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CONTEXT-AWARE RECOMMENDER SYSTEM BY MERGING WIRELESS SENSORS AND MOBILE DATA

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Abstract-In mobile computing we identify mobile data as an important part for research. Context-aware computing in mobile devices enables the device to collect and analyse data of thesurroundings it is used in, their status and adapt themselves appropriately with the context information. In this paper, we merge all the data from mobile and wireless sensors to enable context-aware computing. The data obtained from these sources are manipulated using various algorithms and the results are obtained. Based on these results the recommendations are given.

Keywords - Context-aware computing, Recommendation System, Location-aware system, Machine Learning Techniques, Sensor data.

I. INTRODUCTION

Mobile social network is an important aspect in mobile computing.It includes sensor networks that can enable applications such as context-aware music players, health applications and video screens. Context-aware computing is a computing paradigm that is restricted to a class of mobile systems, which senses physical environment around it and adapts to its behavior [1].

Context-aware system isthe component of a computing paradigm which is recently getting into the trend of Artificial Intelligence [1]. It is also a component of ubiquitous computing or pervasive computing environment.TheThreemain aspects of context-awarenessare as follows: where you are, who you are with, and what resources are nearby. Location is a primary capability in context-awareness. Location-aware systemsdo not capture things of interest that are changing. Context-aware in contrast generally includes nearby people, lighting, devices, network availability, noise level, and even the social situation, e.g., whether you are with your colleague from office or with your family [2].

On the other hand, Recommendation systems determine the statsof a specific user, which is then trained by the existing data that includes user activity and profiles. Recommender systems are usually classified based on the recommendations that are to be made. Collaborative filtering and content-based filtering can be used to generate recommendations. Collaborative filtering assumes that the behavior of the person is similar to the behavior of

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other people and content-based recommendation mines favorite attributes of the interested item and recommends the products with those attributes[4].

Location awareness is the ability of a device to share another person or object's physical location. This may be precise or imprecise and can relate to either the user or the place. Many tools that use sensor data are used to implement location based context-aware systems [3].
The steps following Introduction are Literature survey and Related work, Conclusion,Future scope and References.

II. LITERATURE SURVEY AND RELATED WORK

Context-awareness requires a lot of resources. Resources include sensor data, non-structured data and social data. This data can be obtained through different sources. The sources don't matter, but the work done on them does. A lot of research is done on this field. If we consider the research done by the scientists, context-awarenessdeals with the modelling, preferences of the user and the prediction done on the data. According to context information, the process of recommendation is a classification of explicit data[1,4]. Figure.1 gives us a clear representation of the working of the context-aware recommender system.

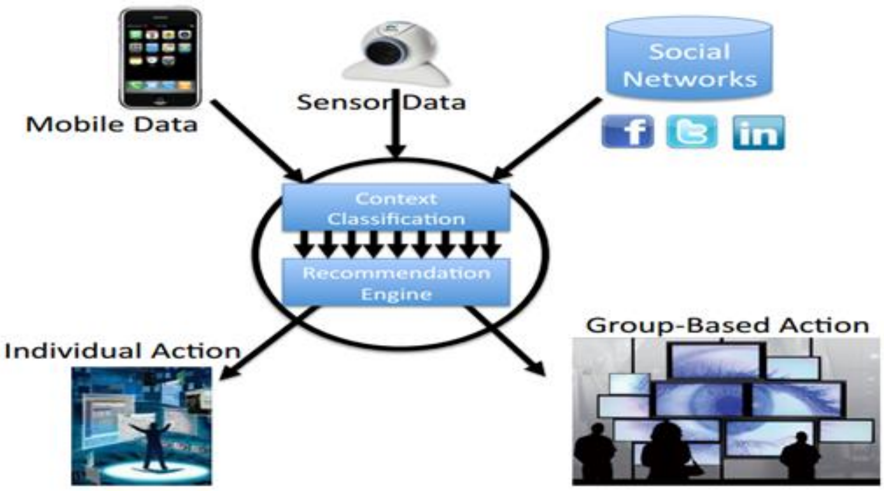

Figure.1: Context-aware Recommender system

Literature on context-aware systems, define context as changes in user location and surrounding objects [5]. Ryan et al. added the conceptual and physical state of a user. Dey et al. gave emotional conditions to the user and refined the definition into data that could be stated regarding the association between user and the application. Brown et al. added date,temperature and season. The context awareness system is able to fish out, manipulate and use the context data and use its performance with the recent interested context of use [4].
Many scholars and institutes have added to the research. Importance of context data in the recommender system is represented by Adomavicius et al. Further, a multidimensional perspective provides recommendations on the grounds of context recommendation achieved through many tools. The improvement in the quality of recommendation with the help of context information is relatively shown in distinct cases.Likewise Oku et al.,uses machine learning techniques and by adding additional fields in the process, provides recommendations to a restaurant's recommender system. Prahaladstates that the ability to contact and get in touch with the customers at any point of time, provides the companies to be competitive and have new products introduced under them. The purpose of purchasing using an e-commerce tool as context information is worked on by Palmisano et al [4,6].
On survey of some more papers, most of the work is done on the recommendation system. Many algorithms have been proposed like the content-filtering, cosine similarity etc. These

algorithms take the data got from the user's input and other sensor data and recommend the appropriate result. This is a tedious process as it involves a lot of calculation. The most famous example is the movie recommender system. It analyses the user's interaction with the application and maps the movies he reviews. The same is done with the most visited or typed keywords. The keywords are mapped and the recommendations are given.

The contextual information can be obtained in a number of ways, including:
• *Explicitly*, i.e., through the mode of information gathering by asking direct questions to the people and through other sources of contextual information. The information can also be obtained by eliciting through other means.For instance, awebsite may obtain contextual information by asking a person to fill out a webform or to answer some specific questions before providing access to certain web pages.
• *Implicitly* from the data or the environment, such as a change in location of theuser detected by a mobile telephone company. Alternatively, temporal contextualinformation can be implicitly obtained from the timestamp of a transaction.Nothing needs to be done in these cases in terms of interacting with the user orother sources of contextual information – the source of the implicit contextualinformation is accessed directly and the data is extracted from it.
• *Inferring* the context using statistical or data mining methods. For example, thehousehold identity of a person flipping the TV channels (husband, wife, son,daughter, etc.) may not be explicitly known to a cable TV company; but it canbe inferred with reasonable accuracy by observing the TV programs watched andthe channels visited using various data mining methods. In order to infer this contextualinformation, it is necessary to build a predictive model (i.e., a classifier)and train it on the appropriate data. The success of inferring this contextual informationdepends very significantly on the quality of such classifier, and it alsovaries considerably across different applications. For example, various types of contextual information can be inferred with areasonably high degree of accuracy in certain applications and using certain datamining methods, such as Naive Bayes classifiers and Bayesian Networks [8,9,10].

The ranking function to find the scores is as follows R: USER x ITEM x CONTEXT → RATING in which the USER is the user domain, ITEM is the item domain, CONTEXT specifies the context based information with their applications and RATING is the scores domain [5].

These concepts are illustrated using the following example.
The example consists of an app that recommends movies to the users. The users and movies have these attributes in common:

➢ Movie: various movies are recommended. Movie(MovieId, Title, LengthOfTheMovie, ReleaseYear, Director, Genre).

➢ User: the end user to whom the movie is recommended. User (UserId, Name, Address, Age, Gender, Profession). Further, the contextual information consists of the following three types that are also defined as relations having the following attributes:

➢ Theatre: the theatrestelecasting the movies; Theatre(TheatreId, Name, Address, Capacity, City, State, Country).

➢ Time: the time when the movie has been or can be watched. Time(Date, DayOfWeek, TimeOfWeek, Month, Quarter, Year). Here, attribute TimeOfWeek has values "Weekday" and "Weekend" and attribute DayOfWeek has values Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, Sunday.

➢ Companion: constitutes a person or a group, with whom a movie can be watched. Companion(companionType), where attribute companionType has values "alone", "friends", "girlfriend/boyfriend","family", "co-workers" and "others".

Depending on how and where the movie is watched, with whom it is watched and the time the movie is being watched, the person rates the movie. Consider an example, the movie watched by Karan Sharma is recommended to him based on,him watching it with his parents on a weekday or on a Saturday night with his girlfriend. The recommender system must work on the differed data.

Taking the example aboveinto consideration, we can see that, theCONTEXT can be classified into different types, each type describing a certain characteristic of context, such as location,time, companion, purpose etc. Likewise, each contextual type may have a complicated structure reflecting complex nature of the contextual information. Mean while, this complexity of contextual information can take various appearances, one of the important aspects being the hierarchical structure of contextual data that can be represented in the form of trees, as it is done in most of the recommender systems and profiling systems. For example, the three contexts can have the following hierarchies associated with them: Theatre: TheatreId → City → State → Country; Time: Date → DayOfWeek → TimeOfWeek; Date: Date → Month → Quarter → Year [5].

Furthermore,Paul Dourish, assumes that the bi-directional relationship between the underlying contexts and activities, may give rise to or call for various types of relevant contexts. These contexts give rise to activities and various contexts. Paul assumes that the context defined with a predefined set of noticeable attributes, may not have a significant change over time [6]. As per the research done previously, it takes symbolic interactionism approach to modelling contextual recommendations. It depicts that, short term memory interactional approach uses these models which are borrowed from psychology. The representational view works on context aware recommendation system. This view can be used in order to assume that the given application contains a predefined finite set of contextual types, each with a well-defined structure [7].

III. CONCLUSION

Context-aware Computing sets a mark in the field of artificial intelligence and virtual reality, the context awareness and recommendation system is so vast that it is used in the field of health care to track the patient’s current health status and agriculture to track the farmer’s daily routine and also give them recommendationsbased on their training results. The people who have worked on it have found it fascinating and they have bigger plans for the future, even more we can expect windows and doors with recommendation capabilities or holograms via sensors and there’s lot more to explore under this domain.For instance, Corning is already working on creating something unique in this field. People have moved their interest from manual searching to auto recommendations.

IV. FUTURE SCOPE

Taking into account the data obtained from the wireless sensors and mobile data we will be offeringDroidFusionMaster. We take into account the various aspects of location-awareness and club it up with some recommendation algorithms and provide context-aware recommendation system. We will be explaining the preliminary results obtained from implementing the DroidFusionMaster vision. The main contribution of this app is that it describes how to orderly achieve the blend of wireless sensor and mobile data to generate context-aware outcome for individuals.

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