations to various systems by admitting progressive awareness through advent of e-commerce systems in the twenty first century. The conventional approach is a solution to automotive engines, complacent with collaborative filtering which promotes the challenges in calculating the recommended position of items for a certain user. The traditional approach makes static users to retrieve highly dynamic context information and gain item information efficiently. The application of context information concedes the interest to entertain mobile computing platforms like Android-phones and Pocket computers at high end in Automotives E-commerce market. The works on brief study of the various risk factors of Automotives propose a conceptual general framework to implement context-aware recommendations on engines, specifically for mobile platforms. E-commerce adds revenue through the fingertip features.

Key Words: *Context Automotives, ED-Commerce system, awareness; context aware information, Context aware recommendation; decision support; recommended systems…*

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I. INTRODUCTION:

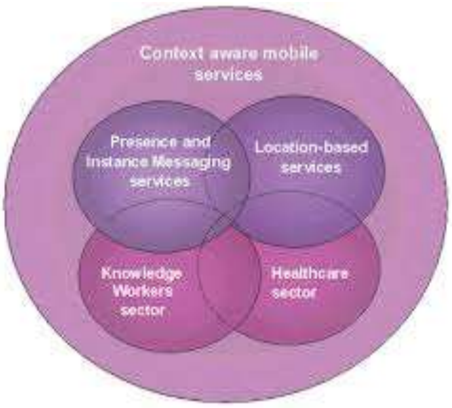
The contemporary consumer is plagued with options and choices. Global marketplaces, for automotives like carwale, zigwheels, automobile18.com, junglee.com, autocorpo, Gaadi.com, infibeem.com, Capegemini offer a huge volume of different products and services in hundreds of categories. The classifications of wide spectrum of product families are from traditional hardware to software and mobile apps, eBooks, electronics, video and music streaming or even food. Today global market places offer unlimited possibilities to publish and instantly deliver all kinds of products and services. The products and services in the context aware recommendations make the companies to present easier to specific product to customers. High volume of products are accessible in international marketplaces and the consumers limit their era and enthusiasm to check the required products like Vehicle engine systems, Vehicle drive trains, vehicle dynamic control systems, vehicle chassis and body design. These recommendations help the customers to choose the appropriate vehicle for their needs. The reference systems such as the automotives product recommendation like carwale, zigwheels, automobile18.com, junglee.com, autocorpo, Gaadi.com, infibeem.com, Capegemini exist from time immemorial. The traditional recommendation systems help the consumers soon to get the right identity within the enormous amount of vacant products. Global market places a familiar need for transparent product recommendations within their systems.

Research is carry on the basic factors of the automotive structures in consumer market on parameters like Engine, Power, Torque, Transmission, Price, Wheelbase, Automotive Exteriors & Interior Systems and Control systems. Technology upgrades the Minor cosmetic which are seen in the day- to- day life in automotives. The automotive industry is a broad range of companies and organizations involved in the united brands with design, development, product , marketing and manufacture, and selling of motor vehicles.[1] All the world's important economic sectors in revenue includes the automotive industry. The countries include industries dedicated to the maintenance of automobiles following delivery to the end-user, such as automobile repair shops and motor fuel filling stations. Automotives is derived from the Greek word Autos which mean Self, and Latin motivus called motion to represent any form of self-powered vehicle.

Hundreds of manufacturers created horseless carriage in the early 19 Century. Decades moved the United States and there arises a revolution in automobile production. The world had 32 Millions of automobiles in use, and the U.S. automobile industry produced over 90%. There was 1 car per 4.87 persons. World War II was the lead and U.S. produced 75 percent of world's auto production. In 1980 all the major countries recognized the high need of automobile industry and the world's gained again in 1994. In 2006, Japan narrowly passed the U.S. in production and held this rank until 2009, when China took the top spot with 13.8 million units. With 19.3 million units manufactured in 2012, China almost doubled the U.S. production. In 1970 (150 models) over 1998 (250 models) to 2014 (1084 models), the number of automobile models in the U.S. has grown exponentially..

2 Related Works:

The recommendation system is an active service technique, in which servers collect and analyze user information to learn about their behaviors and interests to build a model, provide services that meet their personal needs based on the personalized interest model. In recommender systems, the utility of an item is usually represented by a rating, which measures how much a specific user is interested in the item. The collaborative filtering serves the users who are opinioned to possess similar kind as the active user in the past. The recommender systems based on collaboration filtering are particularly popular and used by large online sharing item. Context aware recommendation techniques are used for producing personalized recommendations by computing the similarity between the current user and other users with similar choices.



Since Context Aware Methods only require the information about user interactions and do not rely on the content information of items or user profiles,. The extensive applications are meant for more research studies on filtering. These methods filter or evaluate items through the opinions of other users. The assumptions are the given user prefers the items with other users with similar preferences liked in the past.

The domains are universal and hap-tic computing, mobile computing, information retrieval, marketing and management as well as in several automotive engineering disciplines.

The term context-aware software was first used in the Xerox PARC research project PARCTAB in 1994. The works define the software that is able to adapt conditions of the certainty of location, advanced in Ad-hoc Networking, hosts and accessible devices. The possibility to track the changes of context information over time stores historic context information as mentioned. Different research groups are enriched with basic definition of context and context-aware software. Brown et al. exemplifies the widened scope of context information to Automotive on parameters Engine, Power, Torque, Transmission, Price, Wheelbase, Automotive Exteriors & Interior Systems and Control systems.

Contexts are the circumstantial information of the user and the domain provides data relevant to the consumer needs. The Consumer can interact with the application. The basic classes say Person, Place and the object are identified and the related information is sorted as per the user requirements. The last Decade witnessed multiple architectures and implementations of software middleware frameworks. These emphasize the aggregation and interpretation of context-information.

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Traditional recommendation systems take a set x of users and a set of products (items) S , which should be recommended to a user. A recommendation system then provides an utility function f that measures the relevance of a product out of set S to a given user. This utility function f (f : x S ! A, where A is an ordered set of numbers) assigns a number to each item (or even to a compound set of items) in a way that captures the relevance or preference of an user. The objective of recommendation systems is to find or learn this utility function f. Function f is used to predict the relevance of items out of S and of new appearing items with similar attributes. Traditional recommendation approaches are distinguished into two major strategies: content filtering and collaborative filtering.

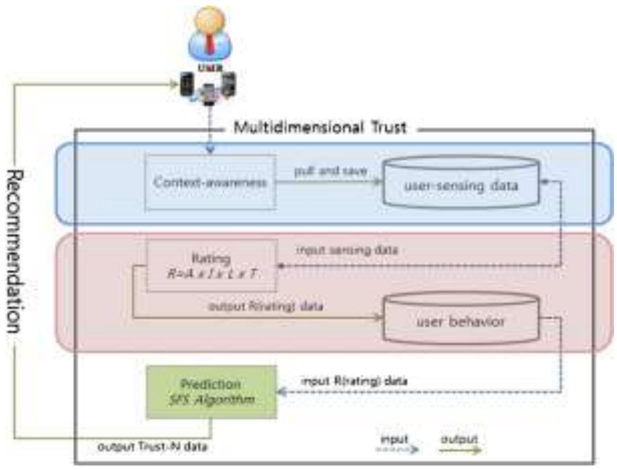
A. Content Filtering:

The content filtering approach creates profiles for each item and user, in order to characterize and compare its nature .Each profile contains a specific set of attributes, which can be used to compare objects. A recommendation function f chooses items that are similar to items the user has already chosen or rated before. The utility function compares the user's profile and calculates the similarity of a user profile with the available items.

B.Multidimensional recommendation

Tensor Factorization is an existing N-dimensional extension of Matrix Factorization. In the current section we introduce the model of Matrix and Tensor Factorization and explain the details of how we have adapted this model for multidimensional filtering. The main idea behind the use of Tensor Factorization is that we can take advantage of the same principles behind Matrix Factorization to deal with multidimensional information. However, before we dive into the details of the Tensor Factorization model, we shall briefly summarize the two-dimensional Matrix Factorization approach.

Multidimensional Architecture for Context Awareness Recommendation in Automotives

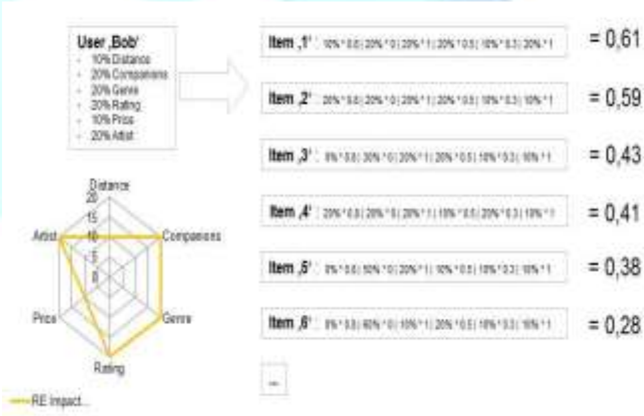


The "Fig. 1" shows the overall process of the Multi-Dimensional Architecture model process. The sensing information from the user includes the information about the user preference and the user's action, received by context-awareness. The context-awareness module monitors the user request and action type to indicate current user behavior. The result of the monitored contexts is stored in a multidimensional cube (see "Fig. 2"). The context-awareness contains the detail information about user's preference including user's action, interest item (product), location and user's devices.

c. Collaborative Filtering:

In collaborative filtering approaches, the recommendation function chooses items that were preferred by other users with similar attributes. Collaborative filtering approaches depend on either explicit or implicit user ratings of items. Rating different items a user can feed explicit ratings into the recommendation engine, while implicit feedback is collected by the system through the analysis of the users be-heavier (previous purchases, navigation path, search terms..). Collaborative filtering is domain-free, which means that it can be applied to any application area and to different data aspects, which could be hard to formulate into an explicit profile. Collaborative filtering is more accurate than content filtering [6], but has the challenge of starting without any initial data sets (cold start problem). It is not directly possible to address new users or objects for which the system has no initial data set available. Popular collaborative filtering methods are neighborhood methods and latent factor models. The Pearson's correlation coefficient sim(x; y) is often used to calculate the popular neighborhood method nearest Neighbor, in order to measure the similarity between the target user x, and a neighbor y. The symbol Au corresponds to an average rating of user x and S denotes the set of products or items.

$$\mathrm{Sim}(x,y) = \frac{\sum_{i \in S} (A_{x,i} - \bar{A}_x)(A_{y,i} - \bar{A}_y)}{\sqrt{\sum_{i \in S}(A_{x,i} - \bar{A}_x)^2}\sqrt{(A_{y,i} - \bar{A}_y)^2}}$$



Another method uses association rules to explicitly model the dependency and similarity of items. So a rule could. be: when a customer buys Item A and buys Item B ,then the rule recommends to buy Item C. One of the most widespread methods for calculating latent factors is matrix factorization, which is described in detail in [6]. Most of the modern recommendation systems use a combination (hybrid approach) of content filtering and collaborative filtering approaches to further improve the accuracy of recommendations. Beside these traditional approaches for implementing recommendation algorithms, several groups are working on the challenge of customizing recommendations and to build flexible recommendation queries. REQUEST: a query language for customizing recommendations was published by Adomavicius et. . in 2011 [7], which promotes accustom query language to build flexible and customized recommendation queries based on multidimensional OLAPcubes. Several contributions have been made by research groups that built various application scenarios for context aware recommendation systems, ranging from tourism [8], restaurants [9], or even people (e.g. glancee.com)

3. FRAMEWORK REQUIREMENTS

Within this section we would like to discuss requirements a general framework for implementing context-aware recommendation systems for auto motives has to fulfill. To discuss each requirement in detail would exceed the scope of our work, so we focus on several requirements that had a high priority for our use-case in VI.

A. Flexible and dynamic customization

A client-centric view on the recommendation process demands for a flexible user interface tenable the customization and fine tuning of recommendation impact factors for non-technical users.So their Users should be able to control the learning and recommendation process at a most fine grain level, while the configuration and presentation should be understandable level. The user should be able to specify a variable number of impact factor dimensions and even to add custom defined impact factors.The framework should normalize all the chosen impact factors and automatically provide a list of recommended items that is sorted according to the weighted sum of normalized impact factors.

B. Temporal aspect

Temporal aspects [10] deal with the change of the context and with the change of the content profiles over a time line recommendation framework has to consider the fact that the importance of specific data sets may change over time. It makes a big difference, if personas bought an item yesterday or 10 years ago. A general framework has to cope with this varying impact.

C. Transparency

To raise the users confidence in recommendations, it is of crucial importance to give immediate and transparent feedback on recommendations. The recommendation framework has to provide a human understandable explanation for a given recommendation set. Sundaresan, from bay research,published a great article about the 6 questions you have to143

Figure 2. General software architecture for the implementation of a context-aware recommendation system address during the design and implementation of recommendation engines[11] (What, Where, When, Why, Who and How). He also points out that recommendation engines that address the transparency aspect (the Why question), off-era better conversion rate in ecommerce applications. There are several user studies that clearly show that addressing the transparency aspect improves the performance of recommendation engines [12].

D. Performance

In order to provide recommendations for mobile applications that consider the actual context of a mobile user, it is necessary to deliver immediate results. Recommendations that consider the location and activity of an user, have to-react in time to provide recommendations in the specific situation, when a user needs them. As actual recommendation approaches harvest and analysis a huge a huge amount of data, this requirement is critical for every implementation.

E. Quality

As users are implicitly bench marking recommendation engines according to the quality of recommendations they are able to provide, it is necessary for a general framework to provide a standard approach for evaluating the quality of recommendation engines. A framework has to provide implicit and explicit quality evaluations, which mean that the framework constantly evaluates the quality of results by using test data sets, as well as to explicitly ask the users for quality feedback.

4. CONCLUSIONS

In this work, we propose a general approach as well as a general software architecture for the implementation of context-aware recommendation systems was presented. The approach as well as the framework offers high flexibility according to the definition and configuration of new impact functions, which influence the recommendation of items forgiven users. The framework is domain-free, which means that this approach can be implemented and adapted for different application domains. The context-aware recommendation of items of all kind, ranging from products in ecommerce to activities and services in sport and fun will get much attention in future software development. We think that a general framework for designing and implementing such recommendation systems for different application domains is of great importance. The next steps within our work will be to gather empirical feedback from the community within the given use-case of recommending music related events-here. Paragraph comes content here. Paragraph comes content here. Paragraph comes content here.

REFERENCES

[1] Y. Koren, R. Bell, and C. Volinsky, ™Matrix factorization tech-niques for recommender systems,∫ IEEE Computer, vol. 42, no. 8, Aug. 2009, pp. 30–37.

[2] G. Adomavicius, A. Tuzhilin, and R. Zheng, ™Request: A query language for customizing recommendations,∫ Info. Sys. Research, vol. 22, no. 1, Mar. 2011, pp. 99–117.

[3] W. Beer and A. Wagner, ™Smart books: adding context-awareness and interaction to electronic books,∫ in Proceedings of the 9th International Conference on Advances in Mobile Computing and Multimedia, MoMM '11. New York, NY, USA: ACM, 2011, pp. 218–222.

[4] V.-G. Blanca, G.-S. Gabriel, and P.-M. Rafael, ™Effects of relevant contextual features in the performance of a restaurant recommender system,∫ in In RecSys11: Workshop on Context Aware Recommender Systems (CARS-2011), 2011.

[5] Y. Koren, ™Collaborative filtering with temporal dynamics,∫ in Proceedings of the 15th ACM SIGKDD international conference on Knowledge discovery and data mining, KDD '09, New York, NY, USA: ACM, 2009, pp. 447–456.

[6] N. Sundaresan, ™Recommender systems at the long tail,∫ in Proceedings of the fifth ACM conference on Recommender systems, ser. RecSys '11, New York, NY, USA: ACM, 2011, pp. 1–6.

[7] G. Adomavicius, A. Tuzhilin, and R. Zheng, "Request: A query language for customizing recommendations," Info. Sys. Research, vol. 22, no. 1, Mar. 2011, pp. 99–117.

[8] W. Beer and A. Wagner, "Smart books: adding context-awareness and interaction to electronic books," in Proceedings of the 9th International Conference on Advances in Mobile Computing and Multimedia, MoMM '11. New York, NY, USA: ACM, 2011, pp. 218–222.

[9] V.-G. Blanca, G.-S. Gabriel, and P.-M. Rafael, "Effects of relevant contextual features in the performance of a restaurant recommender system," in In RecSys11: Workshop on Context Aware Recommender Systems (CARS-2011), 2011.

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