Kernel Fashion Context Recommender System (KFCR): a Kernel Mapping Fashion Recommender System Algorithm using Contextual Information

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Annex A

THESIS ACCEPTANCE CERTIFICATE

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Dedicated
to

To my Parents, family, friends and specially to my elder brother who supported me in all aspects of my life and throughout my career.

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Abstract

In Fashion, Recommender System represents a growing trend. They enable to offer to the customer online fully personalized shopping experience. Many known names on the Fashion market such as Asos (asos.com) or Zalando (zalando.com), has already bet on this technology to retain customers, leading to boosting profits. Multiple filtering approaches exist, developed in order to cope with all the inherent challenges driven by the lack of information and the ephemeral nature of fashion items. However, even if the methods adopted are very varied, the main motive remains the same: reducing at all costs, the margin of error in order to produce the nearest real prediction. Accuracy, scalability, flexibility, and performance have become the keywords when it comes to creating a fully skilled Recommender System. To achieve these objectives, it appears that including in the model user's context information, such as time, location, mood, occasion, weather, or people's influence can be the answer. Obviously, not including contextual information is eluding a fundamental element in the decision-making process for the purchase of a particular piece of clothing. In this paper, we decided to apply to the Fashion domain issues the scalable context-aware algorithm to better target the tastes of the customer producing predictions as close to his preferences as possible. This new algorithm named KFCR uses the kernel mapping framework developed by Ghazanfar et al. (KMR) complements with contextual information. We used the RentTheRunway Fashion dataset which indexes more than 100000 rented garments in the renttherunway.com website. We evaluated and compared this new system to the original KMR , as well as to other widely used context-aware approaches like post-filtering techniques. Once evaluated, the KFCR was found to be more accurate than both non-context-aware and context-aware approaches.

Key Words: Context, Context-aware kernel mapping Recommender Systems (KMR), Fashion, Recommender system, Kernel method

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CHAPTER 1

INTRODUCTION

In this chapter the problem that are to be addressed and analyze in this thesis are discussed. The motivation and design objectives are also discussed in this chapter along with the contribution that are being made to this field. All the necessary information, topic their meanings, usage and all other important that are related to the problem domain are briefly explained like the recommender system and its taxonomy in our problem. The thesis structure and outlines are discussed in the closing of this chapter.

1.1 RECOMMENDER SYSTEM

Due to the advancement of computer networks and technology, an unprecedented increase has been experienced in the volume of online data since 1990. The much more rapid and exponential increasing of the digital information is going beyond our ability to use it practically and efficiently. We are currently overwhelmed by the addition of new online books, articles, journals, conferences and videos and some other online data and information from online streaming services such as Amazon Prime, YouTube, Netflix, data from the online shopping such as eBay, Amazon, Ali Baba and other fashion and costume related data such as RentTheRunWay etc. these services and platform changed our societal behaviors of shopping, entertainment etc, like instead of going to malls the increasing number of individuals prefer to shopping online and watching movies online on Netflix etc instead of going to cinemas, more people specially students and journalist societies spends more on time on internet for searching information, which yields to huge increase in the digital information, and make us hugely dependent on the internet and online information. So, it will take a lot of time, money, and knowledge to process that huge data make some useful information for benefitting the users. However, the internet search engines help the users filter what they need or search for by matching keywords, but still the gradual increase in the digital information creating one of the major problems that how to use and process this data, the information filtering system helps to filter the data.

Recommender System resolve this issue by filtering the huge information and deliver only that information to the user that are needed by the users by looking into the preference to the user need. Recommender systems are design to process and manipulate the data and filter all the information and deliver only the needed information to the users. It helps to recommend items to users based on user profile and preference. RS suggest relatable and interesting stuff (music, books, items, movies etc) to the end users through information filtering system. There are numerous algorithms that process data, model preferences, inferring item and user ratings and then provide the recommendation. like the YouTube, google, amazon, Netflix, Alibaba, and routing recommendations algorithms are reported among the top 10 recommendations algorithms by the Business Insider [2]. The integration and implementation of recommendations system in the eCommerce industry boosted the business and sale in the sector by providing effiecient and relevant recommendations. In the context of eCommerce industry, a specialized and personalized recommendation is used to filter the huge information and only recommend those product to the user which are matched to their profile based on their rating and likes. Efficient recommendation also helps customers churn prediction and retention.

1.2 RECOMMENDER SYSTEM'S FORMULATION

There are two basic and most important entities that need to be considered while creating either a general or personalized recommendation system, User and Item. Both of these terms, their usage and formulation are described in detail below.

***User*:** User is the entity which uses the recommendation system. User provide their feedback of the item's likeness or relevance in the shape of ratings. Users are collectively called the community, which is denoted by U, U is a subset of users denoted as $U = \{U_1, U_2, U_3 \ldots\ldots U_m\}$, where $|U| = M$ are total number of users who have rated the item or product.

Item: Item is also called context of a system; it can be anything like a movie. Song, book, etc. items are things which can be recommended to the user. Item has a finite set of entities denoted by $I = \{I_1, I_2, I_3 \ldots. I_n\}$ where $|I| = N$ denote the number of items.

Rating: Ratings are the feedback of a user about an item, the feedback could be about the quality of the item, the relevancy of item, likeness of the user or user's preference about certain item.

These feedback store in the form of numerical representation ranging from 1 to 10, called rating, these ratings are then used in the recommendation system for provide better recommendation to the user according to their preferences.

Rating Matrix: the ratings that are provides by users to specific items are stored in a matrix called Rating matrix. This matrix consists of rows and columns the rows represent the users, and the columns represent the items generally. The entry in the matrix is denoted by $r_{i,u}$ where 'r' denotes the rating provided to the item 'i' by a user 'u'. mathematically these rating matrices are represented as $\left(r_{u,i} \middle| (u,i) \epsilon \mathcal{D}\right)$. The actual rating matrix always less than the total number of user and item matrix, this denotes by $\mathcal{D} \subset U \times I$ where $\mathcal{D}$ is the total number of rating matrix and $U \times I$ represent the matrix of the total number of user and item. This is because not every user rated every single item, nor every single item being rated by every single user.

1.2.1 Item and User's Profile:

Item profile is the context data of the product or item that are being stored in the data base like the rating of the item, similarly the user profile is the stored data of the user likeness etc. these two profiles are then merged and reshaped in the form of matrix called rating matrix or Item's profile and User's profile. These profiles or rating matrix are then ready to exploit by recommendation system to recommend relevant product to the user according to their profile being build in the database. There has been a lot of literature which have proposed different algorithms for the recommendation but instead of discussing them first we have to briefly describe the Item's profile and User's profile.

User's Profile:

User is the building block of any recommender system. User provide feedback when they buy an item or product generally in the form of rating which describes their like, dislike, quality or likeness, which then stored in database in the form of user profile and use by recommendation system to recommend similar item to the user by exploiting user profile.

Item's Profile

Like user's profile the item's profile is also being generated from the rating that are provided by the user to the item that show specifically the item's features, context and quality of the product, and user's preference generally.

1.3 ORGANIZATION OF RECOMMENDER SYSTEM

Recommender system play a pivotal role in the online business specially in the ecommerce by providing to the point and relevant recommendation, apart from the ecommerce the recommendation system also used in the tourism industry, healthcare and almost every sector of the modern world. There are numerous method and algorithms to provide recommender depending on the nature of recommendation system and the industry where the recommendation to be implemented ranging from general to personalized recommendations. The most trustworthy and widely used in the Collaborative filtering techniques among all, which also known as the base of recommendations system, the complete taxonomy and organizations are first visualized in the following Fig. 1 below and then each one is described in detail with example and usage.

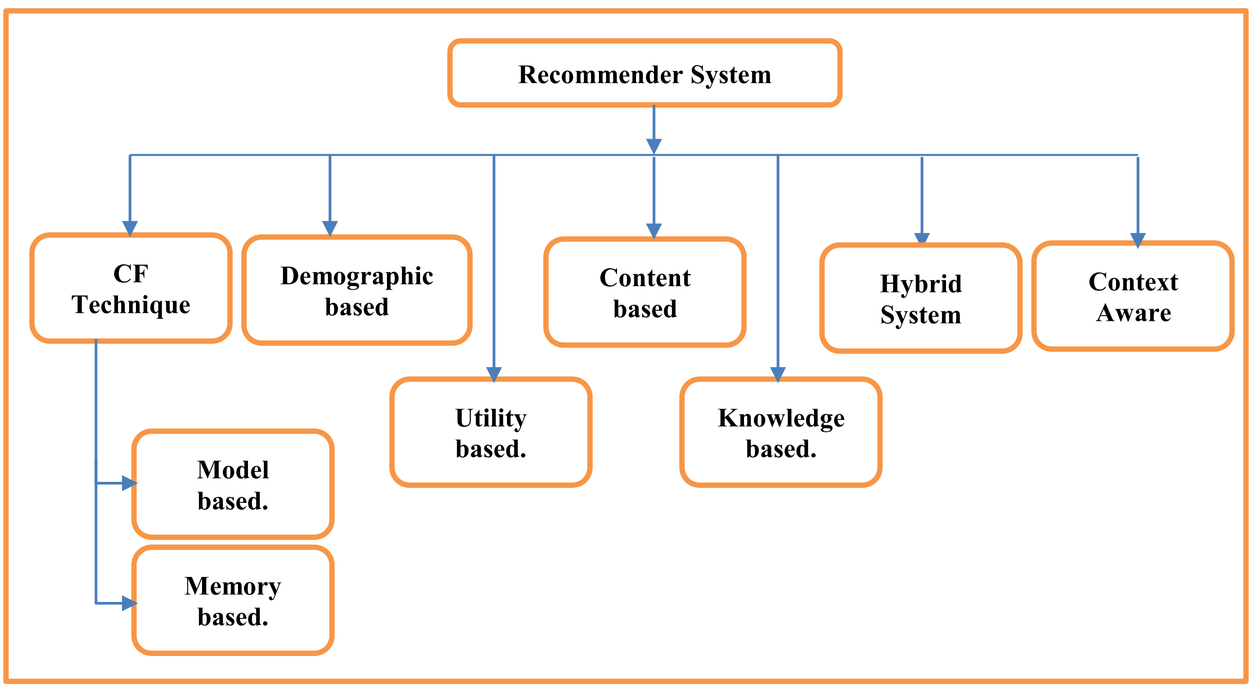

Figure 1 Organization of Recommender systems

1.3.1 Collaborative recommender system: It provides the recommendation of an item to the user by considering the rating or likeness of the similar user in the community, and the similarity of the user n the community calculates by the rating of other item that whether other same category items have been rated by the users similar or not. And only those users from the community are considers who have the same taste or same rating for other similar items. Most of the popular online site are use the collaborative filtering techniques for recommendation of items, Amazon, Ringo, and Usenet news are the most popular among them [4].

The working of collaborative is based on the concept of the neighborhood of the past similar users and assume that that will also be neighbors in the future, the system creates a database of the user's rating for an item, and then find similar users that have rated that item the same way the current user has rated. Then the system checks the ratings of those users for the current item and then decides whether the item should be recommended to the user or not based on mutual interest.

The collaborative filtering has been tried to explain from the following example. There is a rating matrix of 4 users as shown in table I. Some of the users have rated some items but not rated others. The rating ranging from 5 (excellent) to 0 (poor). The system is trying to recommend item 4 to user 4.

Table 1 User item rating matrix

	Item1	**Item2**	**Item3**	**Item4**
User1	4	5	Ø	5
User2	5	1	5	Ø
User3	5	4	3	4
User4	Ø	4	5	**?**

As from the above rating matrix user 3 and user 4 have the same taste. As item 2 and item 3 have been rated highly by both the users, and the item 4 has also been rated highly by user 3, so probably it would be liked by user 4 also. User 2 and user 4 have also the same rating for item 2 and item 3 but the item 4 has not been rated by the user 2 therefore it can be depicted from user 2 profile that whether item 4 will be liked by user 4 or not as shown in table I.

Collaborative filtering has two subcategories, Model based technique and Memory based technique.

1.3.1.1 Model based collaborative filtering technique.

Model based collaborative filtering is working on first generating a model for recommendations, the model is then train on the training data set and finally recommendation take place on real and unseen data using either classification or clustering technique depending on the nature of the data and recommendation model. This model can also be classified as Kernel mapping recommender system and single values decomposition SVD.

1.3.1.2 Memory based collaborative filtering technique.

Memory based collaborative filtering technique using the past rating history of the users that stored in the database in the form of rating matrix and making recommendations using that history.

This technique uses three steps for recommendation.

1. Users previously rating history is stored in the system database for future recommendations.
2. The similarity index is calculated among the current users and neighbor users.
3. Recommendation made for the current user of the current item based on the rating of neighbor's history.

Steps for selecting the neighbors.

1. Using K-nearest algorithm for selecting nearest neighbors
2. Selecting all relative users
3. Selecting top n neighbors or avoiding opposite neighbors.

In collaborative filtering techniques the main thing is to find similarity between the users with the active user and then recommendation is taken place based on that similarity. There are different ways to find the similarity between the users but the two widely used methods are cosine and correlation similarity matrices. This similarity lies between 1 to -1, 1 stand for closes positive similarity and -1 for strong opposite users. The algorithm for finding the similarity through correlation-based technique is given below.

Eq. 1 Cosine Similarity Measure

$$sim\left(u_x, u_y\right) = \frac{\sum_{i \in I_{u_{x,u_y}}} \mu_{i,u_x}\ \mu_{i,u_y}}{\sqrt{\sum_{i \in \mathfrak{T}_{u_x,u_y}} \mu_{i,u_x}^2\ \ \sum_{i \in \mathfrak{T}_{u_x,u_y}} \mu_{i,u_y}^2}}$$

Here μ_u calculate the similarity out put of the algorithm, that lies between 1 and -1, where 1 denote the strong similarity, -1 denotes the strong negative relation ship while 0 shows no relations among users.

Another most popular way of finding similarity is the cosine similarity measure [5]. Where X-dimensional space vector represents the user's profile. Here the two vectors can be used to find similarity between cosine angles. The mathematical calculation is given below.

Eq. 2 Correlation Similarity Measure

$$\mathrm{Sim}\left(u_x , u_y\right) = \cos\left(\vec{u}_x , \vec{u}_y\right)$$

$$= \frac{\sum_{i \in I_{u_{x,u_y}}} r_{,u_x}\ r_{u_y}}{\sqrt{\sum_{i \in I_{u_x}} r_{u\ x}^2 \sum_{i \in I_{u_x}} r_{,u\ y}^2}}$$

Here $(\vec{u}_x . \vec{u}_y)$ shows the dot product of $\vec{u}_x$ and $\vec{u}_y$. the output of this algorithm ranges from 1 to -1, where 1 stand for strong positive similarity and -1 stands for strong dissimilarity.

Memory based collaborative filtering is then classified as Item base collaborative filtering and user based collaborative filtering. Both are discussed below.

Item based Collaborative filtering: In this technique the take into account the profile of current user, then the current item's similarity is calculated with all the previous item that are being rated previously by the current user [9,10]. The k nearest items and their similarities are then calculated. The rating of these similar items is then normalized. The prediction of the current item to the current user are then done by calculating the average of all similar items which are rated by the current user previously. The highest average rating item is then recommended to the user.

User based collaborative filtering: the user based collaborative filtering first of all find all the similar users through cosine, correlation or any similarity finding matric. Then select k nearest similar users, these ratings are then normalized [5,6,7,8]. The prediction is provided by average calculated rating of all the similar users.

1.3.2 Content Based Filtering Technique:

Collaborative filtering is working excellent with a data having normalized matrix and small number of features, which leads to rating sparsity and cold start problem. To minimize these problems a content-based filtering technique has been introduced. Which instead of rating of similar users or similar item profile using only the current user profile and the item profile. The item profile consists of the textual information about the item while the user profile based on content based composed of the weighted vector of the item. It considers that the current user will like an item, that has been liked by the user previously. Pandora Radio and IMDB are using this type of recommender system. Content based filtering technique widely used Decision tree, Cluster analysis, Bayesian tree, Artificial neural network. NewsFeed [16] is the best example of Content based filtering technique.

1.3.3 Knowledge Based Filtering Technique.

This type of recommender system doesn't take into account user's rating or item's profile, neither consider their rating matrix. The knowledge-based recommender system considers the knowledge of the item like the features of items and user's knowledge such as likes, dislike, interest, and requirements of the user. This knowledge is then exploited to recommend an item to the user which is assumed to be liked by the user.

1.3.4 Demographic Based Filtering Technique:

Instead of user and item rating the Demographic recommender system is first exploit the demographic knowledge of an individuals for the categorization of the users and generating the demographic-based classes. The detail item features are extracted from the database and then recommendation take place based on these demographic classes.

1.3.5 Utility Based Filtering Technique:

In the Utility based recommender system, the best fit item to the current user can be fine by the exploiting the profile of user as a utility function while applying the widely used technique called constraint contentment. On based of every object's utility the computation of recommendation take place for the current user. The Utility based recommender system doesn't

Look into long term user's generalization instead compute match through utility function for the current scenario only.

1.3.6 Hybrid Recommender System:

While using individual recommender system has their own advantages and disadvantages. One of them surpass the other in some domain while performs low in other domain. To solve this issue the Hybrid recommender system is introduced. In which all the important recommender system can be integrated to eliminate the drawback of single one and merge the advantages of each recommender system to alleviate the performance of recommendation system. Hybrid recommender system can be integrated through different techniques like cascading, unifying, switching, and mixing depending on the application domain.

1.3.7 Context Aware Recommender System:

There are many definitions of the term "context" within the framework of RS. This complex and multifaceted concept has been studied extensively in a wide range of fields of application and it has been brought to conclusion that it is very difficult to find a unifying definition. However, the notion of context can be split into two views of context : the representational view which is stable and the interactional view which is dynamical according to Dourish [12].To keep a precise view of the subject studied, we will quote the widely used definition of the concept of context given by Dey et al. [14]:

"Context is any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves."

Therefore, context may include the notions of environment, location, weather, purchase purpose, date, time, season, gender and age of user, social circle, shopping companion, size, mood, trend, influence. All those information have an impact on the customer shopping experience and a way to improve the user's shopping experience should be to adapt to his rating behavior considering his context at the time of the purchase. Furthermore, as per previous observations, the items which are purchased or viewed in the similar contexts tend to have similar meanings.

1.4 RESEARCH OBJECTIVES

Recommender System concept arises in the early 21st century and remain one of the trending topics for research in academia and industry. Specially it become a hot topic for research after the Netflix price [19] announcement for the improvement of the algorithm baseline performance.

Numerous algorithms have been introduced for the automatic recommendations. Every algorithm has their own advantages and disadvantages, some algorithms perform very well in on ideal data set but fails to work on sparse data set or on data set having cold start scenarios while perform poor on general recommendations. Different recommendations systems found in the literature, but the Kernel mapping recommender system outer performed each other recommender system in special scenarios. Therefor we applied kernel mapping recommender system in our data set which is related to fashion industry and introduced a novel approach by incorporating contextual information in Kernel mapping recommender system which filter the recommendation by incorporating each context in the algorithm and provide the best and most suitable recommendations. This recommendation system performs in each scenario.

Some of the most viable objectives that considered while implementing this recommender system are given below.

1. **Accuracy**: Accuracy is one of the most viral features while talking about recommendation. An accurate recommender system may likely to improve buyer decision and increase the retention of customers in the business and may also stop customers churns.
2. **Sparsity robustness**: Traditional recommender system always perform on balances and complete data set but may perform very poor on sparse data set. In general, the data set may be very imbalanced for example some user may have rated every item but may have rated very less or even none. Same in the case of item, some items have complete rating but may have very less or even none. Which leads to a poor performance of traditional recommender systems.

3. **Cold start scenario**: Generally, some users may not be interested in rating items and have very less knowledge of their taste in the data base, therefore it's very confusion for traditional recommender system to recommend new item to user, same for the item.
4. **Long tail scenario**: The recommendation engines look for the item profile or user profile. Theses profiles generally contain rating information of the item and the user, but when a new item is introduces it's impossible to be recommended to user due to the unavailability of item profile and hence same is the case for new user problem.
5. **Scalability:** in most of the cases the performance of recommender system decreases when the data becomes dense and complex. Therefor it's very important for the recommendation to be accurate on each type of data.

To solve the problems faced by the traditional recommender engines and to achieve the above objectives and novel approach is introduces in this research called the kernel fashion context aware recommender system. Kernel mapping is considered to be the pioneer of modern recommender system which is introduced back in 2013. Kernel mapping is negligibly used in the fashion and garment industry; therefore, we incorporated the most used contextual information of the fashion terms and proposed a novel recommender system for fashion industry which surpassed all other recommender system till to date in term of accuracy and scalability.

1.5 OUTLINE

Rest of the Thesis are organized in the following chapter wise order, Chapter 2 [Literature] discusses the work of the prominent author conducted on the topic of Recommender systems. Chapter 3 [Methodology] discusses about the process to conduct this research like the dataset we used to train our model, the assessment process to evaluate proposed model etc. Chapter 4 [Result] describes the overall performance of our proposed recommender system, also compare the performance of our proposed recommender system with state-of-the-art recommender systems. The final chapter 5 [Conclusion and Future Work] concludes the overall work. It's performance and the future work in detail.

1.6 SUMMARY

A novel Kernel Fashion Context Aware Recommender System (KFCR) introduced in this research which is based on the Kernel mapping recommender system, this chapter provide the background study for this work like the recommender and it’s type, how recommender system work, the objective of this work, the problem statement and the outline of this thesis.

CHAPTER 2

LITERATURE

This section reviews the literature in the field of recommender system. The first part of this section summarizes the review on general recommender system, tools and techniques used in recommendations, second part focused on the context aware recommender system which is the main recommender system technique we have implemented in our work, the third and last section gathered the most prominent work conducted in the domain of fashion industry recommendations.

2.1 RECOMMENDER SYSTEM

Recommender system is a machine learning framework that that filter different information from data utilizing data mining and machine learning techniques to predict the new rule which tells whether the user would like a specific given item/product or not, this type of recommender system first of all retrieve the data about the users and items and then process that data to make it suitable for applying different Machine Learning ML techniques while taking into account the rating matrix of user and items [1,2,3,4]. The standard Recommender system use the two primary entities (item and user). Users generally use the item and give some ratings or comments with respect to their taste and product quality which is called the user's profile the same way the item's profile consist of some description about the item like the keywords etc, these two profiles are then merges to form matrix called the rating matrix. Machine learning uses these two profiles or simply rating matrix to recommend items to users according to their taste and relevance [4,5]. Recommender systems are further divided into six different well-known types, these types are Collaborative recommender system, Content Aware system, demographic recommendations, knowledge base, Hybrid recommender and Utility base recommender system, all these recommender systems have their own advantages and limitations depending on the domain, some recommenders give the accurate recommendation while less accurate in the other domain [5].

Collaborative Filtering (CF) recommender system focus on users, items are recommended to the user in such a way that if the specific item either been liked or rat positively by the other user's that are similar to the new user in term of item preference then these items are rated the similar way in the user or item profile to form the complete rating matrix which then use for item recommendation, the Collaborative Filtering is one of the most widely used recommender system, but it come with accuracy and performance problem if the rating matrix have sparsity or cold start problem it mean either the new item that is not rated by any user yet or a new user who haven't rated any item yet [6], Group Lens Systema and Ringo.com [7] are the examples which uses Collaborative Filtering (CF) recommender system. CF is then subdivided into model base and memory-based approach. In Model base approach the model is first trained on the trained data and then apply on real data to predict the unseen products or items, examples of Model base approach are Kernel mapping recommender system [2] in which the similarity matrix are sparse in multi-dimensional rating matrix and then relevant kernel are mapped with each other , Cluster Model [8, 9], in which similar users based on the rating similarly the similar items are grouped together called the cluster, which denote as rating matrix and recommendation placed based on each cluster or group and Single Value Decomposition [10], in which a dense user item matrix *N* x *N* is reduced to an efficient *M x N* rating matrix, where *M x N* is always less than *N* x *N* matrix . In the Content based recommender system the item is recommended to the user on the base on the activity of the users and the contents of the item like the keywords of the object and attributes of the object being stored in the repository which matches the user profile, News Weeder is the example of the Content base recommender system [11] which recommends the blogs and news to the user based on who the user is following etc. Knowledge base recommendation consider the knowledge and information about the item and users and then recommend item to the user according to their likes and interests. The knowledge base recommendation needs the item's attributes, user's specifications and domain knowledge of the market as an input for the recommendation [12]. Demographic base recommender system basically is the solution for the cold start problem in the recommendation. This model doesn't look for rating of user or knowledge of item, but recommendation take place based on demographic information of the users such as age, ender etc [13]. Utility base recommender system compute all the utilities of the item for the user and then recommend item accordingly [14].

Bobadilla et al [15] conduct a survey about such as similarity measurement, cold start, sparsity in rating matrix and evaluation of recommender system in recommender system implementation. In their research they emphasized the importance of hybrid recommender system to resolve these issues specifically the implementation of content and demographic collaborative system. Ghazanfar et al [3], work to minimize recommender system issues like sparsity, scalability, cold start and coverage problem by integrating the demographic information, features and rating of items in the proposed algorithm. Yan-ni Chen et al [16] work on the integration of item based collaborative filtering and user based collaborative filtering to get the full advantage of recommending an item or product with improved efficiency by fulfilling the deficiency that causes by single collaborative filtering. To achieve optimum result, they used the similarity index between the item and user. But Hu and Lu in [17] instead of using the item based and user based collaborative filtering that work on using mutual matrix of user item matrix using the linear combination of user similarities and item similarities linearly which also increase online scalability with the same quality output. According to the study of Wang et al [18] showed that the most used recommender system is the collaborative filtering system but this system mainly comes with cold start problem and sparse rating matrix which badly affect the recommendation accuracy for data set having such issues, therefore Wang et al presented a new hybrid user model, in such a model three layers , model layer, feature layer and collaborative filtering layer has been combined, in this algorithm first of all the features of the item are obtained from the content of item, then on the base of these features a model is build and then finally a collaborative filtering algorithm is applied for the final recommendations which leads to the increased scalability and accuracy. Asela and Christopher [19] found that content based recommender system has a low accuracy than collaborative filter recommender system but it overcome the cold start problem and sparsity. On the other hand the collaborative filtering recommendation has high accuracy while predicting item but come with problem of cold start and rating sparsity for new user or new item, to overcome these problems while to maintain the accuracy of collaborative filtering they author introduced a hybrid model of recommendation in which they take the item content and the collaborative data as input and then on the wight schema a model is build, which produce the accurate recommendation on both on the sparse data and cold start user without affecting the quality of recommendation system. L. Martínez, et al [20] discuss the cold start or new user problem of collaborative filtering, the overcome this problem they proposed a model in which they integrate knowledge base model with collaborative filtering model and applied this model on hotel data set, in their study they found that the accuracy remain the same for cold start data also. In this model they provide an example to user that matches their needs through knowledge base model, when the user file is generated then they user this profile for recommendation through collaborative filtering model. Some social media sites use the group recommendation to recommend things to the group of users instead of individual recommendations, for this purpose they use the collaborative filtering and demographic base hybridization technique. Li et al [20] tried to improve the accuracy and performance of recommender system by implementing the clustering technique, in which they first cluster the item contents using the different item's content knowledge then gather the same nature users and generate a user rating on the base of that cluster content and user information for better prediction of product than traditional singular model recommender systems. WU et al [21] talks about the real time recommender that involve with customer directly to recommend thing to the user without knowing their prior taste of product. For this they propose the online module of integrating the user based collaborative filtering and item base collaborative filtering to help generating the recommendation list, that can help for the accurate real time recommendation system. Charkaoui et al [22] presented another hybrid recommendation engine that integrate the content base system, the demographic recommender system and the collaborative filter system to predict the accurate rating for cold start problem data set, this rating can be achieved by the confident measurement of any recommender system algorithm. This confident measure solely dependent on the user's rating which often changes dynamically, that help to resolve the cold start problem in simple collaborative filter recommender system.

One the of the major problem of the of the different recommender system is the tradeoff between the performance and accuracy of the recommender system, one of the recommender systems will show a better performance but won't have a better accuracy. To solve this problem, Hwang et al [23] proposed a novel approach called Category Expert CE, in this method the system chose some user as an expert from each category and benchmark their ratings are the matching ratings instead of common neighbors, this method further extended to CEP and CES, in CEP choose the user interest (preference) instead of rating similarity while in the CEP the system choose the similarity between the active user and the expert category. Finally, all these methods combine to create a new model called CESP, this method simultaneously consider the preference and similarity, this method shown a better performance than user-based model and higher accuracy than item base model at the same time. Yongfeng et al [24] address the problem motion ignorance in recommender system, that recommender system provides the recommendation on the basic of rating and liking ignoring the emotion of the users, to overcome this problem they proposed a novel approach called EARS: Emotional Aware Recommender System. This is a hybrid system in which three different types of information are integrated to from a user feature, this information is the user rating as an explicit data, user implicit information from their social network and user's emotional information extracted from their comments or review. According to the study of Wang et al [18] showed that the most used recommender system is the collaborative filtering system but this system mainly comes with cold start problem and sparse rating matrix which badly affect the recommendation accuracy for data set having such issues, therefore Wang et al presented a new hybrid user model, in such a model three layers , model layer, feature layer and collaborative filtering layer has been combined, in this algorithm first of all the features of the item are obtained from the content of item, then on the base of these features a model is build and then finally a collaborative filtering algorithm is applied for the final recommendations which leads to the increased scalability and accuracy. Zhang et al [25] discuss the importance and role of Artificial Intelligence and machine learning in the recommender systems, also discuss the development and issue of recommender system, the paper organized all the major algorithms of Artificial Intelligence and machine learning like fuzzy techniques, deep learning, convolutional neural networks CNN, active learning, transfer learning, evolutionary algorithms and genetic algorithm. This work not only review different techniques used in recommender system but also discuss about the problem and research gap in the current modern and robust recommender system which can provide road map for the researcher to conduct research in this field.

2.2 CONTEXT AWARE RECOMMENDER SYSTEM

Context is the knowledge or information about the situation of object's interest like the location, event, things, people, media, or any other information which elaborated certain object's interest, in other words the context of object is the setting of circumstances to fully understand the idea and logic behind any object [26, 27]. Abbas et al [26] conducted a survey about the context aware recommender system in which they discuss the problem with the recommendation and then the importance of legitimizing the context of the item or user in recommendation process, they also summarized some state of the art computational intelligence (CI) techniques that have adopted while using the context in recommender system such as Fuzzy Sets, Swarm Intelligence SI, artificial neural network ANN, Artificial Immune System AIS, and Evolutionary Computing EC. Champiri et al [27] worked on the ways that how the right contextual information can be identified, they adopted the Kitchenham systematic review methodology for the survey and research of the right contextual information for the case study of digital library recommender system, they divided the contextual information into three different contextual categories, the item's context, user's context and the environmental context. The four different popular ways they used for collection the relevant contextual information is self-definition, citations of past definitions, field query research and citations of past studies, in these four ways they found the citations of past studies the most efficient way for collecting the relevant contextual information. Moshe Unger [28] presented a work that tried to improve the accuracy of context aware recommender system, they tried to minimize the dimensionality problem as contextual data gathered from multiple sources which reduce the quality of the data for recommender system, therefore they presented a new approach in which the contextual information is collected form mobile's sensor, then the latent data extracted from the collected data through mobile sensors, using deep learning unsupervised learning technique.

Context aware recommender system work by integrating the contextual information of user and item into the recommender system, there are two major ways to integrate context into recommender system, contextual modeling and context filtering, the most used technique is the contextual modeling which measure the deviation from the rating matrix while Zheng [29] presented alternative model called context similarity contextual modeling to incorporate context in recommender system through matrix factorization algorithm and sparse linear method, their result overpass the other model in term of accuracy and performance. Salman et al [30] proposed a push recommendation concept of context aware recommender system, their system design mainly depends on the internet of things IOT for the contextual information gathering, in which all the personal information of the user that are connected with IOT devices and then that information is used to recommend items or services to the user for different domain like the hotel, ecommerce etc without being explicitly requested by the user using the artificial neural network techniques, Omar et al [31] presented a novel recommender system called

“RecomMetz”, this is mobile based recommender system, in this design they took location, time and crowd as context, the researchers uses the semantic web technology to implement the said recommender system, this system design recommends movies with a composite form like the showtime, theater and movie title, the system integrate the crowd context and movies time in a context aware recommender system, this system implemented multi-platform mobile interfaces using mobile sensors for contextual information, RecomMetz system perform better in both cold start scenario and sparsity rating matrix. S. Sharma and D. Kaur [32] designed a location-based context aware recommender system, which defined the context in the form of RuleML, when a user want a recommendation, the system extract the contextual data from the RuleML, then evaluated and finally recommend the top-k nearby places to the user. In the Context aware recommender system generally the contextual feature rake into account according to the domain like mode and time can be taken for movies and music recommendations, season and weather can be consider for traveling recommendations etc, Zheng et al [33] integrate emotions in the Context aware recommender system along with other required domain context, as a domain independent feature, in their result they found that the accuracy and performance of recommendation increases with the inclusion of emotions along with other contextual features in the recommendation process. Generally the addition of the of the contextual features in the recommendation increasing the dimensionality of the data, which may lead to the sparsity of the data set and effect the accuracy of recommendation, therefore the researcher takes some pre-defined context to create accurate context aware recommender system, and these less pre-defined context not necessarily represent the true users, therefore novel approach is been introduced in which the contextual features of the users are generating form the their mobile sensors and that data is then filtered by latent variable to select only relevant context of the user and avoid the sparsity of the data matrix, this novel increase the accuracy of the context aware recommender system by almost 20% [34]. Dongjing et al [35] tried to solve the problem in music recommender system, in general music context aware recommender system, the contextual information taken from the music meta data and user contextual data form the user profile, but this research don’t consider the music meta data form the play list instead the music information can be extracted from the pieces of music playing through low dimensional vector space, and user’s contextual information can be taken form the past history of the music they have played. Then the proposed recommender system recommends the most suitable piece of music, in the finding the proposed model overpassed in term of performance the standard music recommender system. Khoshkangini et al [36], proposed a novel approach that solve the group context aware recommender system in which the decision takes by group of user instead a single user, the users in the group have categorically different importance with respect to decision taking, then these decision be taken as a contextual information and these contextual information often taken in a dynamic domain where user decision and likes changes frequently, and the acquired contextual information not always be correct, in the proposed approach they use the time and conditional preference networks (CP-nets) for modeling preference of users. The sequential rule of voting is also being used for the aggregation of preferences of users. The proposed model is deployed on three different data set and outperform the base line methods. Ashley et al [37] proposed context aware recommender system for tourist called "Proactive Context Aware Recommender system" the contexts that are taken are location, weather and time, and collaborative filtering is used to make more accurate recommendations of the tourist places to the tourists on in real time. The model is tested with different data set and proved the greatest efficiency and efficacy of the model. Zahra Bahramian et al [38] presented a hybrid context aware recommender system for the tourist, in which the contextual information is gain by the feedback of the user and other general contextual information like the location, weather, resources, etc, the model in based on the artificial neural network ANN and case-based reasoning that offer a personalized recommendation of the tourist places. This in terms of accuracy, user's satisfaction and performance this model showed better result than the previous ANN based context aware recommender system. The continuously increasing in the volume of online and offline data, tends the increasing demands for recommender system, the most suitable recommender system in the current recommender systems is the context aware recommender system, but there is huge for the defining of the contexts for the recommender system, because the context varies with change in domain and user preference, the researchers tried to define a common method for the selection of context in any domain [39]. M. Abbas et al [40] proposed a context aware recommender system for YouTube video recommendations. In this work the researchers want to solve the dynamics contexts variation of the users, in which the user gets the recommendation with very low accuracy because the same time the user follow different contents, which the YouTube recommender can't explicitly differentiate when to recommend which type of content to user. The proposed algorithms keep the different interested content and video recommendations done just on the current context that the user have some interest, Orciuoli, F and Parente, M [41] presented an ontology base context aware recommender system which provide the recommendation to user by suggesting them the best deal to their nearest locations base on their wish list. The system uses the indoor navigation system, this system based on the algorithm of cellular automata and computational ontologies. Whereas the computational ontologies use the web stack tool and technologies, and cellular automata used the formal computational model. By integrating these tow algorithms solve the problem of robustness, scalability, low cast and adaptability. By increasing the volume of the music and the music stream recommender system become too popular int this field. The most popular recommender system used in music recommendation is the context aware recommender system, the standard system work on pre filtering context which led to the split of the data and not accurately recommend the music. The proposed method based on the factorization method that collect the user's contextual information from the user playlist and recommend music accordingly [42]. Ilarri et al [43] discussed the availability problem of contextual data set for the context aware recommender system, as the online services provider mainly the music stream, YouTube and similar channel hugely depend on the context aware recommender system. That led to trend of context aware recommender system. But context extracting is one of main problem for modeling such system. As there are scarcity of the data set that have the exact contexts of its domain, and in case if exist the data set in then very sparse. Therefore, this research work is focused on the alternate ways of the availability of such data set and future direction to get the contextual data set. Laizhong Cui et al [44] proposed a novel approach to the context aware recommender system with double layer SVD called CTLSVD, the basic SVD just collect the item and user's features vectors, but in CTLSVD, the first the SVD extract the item matrix and user matrix from the rating, then the SVD further multiply the item matrix and user matrix to two different matrices. The STLSVD then filter the first impure recommendation result for the purification and improvement of the last and final recommendations by taking the time as a contextual information, the model then applied on two different real data set of movies and found that the proposed model outperform the basic context aware recommender system in term of accuracy and performance. Linda et al [45] presented a Decision tree context aware recommender system utilizing pre-filtering contextual paradigm. Which take the benefits of both CF and CBF. ID3 algorithm has been used to exploit the user's contextual preferences and the formation of neighbor done by utilizing ruled from decision tree. U. P. Ishanka and T. Yukawa [46] incorporate personality traits with the emotion feature in a tourist travel context aware recommender system. The personality traits can provide an accurate recommendation because features of recommendation vary with the changes in personalities, and for this the five-factor model is one of the suitable models to select personality traits information into a recommendation process, along with the personality emotion also play a very important rule in the context aware recommender system, specifically in the tourist recommender system. In this article for the emotion accession the Plutchick's emotion classification has been used. The collaborative filtering is used while emotion and personality are collectively used with showing the inter relationship between them. M. Iqbal et al. [47] proposed a novel approach to the context aware recommender system called KCR a scalable kernel context recommender system. In the proposed system the author took location, mood, time, social circle, language, weather as context of the user and item, because the user's rating behavior changes with changes in different context, these contexts are then incorporated with the help of kernel trick making recommendations. The proposed algorithm applied on different movies data set ranging from small to large and dense to sparse to check its performance under different circumstances, the proposed algorithm is also cross checked with the two most likeable and used approaches called the post filtering and pre filtering approaches, the experiment shows that the increasing the suitable context increases the performance, relevancy and accuracy of the recommendation in term of F1 score, MAE and other useful evaluation metrics. Rehman, F et al. [47] proposed an intelligent context aware recommender system for a real estate business, the proposed system is based on the Weighted Cousin Similarity and Gated Orthogonal Recurrent Unit (GORU). The Weighted Cousin Similarity is used for the rank improvement of the relevant features and GORU help to get the search content of the users. The proposed model in applied on a public data set of a real state website "AARZ.PK", which includes the real behavior of the user's activity. The model evaluated with different evaluation metrics like User Coverage, MRR and Recall. Singh, M et al. [48] worked on a personalized context aware recommender system, in which they took both item and user's preferences on the based splitting criteria, of a movies data, the algorithm first split the signal item into two different virtual items based on the explicit difference, the same way the single user also been split into two, the Collaborative filtering technique is used for the recommendation, the data set used for the evaluation of the algorithm is the LDOSCOMDA.

Moshe Unger et al. [50] proposed deep context aware recommender system that integrate the context data into a neural based collaborative filtering algorithm. Basically, the contextual data have different features and different multiple dimensions for different domain and application, but in the proposed framework it is used for rating matrix, classification of user preferences and top-k recommendation. This framework is divided into three different models, unstructured, structured and explicit latent representation of contextual information. This model outperforms all other standard context aware recommender system. And among these models the structure model shows better results on all data set. Deepa, and N. Pandiaraja, [51] developed a new hybrid context aware recommender system for the health care system, the main purpose of the said system is to improve the security and less the computational time as the data to process for the recommendation is store on cloud, the Merkle hash tree with the evolutionary algorithm is used for the index generation as this method is fast and secure than all other tree, working model of this algorithm: when a patient search for the doctor related to their illness first of the patient enter their illness on the website then the system recommend them with top-k doctor based on the rating, and then the patient consult the doctor either online or in the clinic , after treatment the patient rate the doctor based on different context like service, medicine prescription, behavior etc, the system then evaluate the model by comparing the expected rating with the actual rating using collaborative filtering technique. Amit Livne et al. [52] worked on the features selection for the better and accurate context aware recommender system, for this purpose the researchers select the contextual information of low dimension in multiple steps approach for the incorporation n the context aware recommender systems. The dimensionality reduction done by using genetic algorithm to improve the interpretability and accuracy of the recommendations.

2.3 RECOMMENDATION SYSTEMS IN FASHION

Much research has been carried out in the field of recommender systems in general and more specifically in the domain of recommender systems in Fashion. Among the number of approaches that have emerged in the last two decades, we can quote for instance collaborative filtering [5], [4], [8] content-based filtering [7], [9], demographics based [16], or knowledge (Ontology) based filtering [10]. Of course, all those approaches have been combined to create more accurate Recommender Systems that could cope with the challenges brought by each single filtering method (such as the cold start issue), namely hybrid Recommender Systems like the system FDRAS in [6]. The FDRAS combines both collaborative and content-based filtering to recommend the textile design that matches the customer representative sensibility and preferences. Furthermore, it is obvious that images play a prominent role when discussing Fashion. After all, we choose a garment, an accessory or an outfit based mainly on the following information: type (is it a dress, a jean or a jacket), shape (Uneck, long-short sleeves, over size, fitted, ruffle…), material (cotton, linen, wool, leather…, pattern (polka dots, stripes, plain, floral, squared…) among a wide range of possibilities… All these information can be spotted just by visualizing the item: they are all visual features. Therefore, it is logical to think that, when it comes to Fashion, items should be recommended mainly based on their visual features that are quite difficult to express in a textual way. As say the famous English adage: "A picture is worth a thousand words". That is why the CNN has become mainstream when discussing Fashion predictions: researchers use CNN to shade light on the similarities between items and to classify them according to their style or their type as shown in [11]. It's also a solution to tackle the issue of cold start brought by other approaches of recommender System like collaborative filtering. In the current recommender systems literature, the subject of Fashion is treated under a wide range of point of views regarding the purpose of the recommendation. For instance, some researchers aim at proposing a full outfit for a user by matching a bottom garment with a top garment focusing on style (complementary query), whereas others aim at recommending clothing based on the fashion style provided by a query item (similar query). Other focus on textile [6]. In [23], the authors propose a recommender system to coordinate clothing using full-body photographs from fashion magazines. They use a probabilistic topic model to learn information about current how to coordinates fashion items to produce a fashionable outfit from visual features in each fashion item region. Apart from style, other problems are driven by Fashion and among them the understanding of user size and fit. Researchers focused their work on helping the customer finding the ideal size and shape of garments for their body type and morphology. For instance, Abdulla et al. [22] managed to preselect consumer's size based on past purchase and content data without being invasive by asking their measurement. They used a skip gram based word2vec model to learn the latent representation from the purchase history on fashion items, as well as a gradient boosting classification model on latent and observable features to output a prediction of the perfect size for a given customer and item. In [18], the authors also worked on the subject for the website 24egitim.com and propose the Sfnet, a deep learning-based methodology which combines collaborative and content-based methods to learn input and latent representations of customers and fashion items for size and fit prediction. As in this paper, they used the RentTheRunway full dataset as well as the Modcloth dataset to evaluate their model. Q. Tu and L. Dong [53] proposed an intelligent personalized recommender system for outfit design selection and recommendation. Their research work implemented three different model in their system which work independently. Their focus is on multimedia mining virtual space for helping customers to select the best choices in fashion. The three model are: interaction and then recommender system that help user's demand of current fashion trend and recommendation of the most suitable outfit according to the current trend. The second model is based on multimedia mining in webspace, that filter the import features in a fashion domain and based on multimedia information of webspace. The third model is based on the analysis of color tone of a skin and outfit and provide the recommendation accordingly. These systems improve the efficiency of recommender system in webspace compared to the human interaction models. Y. Shin et al [54] used a single feature of clothes category instead of mixed different categories when all the features mixed together then this clothes vector is not distinctive and result an unmatched recommendation, in the example this research extract the features of style and category of the clothes vector separately which were used combined in the literature and then provide the recommendation based on single features and in the result they found that the single features recommendation outperformed the combined features model even using simple CNN technique. Tsarouchis, SF et al [55] present an intelligent semi-autonomous recommender assistant system. Which helps the fashion designer to select the accurate and most suitable outfit. This system implemented two different modules, where the module first collect data from online sources then extract knowledge from that data, then cluster the information and finally recommendation take place. The first from the two main modules based on clustering techniques which cluster all the data through different techniques and then vote the best cluster and the feedback and recommender module take input from the designer and provide the suitable recommendations. C. Stan and I. Mocanu [56] present a personalized fashion recommender system. That uses two convolutional neural networks based on AlexNet. The system differentiates the clothes and their corresponding features through neural networks and recommend to the user accordingly. The system evaluates based on the prediction accuracy using different evaluation metrics and resulted better system in term of prediction accuracy.

Regarding Context-aware fashion frameworks, few have been implemented despite the prominent part played by the context in which a garment is purchased by a specific customer. However, the main context information used in such current literature are mainly time, location, occasion and weather. In [17], the authors used smart fitting room with the ability to detect products and customers as a showcase as well as transactions dataset from a German leading fashion retailer and contextual information about the time, the location, and the weather conditions, to answer the question whether "the integration of contextual information can improve the quality of such recommendations". In [13], Wrong et al. includes contextual information such as size, occasion, trend, and silhouette in their two intelligent systems implemented thanks to RFID technologies. The first, called the Smart Dressing System (SDS), identifies product information, collects customers' preference, and offers mix-and-match recommendation. The second, a hybrid intelligent system called IPCS, is developed to match customers' chosen fashion items with other garment for mix-and-match purposes. Furthermore, in [19], Vaccaro et al. use latent fashion contextual information such as styles, seasons, events, and environments to develop a data-driven that learns correspondences between high-level styles (like "beach," "exotic," and "wedding") and low-level design elements such as color, material, and silhouette. They created an automated stylist recommender system that can rely on natural language specifications to recommend a fully personalized fashion outfit. Seema Wazarkar et al [57] proposed a novel deep learning recommendation system for outfit recommendations according to the body type or body shape of the end users. This model considers the body shape or type of the user as a contextual information of the user, then this contextual information is used for the recommendation of the best match outfit to the customers, the model is evaluated through different deep learning techniques as well as normal machine learning algorithms and found the 94% accuracy of the recommendation. Yuan, Y et al [58] studied a case study of the Chinese shopping mall and then implemented a personalized recommendation system based on the exact size of Chinese standard size chart only of the user for the matched recommendation. For this model they first making a body size metrics of the user which have been collected from the users during online shopping from the whole data base, this size metric is then considered for recommendations. Shintami Chusnul Hidayati et al [59] tried to solve the problem of what to wear for a good fashion sense. The proposed framework focused on the body size and type that can recommend the customer what to wear according to their body (goal. Thin, stretch etc).

Werneck, H. *et al* [60] proposed a novel ensembled recommender system in the fashion on outfit marketing. This model uses the contextual information of user like preferences etc and item contextual information like features of an item for the item recommendation. The model is based on neural collaboration filter techniques that assemble any of the contextual information of the user and item with any recommendation system to provide a customized and personalized recommendations, the model performed well against the traditional and general recommendations system in term of MRR, NDCG and Hits. Min Dong et al [61] rathe to recommend a fashion outfit to the user, the authors tried generating a recommendation system for the outfit designer to recommend which type of fashion or outfit would be like the most by the customer, as the outfit should be fit and design according to the body shape. For this system the system first use 3D of the user body to explicitly the body type and shape of the users. Then the technical parameter of the dress and the design knowledge utilized by the system through different techniques. Then the fuzzy algorithm is used for understanding the relation among designs factors, body types and fashion theme. The ontology based knowledge technique is used with the proposed process "consumers' emotional requirement identification – design schemes generation – recommender – 3D virtual prototype display and evaluation – design factors adjustment" repeatedly until designer satisfaction to recommend fashion and outfit design. Which would have the highest probability of likeness by the consumers. Ruining He and Julian McAuley [62] proposed a visually performed recommender system. They used the collaborative filtering technique to extract the user past fashion related rating history, deep neural networks used to extract from user's past feedback and community trends, the visual related features of the outfit. The researchers used two different fashion related data set from amazon to evaluate their system and resulted a better system in term of ranking. M. Mameli et al [63] refers to the fashion trends and fashion knowledge on social media, it's believed that the fashion knowledge on social media and the fashion taste of users on social media can be the best data to recommend the rightly matched fashion items to the user, the best technique that can be used to extract fashion related data and generate recommendation algorithm will be the deep learning technique due to its capabilities of self-learning iteratively. This model will imply further five processes namely, detection of fashion of objects, parsing and retrieval of clothes product, classification of clothes, generation of clothes and knowledge extraction and clothes recommendations. The proposed model processes outperformed all other traditional and deep learning techniques in terms of accuracy and timely processing. Y. Wakita, et al [64] proposed a novel approach for outfit brand recommendations called association rule brand recommendations, this approach uses the fashion-features and association rules of brands. Association rule utilized for the selection of new brands for the consumers based on their past likeness, and the fashion features used to find the similarities among different brands. The researchers also proposed the serial hybrid mode of brand association rules and fashion brand features. Both the techniques are implied on data sets and evaluated through different evaluation metrics which showed that the hybrid model surpass the other techniques in terms of accuracy and F-score. Ruiping Yin et al [65] highlighted the problem of visual of fashion and the uncomfortable with body style. The proposed model in the article tries to over this problem by introducing the new type of recommendation engines called the "fashion compatibility knowledge learning" method. This method combines the information of style with the relationship of visual compatibility. The recommendation system uses the strategy of domain adaptation for minimizing the space between the contextual compatibility of outfit item and the target item domain. The model can learn efficiently the visual compatibility of outfit and style. Wen Chen et al [66] present a novel recommendation algorithm called "Personalized Outfit Generation (POG) model". This model covering the gap between the fashion outfit generation compatibility and recommendation of personalized outfit. Though the analysis of huge data set it is found that the consumers almost have same taste of the outfit and an item. Therefore, the POG model uses the transform architecture to combine the consumer's preference regards the outfit and item. The model being tested both on online and offline platforms and found that the model is better than all other model in the literature in term of personalization and outfit compatibility. The said system is also deployed on real world online fashion system called "IFASHION" which is based on Ali baba. Banerjee, D et al [67] proposed to integrate and considered style (outdoor, indoor etc) as the must contextual information in the recommendation system of fashion. And the style must be assumed from real scenarios. Each item to be assumed to be mapped with high level classification based on the online portals like the indoor and outdoor outfit with the images of the outfit. A new encoder network in been utilized to smoothly and efficiently changes and updated the different styles and trends in fashion in a latent space. After extensive experiments the said approach outperformed all other baseline methods and approaches mentioned in the literatures.

2.4 SUMMARY

This section reviews the literature in the field of recommender system. The first part of this section summarizes the review on general recommender system, tools and techniques used in recommendations, second part focused on the context aware recommender system which is the main recommender system technique we have implemented in our work, the third and last section gathered the most prominent work conducted in the domain of fashion industry recommendations. This literature reveals the importance of contexts in fashion industry recommendation system that integrating context in rating matrix can improve the performance of recommendations.

CHAPTER 3

METHODOLOGY

3.1 INTRODUCTION:

Research methodology is the systematic, theoretical analysis of the procedures applied to a field of study. Methodology involves procedures of describing, explaining and predicting phenomena so as to solve a problem; it is the 'how'; the process, or techniques of conducting research.

(Kothari, 2004)

In this section the data set and the proposed framework is being discussed along with the evaluation metrics for measuring the performance of the proposed framework. First of all, the dataset "RentTheRunWay" is discussed in detail with all the features and contextual information before and after the preprocessing. After that the proposed framework with the all the applied ML algorithms is elaborated. The assessment procedure and evaluation metrics discussed in the last section of this chapter.

3.2 DATASET

In this paper, we used the **RenttheRunway** fashion dataset. This dataset indexes all the fashion items rented via the website www.renttherunway.com which is an online facility where particular can rent for instance a dress for a special occasion or not for a more or less short or long period. This data is a contextual data set which contains the complete contextual information of the items and user along with user item rating matrix, this data is one of the widely used data set for modern recommendation system based on contextual information. So, it can bring a value for a work of recommendation to be tested or evaluated as the benchmark performance. This data set is updated daily as new users registered on the website daily and new items or outfit also added for better experience, this will lead to addition in the user item rating matrix also, so there can be great chances for the data sparsity in this data set as the addition of new item and user doesn't confirm the full item user pair rating, as there may be new users who have not rated the item yet or there may be new item which have not been rated yet. So therefore, we are using a fixed version of the data set, but this data still has sparsity. Therefore, it would need some preprocessing for the continuous distribution of the data. The thorough detail of the dataset is elaborated ahead. The full dataset acquires 105571 users, 5850 Fashion items like dresses, jackets, or jeans as well as 192 544 ratings in a scale from 0 to 10, where 10 is considered an excellent rate and 0 as a really poor one. The ratings can only take even numbers i.e., 0, 2, 4, 6, 8, 10. The partition of the ratings from 0 to 10 going through the complete dataset is given by Fig 2. Given the fact that this dataset is very sparse as indicated in figure 2. we decided to pre-process it in order to make it denser. So first of the full data set is described in detail with their full contextual information and then the denser dataset is created after preprocessing which is described also in detail.

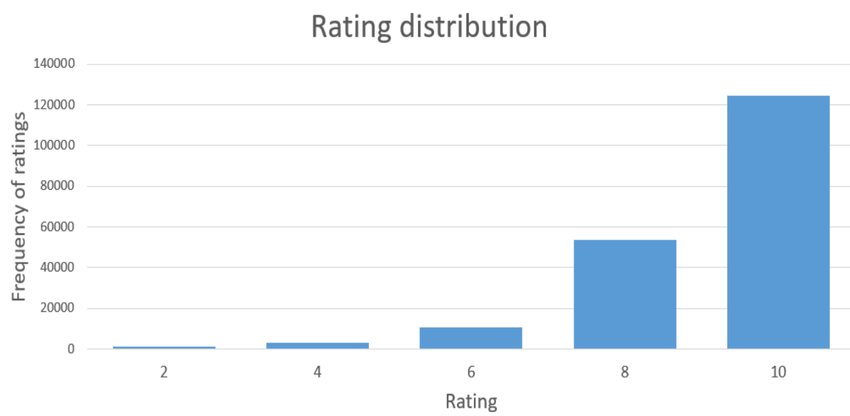

Figure 2 Rating distribution for the RentTheRunWay Dataset

- **Full Dataset**

The full dataset acquires 105571 users, 5850 Fashion items like dresses, jackets or jeans as well as 192 544 ratings, the description is given below in table for easy to read and understanding. Table1 contain the user's contextual information and table2 contain item's contextual information. There are 8 possibly relevant user's context information:

- Season: this talk about the season for which the outfit to be buy or hire, like Spring, Summer, Autumn, Winter etc
- Rented for: this feature acquires the reason for the outfit to be hire, such as weather the outfit is hired or bought for Wedding, Vacation, Party, etc.
- Age: the age features contain the information about the age of the user, the age ranges from 0 to 100.

- Body Type: this attribute is about the type of the body whether the body of the user is Athletic, straight, pear shape etc, according to which the selection of outfit take place for perfect match recommendation.
- Fit: the fit context is the information about the comfortability of the body like small, fit etc.
- Weight: Weight is the wight information about user, the weight is measured in lbs ranging from 50 lbs to 300 lbs.
- Heigh: Hight feature is the information about the height of the users which is measured in ft and ranging from 4 feet to 7 feet.
- Bust Size: this feature stores the size of users but.
- Category: this feature describes and stores different category types of the outfit like jackets, trousers, kaftan etc.
- Size: this feature talks about the size of the outfit category.
- Rating vector: the rating vector stores the rating provided by the users to the items. These rating ranging from 0 to 10, 0 mean not similar and 10 mean very similar.

All the information linked to their types of features can be found in Table II and table III. In table II all the user related contextual information along with values and ranges are summarize for better understanding. While tables summarized the contextual information of items.

Table 2 Context feature vectors and User's contextual information of RentTheRunWay Full Dataset

Context	Number of values	Context Feature Information
Season	4	Spring Summer Autumn Winter
Rented for	9	Wedding Vacation Party Date Formal Affair Work Everyday Other Nan

Age (years)	90	Range [0, 117]
Body Type	8	Apple Athletic Full bust Hourglass Pear Petite Straight & narrow Nan
Fit	3	Small Fit Large
Weight (lbs)	191	Range [50, 300]
Height(ft)	25	Range [4'6", 6'6"]
Bust Size (US)	107	Range [28A, 48DD]

Table 3 context feature vectors and item's contextual information of renttherunway full dataset

Context	**Number of values**	**Context Feature Information**						
		Subcategories (7)						
		Dress	**Coat**	**Overalls**	**Jacket**	**Top**	**Bottom**	**Sweater**

Category	68	Mi di Dress Gown Sheath Shirtdre ssMaxi Shift Mini Ballgo wn Frock Caftan Blouso n Print Kaftan	Coat Parka Peacoat Duster Trench Overcoat	Romper Jumpsuit Overalls	Jacket Down Bomber Blazer Vest Suit Kimono	Top Shirt Blouse Tank TurtleneckT-shirt Tee Tunic Cami Combo Henley For Button down	Pants Skirt Leggings Tight Jeans Trousers Skort Culottes Jogger Skirts Legging Pant Trousers Culotte Sweatpants	Cardigan Sweater Pullover Hoodie Sweatshirt Knit Cape Poncho Crewneck Sweatershirt
Size	56	Range [0,58]						

The given full data is very sparse which can be easily observe from figure 3,4, the age, height, and size distribution shows that the data is too much skewed either left side which may also can cause outliers that results in the faulty mean and average distribution that may lead to the irrelevant and unmatched recommendation in our system. So, to avoid these issues and to make the continuous distribution of data for better recommendation performance of our system, we preprocessed the data by applying different preprocessing techniques.

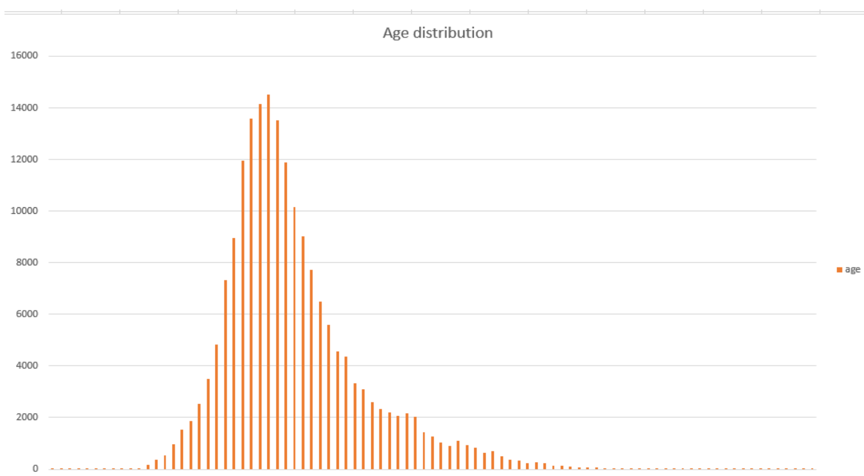

Figure 3 Age distribution for the RentTheRunway Dataset

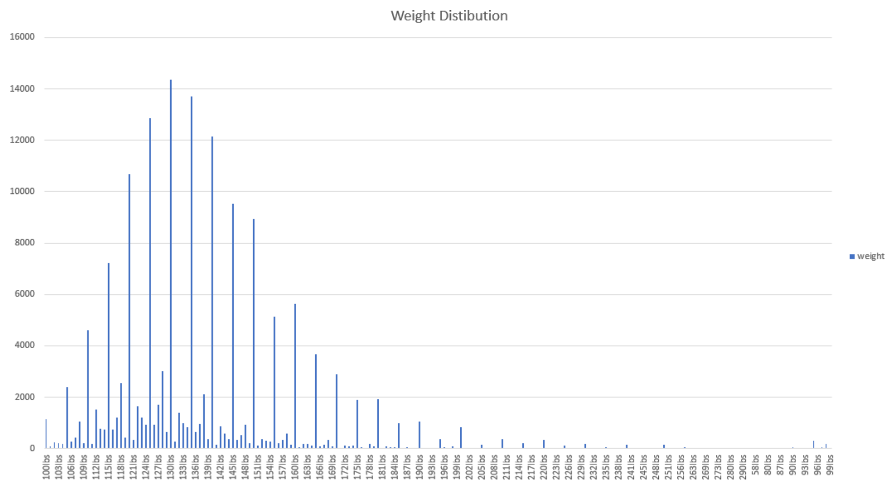

Figure 4 Weight distribution for the RentTheRunway Dataset

- **Denser Dataset**

  Given the fact that this dataset is very sparse as indicated in Table IV, we decided to preprocess it in order to make it denser. To do so, we've established the following rules:

  - Dropping all Data lines with missing values (NAN).
  - Dropping all the rented clothes rated less than 5 times.
  - Dropping all the customers who distributed less than 5 ratings.
  - Dropping all outliers

This dense version of now the dataset acquires 5414 users, 4530 Fashion items as well as 47229 ratings in a scale from 0 to 10. It still contains the same contextual parameters as the full version regarding both user and item's perspectives. Moreover, this pre-processed dataset contains.

Table 4 Context feature vectors and User's contextual information of RentTheRunWay Denser Dataset

Context	Number of values	Context Feature Information
Season	4	Spring Summer Autumn Winter
Rented for	8	Wedding Vacation Party Date Formal Affair Work Everyday Other
Age (years)	60	Range [0, 117]
Body Type	7	Apple Athletic Full bust Hourglass Pear Petite Straight & narrow
Fit	3	Small Fit Large
Weight (lbs)	116	Range [89, 265]
Height(ft)	20	Range [4'10", 6'4"]
Bust Size (US)	64	Range [28A, 44F]

Table 5 Context feature vectors and Item's contextual information of RentTheRunway Denser Dataset

Context	**Number of values**	**Context Feature Information**						
		Subcategories (7)						
		Dress	**Coat**	**Overalls**	**Jacket**	**Top**	**Bottom**	**Sweater**
Category	57	Midi Dress Gown Sheath Shirt dress Maxi Shift Mini Ball gown Frock Caftan Blouson Print	Coat Parka Peacoat Duster	Romper Jumpsuit Overalls	Jacket Down Bomber Blazer Vest Suit	Top Shirt Blouse Tank Turtleneck T-shirt Tee Tunic Cami Combo Henley For	Pants Skirt Leggings Tight Jeans Trousers Skort Culottes Jogger	Cardigan Sweater Pullover Hoodie Sweatshirt Knit Cape Poncho
Size	44	Range [0,57]						

multiple information that can reveal themselves pertinent contextual parameters for fashion items purchase. The above table II and III are now updated according to denser and preprocessed data set.

The updated contextual information of the user's and items are given in table IV and V.

Summary of Data is that after preprocessing of the full dataset for purpose of continuous distribution of the data is that the number of users who used and rated the product online on the RenttheRunway website reduced from 105571 to 5416 and number of fashion item reduced from 5850 to 4530, while number of ratings reduced from 192544 to 47229 because all the users didn't rate the item and all the items are ranked as there might be new user who haven't rented or buy item yet and there may an item which is new and haven't received any rating yet. Therefore only 47229 pair of ratings are valuable for generating recommendations engine, the total summary of the characteristic of dataset before processing and after preprocessing is given in table VI.

Table 6 Characteristics of RentTheRunWay dataset

RentTheRunWay Dataset		
Characteristics	**Full Dataset**	**Denser Dataset**
Number of Users	105 571	5 414
Number of Fashion item	5 850	4 530
Number of Ratings	192 544	47 229
Rating Scale	1 (bad)-10 (excellent)	
Contextual Information	season, rented for, age, body type fit, weight, height, bust size.	

3.3 EVALUATION METRICS

As pointed out beforehand, the purpose of this research is to give birth to a brand new efficient, flexible, and fast fashion recommender system that incorporate user's or item's contextual information with a view to enhance the capacity to predict relevant recommendations.To make sure that this new recommender system is as accurate as intended, its efficiency has been assessed using the evaluation method explained in [2]. As done in the latter, we have been using two highly popular evaluation metrics in the field of recommender systems, namely the F1-Measure and the Root Mean Square Error (RMSE) to evaluate the KFCR and to compare its performance to others such as the non-context-aware KMR system in [20].

Both evaluation metrics are described below:

- **F1-Measure or F1-Score:** F1-Measure represent an evaluation metric applied to recommender systems to analyse if they are efficient enough. It is actually the harmonic mean of precision and recall as mentioned thereafter. Precision can be described as the probability of making a meaningful prediction from all predictions made by the recommender system. Formally, F1 score can be written as:

Eq. 3 F1 Score

$$F1 = \frac{2*Precesion*Recall}{Precesion+Recall}$$

- **Root Mean Square Error (RMSE):** measures the distance between predicted likely to be liked items and true liked items. It is one of the most mainstream metrics when it comes to assess a RS. RMSE is highly linked to the Mean Absolute Error (MAE) and correspond to the square root of the average of squared differences between real observation and prediction. The particularity of the RMSE is that it increases the weight of large errors. Therefore, the lower is the RMSE value, the better is the accuracy of the system. Formally, it is computed as:

Eq. 4 Root mean square error RMSE

$$RMSE = \sqrt{\frac{1}{|D^{test}|} \sum_{\substack{ri,u=1 \\ \ldots,u \epsilon D^{test}}}^{|D^{test}|} (r'_{\ldots,u} - r_{\ldots,u})^2} \qquad \text{Eq. 4}$$

Where, |Dtest| are the test set records $r'_{I,u}$ are predictive ratings and ri,u are actual ratings given for item i by user u.

3.4 ASSESSMENT PROCEDURE

We chose to apply the widely used 5-fold cross validation technique in order to assess our algorithm's performance . To start with, this evaluation approach consists in splitting randomly into two sets the RentTheRunway fashion dataset: 80% are dedicated to the training set and the 20% left constitute the test set. To make the model learn the pattern of the dataset, the training set is once again split into two new sets, namely the actual training set (80%) and the validation set (20%). Eventually, we train our model on the training set by computing the missing ratings for a given user to fill in the rating vector and to produce a prediction.

3.5 PROPOSED KERNEL FASHION CONTEXT-AWARE RECOMMENDER (KFCR) SYSTEM ALGORITHM

In the following section will be described the Kernel Fashion Context-aware Recommender System Algorithm also named KFCR. As its name indicates, the heart of this system is to consider contextual information regarding both the user or the item to enhance the performance of the algorithm and to produce a valuable prediction that matches the customer's tastes and preferences. We are using the method of Kernel Mapping in collaborative filtering based on the work of Ghazanfar et al. in [20], to introduce a new Fashion Context-Aware Algorithm for both user and item version. This new framework called KFCR is adaptable enough to deal with user's and item's contextual information during the recommendation process by means of various context kernels. These latter have a great impact on the general performance of the algorithm. Their use enhances parameters like precision, scalability as well as adaptability. Figure 5, which is a simplified graphical representation of the KFCR algorithm, illustrates how our framework operates as well as what kind of information does it needs as inputs to be able to produce a relevant recommendation.

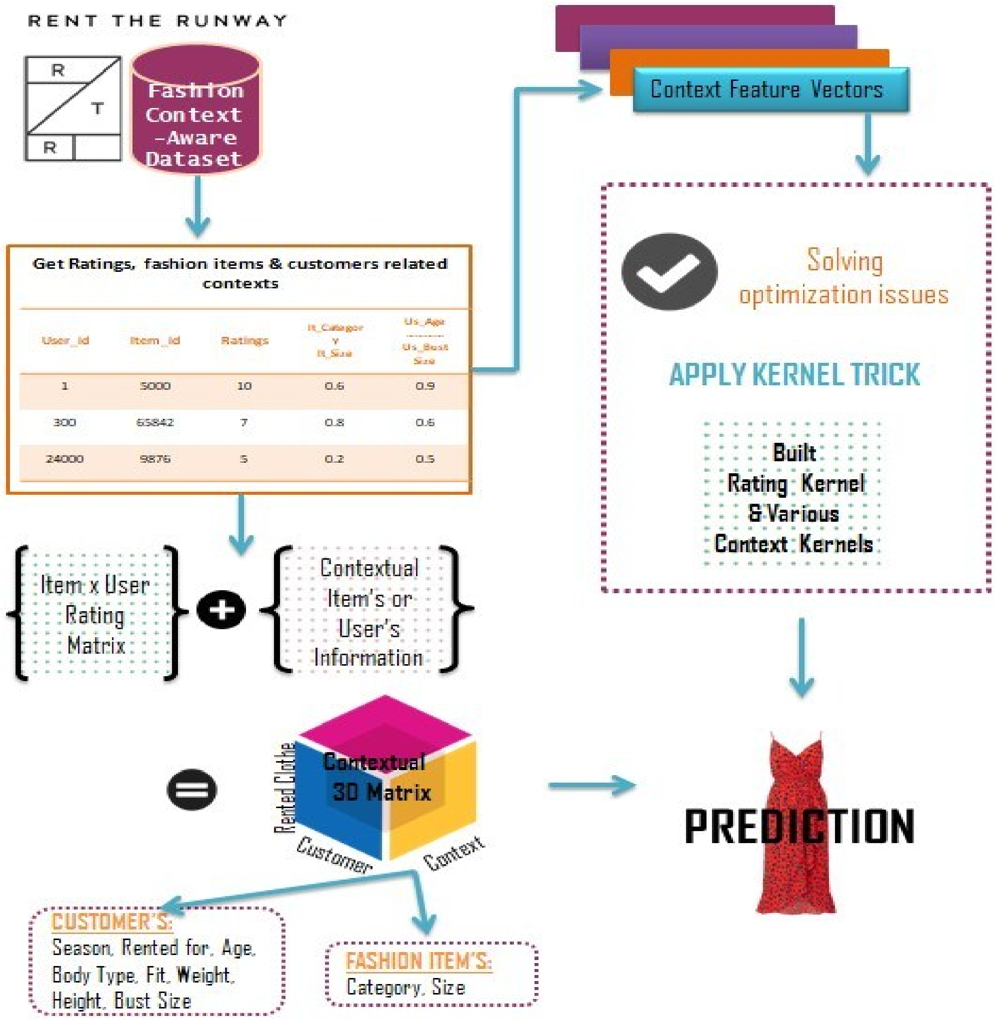

Figure 5 Graphical representation of proposed Kernel Mapping Fashion Context-aware Recommender (KFCR) System Algorithm

Our KFCR model is built around the idea of adding to a basic Customer × Rented Garment Ratings matrix fashion item's or customer's contextual information to create a 3D model. Furthermore, whereas current widely used models, namely pre and post filtering, add contextual information before and after the recommendation process to adjust the prediction, our novel algorithm combines ratings and context while generating predictions by integrating context feature vectors linked to each customer or item context. Building on the work done in [2] and [21], we included multiple contextual kernels to the simple non-context aware KMR algorithm which was originally only constituted of a Rating Kernel. These kernels were introduced using both Additive and Multiplicative models for user and item-based versions. Eventually, we engendered a post filtering version of our proposed framework in order to legitimize the existence of our bran new algorithm by comparing its performance to a model that is widely used in current literature.

3.5.1 Including Context in Item-Based KFCR Algorithm

The KMR original algorithm uses kernel mapping trick to produce meaningful predictions for a given customer or a given rented garment in our case. It uses a basic 2D Ratings matrix that incorporates only rating information. Even though this has been revealed to be the state-of-the-art in Recommender Systems, it still doesn't take into account context, which is essential in Fashion, due to its great influence over customer's rating behaviour.Therefore, our proposed framework KFCR takes advantage of the high flexibility of the KMR to transform it into a Fashion Context-Aware System that includes user and item related contextual information. Among the two versions developed, the item-based one requests user's contextual information. In this particular model, we consider the various customers that have rented and rated a specific piece of clothing. Hence, customer-related context requires to be taken into consideration alongside the given garment rating. Prior to merging them linearly or non-linearly along with the basic residual Rating Kernel to generate a recommendation, contextual Kernels are constructed one by one by means of user's contextual information e.g., age, fit, height, weight, rented for, season, bust size, body type. The formal representation of the Residual Rating Kernel is given below:

Eq. 5 Residing Rating Kernel

$$K_{r'}(r_{iu}, \hat{r}_{I'u})=(\psi(r_{iu}), \psi(\hat{r}_{i'u})) \rightarrow ResidualRatingKernel.$$

In a similar fashion, Context Kernel can be described as follows:

Eq. 6 Context Kernel

$$K_{context}(contextvector_{iu}, contextvector_{i'u}) \rightarrow ContextualKernel$$

Where 'context' can be season, rented for, bust size, body type, weight, height, fit and age of a user.

3.5.2 Identifying the Diverse Context Kernel

In this work, 8 types of user related contextual information have been used. In the following paragraph, you will find a detailed presentation of those different context kernels:

1) **Season Kernel**, denoted by $\mathbf{K}_{season}$, considers a season vector. The values associated to this type of context are the four seasons, meaning: summer, winter, autumn, spring.

$$K_{season}\ (s_{i\ u,}\ \hat{s}_{i\ u}) \rightarrow SeasonKernel.$$

2) **Rented for Kernel**, denoted by $\mathbf{K}_{rentedfor}$,, considers a rented for vector. It describes the special occasion in which the garment has been rented for such as: wedding, formal affair, work, vacation, date, every day, party, other. It is a social context.

$$K_{rentedfor}\ (s_{i\ u,}\ \hat{s}_{i\ u}) \rightarrow RentedforKernel$$

3) **Fit Kernel,** denoted by $\mathbf{K}_{fit}$, considers a fit vector. It describes the fit feedback i.e., how well does the item fit. Three values are associated to this type of context: small, fit, large.

$$K_{fit}\ (s_{i\ u,}\ \hat{s}_{i\ u}) \rightarrow FitKernel$$

4) **Body Type Kernel**, denoted by $\mathbf{K}_{bodytype}$, considers a body type vector. It describes the body shape of each user. The values associated to this type of context are: Hourglass, Straight & narrow, Pear, Athletic, Full bust, Petite and Apple.

$$K_{bodytype}\ (s_{i\ u,}\ \hat{s}_{i\ u}) \rightarrow BodytypeKernel$$

5) **Age Kernel**, denoted by $\mathbf{K}_{age}$, defines the age of the user at the date of the rent. It is expressed in years and takes values in the range: [0, 117].

$$K_{age}\ (s_{i\ u,}\ \hat{s}_{i\ u}) \rightarrow AgeKernel$$

6) **Weight Kernel,** denoted by $\mathbf{K}_{weight}$, defined the weight of the user as the date of the rent of the fashion item. It is expressed in ponds (lbs) and can take a value in the range between 89 and 265 lbs.

$$K_{weight}\ (s_{i\ u,}\ \hat{s}_{i\ u}) \rightarrow WeightKernel$$

7) **Height Kernel,** denoted by $\mathbf{K}_{height}$, defines the height of the user as the date of the rent. It is expressed in feet and inches. It can take a value between 4’10’’ and 6’4’’

$$K_{height}\ (s_{i\ u,}\ \hat{s}_{i\ u}) \rightarrow HeightKernel$$

8) **Bust Size Kernel,** denoted by $\mathbf{K}_{bustsize}$, describes the bust size of the user expressed in the dedicated US/UK metrics. It can take a value from 28A and 44F.

$$K_{butsize}\ (s_{i\ u,}\ \hat{s}_{i\ u}) \rightarrow ButSizeKernel$$

9) **Category Kernel,** denoted by $\mathbf{K}_{category}$, describes the kind of fashion item. It takes 68 different values such as jackets, dresses, jeans, romper, skirt….

$$K_{category}\ (s_{i\,u,}\ \hat{s}_{i\,u}) \rightarrow CategoryKernel$$

10) **Size Kernel**, denoted by $\mathbf{K}_{size}$, describes the standardized size of the fashion item from 0 to 57.

$$K_{size}\ (s_{i\,u,}\ \hat{s}_{i\,u}) \rightarrow SizeKernel$$

3.5.3 Merging Multiple Context Kernels

When it comes to forecast which fashion item may comply with the current tastes of a customer, plenty of data sources may be used. In order to make those sources usable, we have to merge the above defined kernels. By combining these contextual kernels and including them in the algorithm, it makes it possible to improve the accuracy of the recommender system. The above quoted Contextual Kernels are merged linearly in equation (7).

Eq. 7 Merging Contextual Kernel

$$K = K_{\mathrm{rat}} + K_{season} + K_{rentedfor} + K_{age} + K_{fit} + K_{bodytype} + K_{weight} + K_{height} + K_{bustsize}.$$

It appears that each contextual kernel benefits from the identical contribution in the model, as we can notice in Equation (7). However, each contribution can be adjusted by introducing a multiplicative factor associated to each kernel as illustrated in the Equation (8). In facts, these parameters, that aim at representing how much a context kernel contributes to the model, will be deduced of the analysis and the computation of its performance over the training set.

Eq. 8 Convex combination of Contextual Kernel

$$K = \beta_{rat}K_{rat} + \beta_{season}K_{season} + \beta_{rentedfo}\mathrm{r}K_{rentedfor} + \beta_{age}K_{age} + \beta_{bodytype}K_{bodytype} + \beta_{fit}K_{fit} +$$

$$\beta_{weight}K_{weigh}\mathrm{t} + \beta_{height}K_{height} + \beta_{\mathrm{bustsize}}K_{bustsize}$$

The kernel K is a convex combination of the contextual kernels. Where β_{rat}, β_{season}, $\beta_{rentedfor}$, β_{age}, $\beta_{bodytype}$, β_{fit}, β_{weight}, β_{height} and $\beta_{bustsize}$ are different parameters. We suppose that $\beta_{rat} + \beta_{season} + \beta_{rentedfor} + \beta_{age} + \beta_{bodytype} + \beta_{fit} + \beta_{weight} + \beta_{height} + \beta_{bustsize} = 1$ without the loss of generalization. Consequently, these contribution parameters are adjusted from the range of 0.0 to 1.0. As we have accommodated the different kernels this way, we must deal with the vectors which belong to theses contexts. They are depicted as follow in equation (9):

Eq. 9 Additive Kernel

$$\varphi_{context} = \varphi_{rat} + \varphi_{season} + \varphi_{rentedfor} + \varphi_{age} + \varphi_{fit} + \varphi_{bodytype} + \varphi_{weight} + \varphi_{height} + \varphi_{bustsize.}$$

The context Kernels are merged linearly and non-linearly for both additive and multiplicative models.

3.5.3.1 Additive Model

The way in which kernels are combined in Equations (7) and (9) can be string together in the additive model as presented in equation (10).

Eq. 10 User Additive Kernels

$$\varphi_{context} = \varphi_{rat} \oplus \varphi_{season} \oplus \varphi_{rentedfor} \oplus \varphi_{age} \oplus \varphi_{fit} \oplus \varphi_{bodytype} \oplus \varphi_{weight} \oplus \varphi_{heigh}t \oplus \varphi_{bustsize}.$$

Where '$\oplus$' represents direct sum of the feature vectors.

3.5.3.2 Multiplicative Model

As another option, these vectors or kernels can also be merged in non-linearly as in the following model in equation (11) and (12):

Eq. 11 User Multiplicative Kernels

$$K = K_{rat} . K_{season} . K_{rentedfor} . K_{age} . K_{fit} . K_{bodytype} . K_{weight} . K_{height} . K_{bustsize}$$

Where '.' represents the point-wise product of these kernel matrices.

multiplicative model.

Eq. 12 Multiplicative Kernels

$$\varphi_{context} = \varphi_{rat} \otimes \varphi_{season} \otimes \varphi_{rentedfor} \otimes \varphi_{age} \otimes \varphi_{fit} \otimes \varphi_{bodytype} \otimes \varphi_{weight} \otimes \varphi_{heigh}t \otimes \varphi_{bustsize}.$$

Where '$\otimes$' represents the tensor product of contextual feature vectors.

3.6 SUMMARY

This chapter summarized the overall methodology that is followed to conduct this research, first of all the data set that is used for training the algorithm is been discussed in detail, followed by assessment procedure and evaluation metrics to evaluate the performance of the proposed model after that the proposed framework is discussed in detail, the proposed KFCR is actually the augmented model of the basic KMR which generate recommendation on the basis of only rating matrix while our proposed framework integrate the contextual information such as weather, mood, location, height, size etc in the basic rating matrix. These contexts integrated both linearly and non-linearly through additive model and multiplicative model for both item contextual and user contextual information.

CHAPTER 4

EXPERIMENTAL SETUP

4.1 INTRODUCTION

In the following section are described the various results generated by the assessment of our various models namely the item-based version applied with both additive and multiplicative models (respectively the $\boldsymbol{KFCR_{ib\oplus}}$ and $\boldsymbol{KFCR_{ib\otimes}}$ models) as well as the user-based version also combined with both linear and non-linear models (respectively the $\boldsymbol{KFCRu_{b\oplus}}$ and $\boldsymbol{KFCR_{ub\otimes}}$ models). We also assessed the post filtering version of our model with an effort to compare those widely used context-aware methods to our proposed framework.

4.2 ASSESSING EFFICIENCY ON RENTTHERUNWAY DATASET

4.2.1 Item-Based Version:

1. ***Additive Model:*** The performance results in terms of Root Mean Square Error (RMSE) of the process of concatenating linearly and gradually user Contextual Kernel to the additive model i.e., $KFCR_{ib\oplus}$ for the item-based Version are illustrated in the Figure 6. This latter reveals that the RMSE drop while including more contextual kernel.

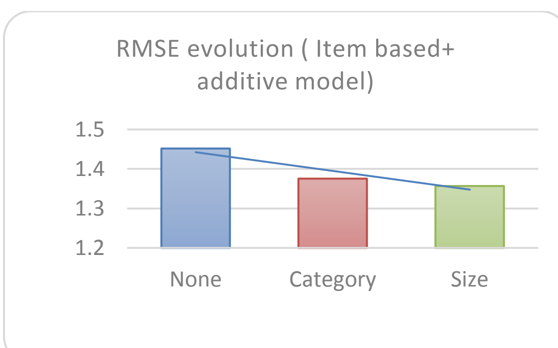

Figure 6 Decrease in RMSE value using additive model for item based contextual information

2. ***Multiplicative Model:*** In a similar fashion, Figure 7 shows the results in terms of RMSE of integrating gradually various user Contextual Kernels by means of the multiplicative model i.e., by multiplication them point wise for the item-based version of the model ($KFCR_{ib\otimes}$)

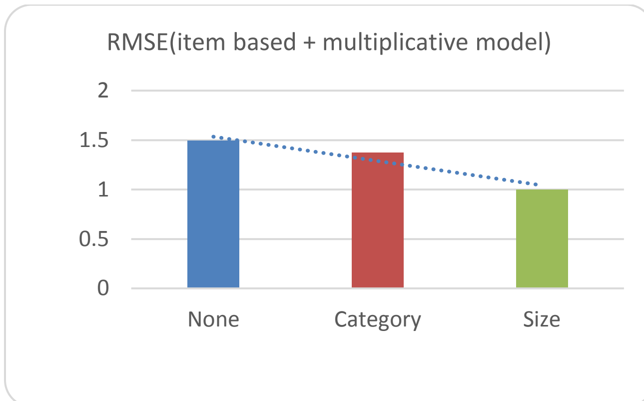

Figure 7 Decrease in RMSE value using multiplicative model for item based contextual information

4.2.2 User-Based Version:

1. ***Additive Model:*** The performance results in terms of Root Mean Square Error (RMSE) of the process of concatenating linearly and gradually user Contextual Kernel to the additive model i.e. $KFCR_{ub\oplus}$ for the user-based Version are illustrated in the Figure 8

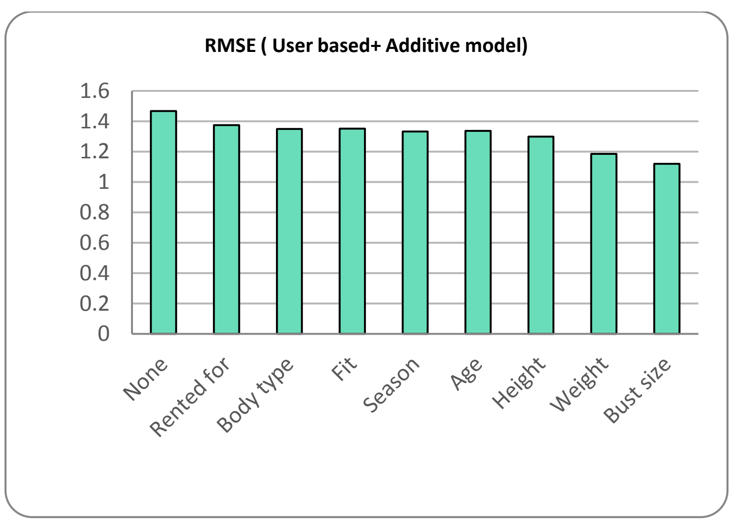

Figure 8 Decrease in RMSE value using additive model for used based contextual information

2. ***Multiplicative Model:*** Similarly, Figure 9 shows the results in terms of RMSE of integrating gradually various user Contextual Kernels by means of the multiplicative model i.e. by multiplication them point wise for the user-based version of the model ($KFCR_{ub\otimes}$).

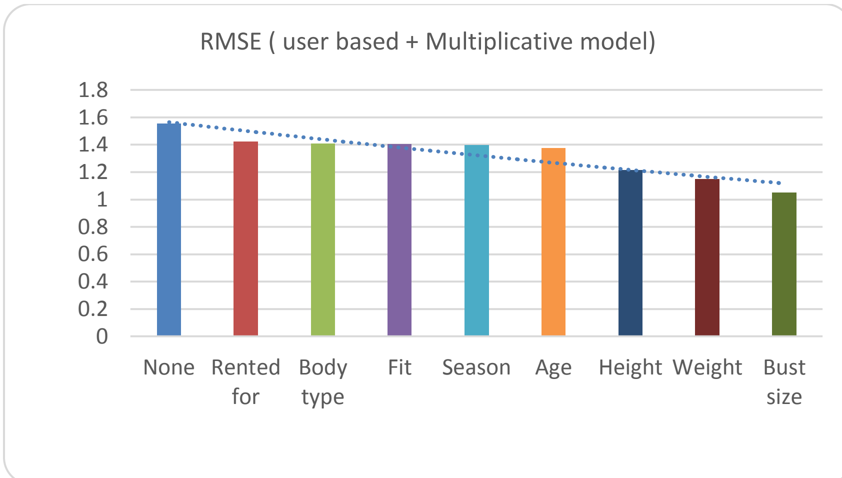

Figure 9 Decrease in RMSE value using multiplicative model for user based contextual information

4.2.3 Overall Result

1. ***Performance in terms of RMSE and F1 score while using polynomial kernel:*** The performance of KFCR evaluated using RMSE value and F1 score for both polynomial kernel and polynomial kernel. Result for poly gaussian kernel is given in Table VII.

Table 7 Results of proposed Fashion Context-aware models for polynomial kernel

Result in terms of evaluation parameters when kernel is polynomial		
Approaches	**RMSE**	**F1-score**
KFCRib⊕	**1.39**	**0.31**
KFCRub⊕	**1.21**	**0.35**
KFCRib⊗	**1.03**	**0.46**
KFCRub⊗	**1.19**	**0.37**

2. ***Performance in terms of RMSE and F1 score while using poly gaussian kernel:***
The performance of KFCR evaluated using RMSE value and F1 score poly gaussian kernel is given in Table VIII

Table 8 Results cof proposed Fashion Context-aware models for Polyguassian kernel

Result in terms of evaluation parameters when kernel is poly gaussian		
Approaches	**RMSE**	**F1-score**
KFCRib⊕	**1.39**	**0.30**
KFCRub⊕	**1.21**	**0.35**
KFCRib⊗	**1.11**	**0.41**
KFCRub⊗	**1.20**	**0.35**

4.2.4 Comparison of KFCR with Base Models

Comparison of the Proposed KFCR with Different Versions of KMR

Simple KMR is the recommendation algorithm as proposed in [20], which recommend the item using simple user item rating matrix without incorporating the contextual information of users and items as we have proposed in our model, in our work we compare the simple KMR with our proposed framework on the same data set in term of RMSE and F1_score to show the efficiency of our framework in table IX

Table 9 Results comparison of proposed Fashion Context-aware models for multiple evaluation parameters

Result comparison in terms of evaluation parameters		
Approaches	**RMSE**	**F1-score**
KMRib⊕ KFCRib⊕	**1.33** 1.39	**0.37** 0.31
KMRub⊕ KFCRub⊕	1.38 **1.21**	0.33 **0.35**
KMRib⊗ KFCRib⊗	1.35 **1.03**	0.37 **0.46**
KMRub⊗ KFCRub⊗	1.28 **1.19**	0.31 **0.37**

1. **Comparison of the Proposed KFCR With Simple KMR And Post-Filtering Models**

In this part, we compare our proposed framework with other state-of-the-art frameworks widely used in current context aware recommender systems literature. In our case, we will compare the **KFCR** model to: The **Simple KMR** model based on basic Rating Kernel.

The Post-filtering KFCR model based on including contextual kernels after training the context-free KMR model. In other words, the post-filtering method, as described in [12], firstly ignores all contextual information to generate ratings prediction using the traditional Recommender System based on the 2D User × Item Rating matrix. Once the ratings predicted, the output is contextualized using context information to adjust the model.

Figures 10,11,12 and 13 show the comparison between **Simple KMR, Post-filtered KFCR** and proposed **KFCR** with multiplicative model of item based contextual information user based multiplicative model, item based additive model and user based additive model respectively.

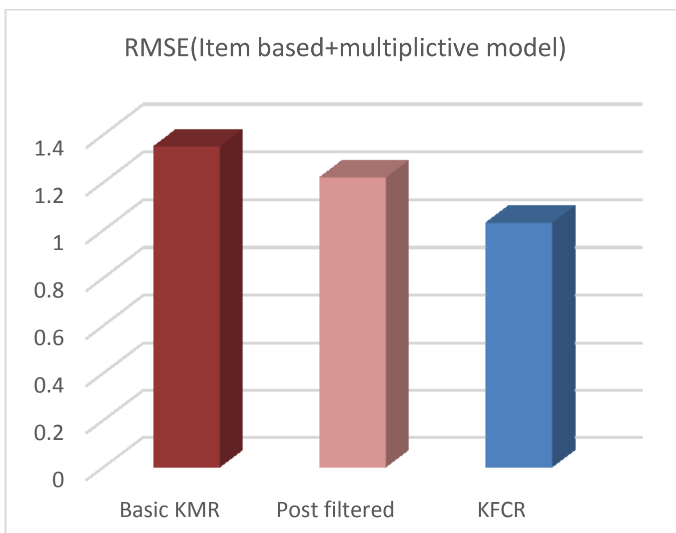

Figure 10 Comparison of Basic KMR, Post-filtered KFCR and Proposed KFCR in term of RMSE for item based multiplicative model

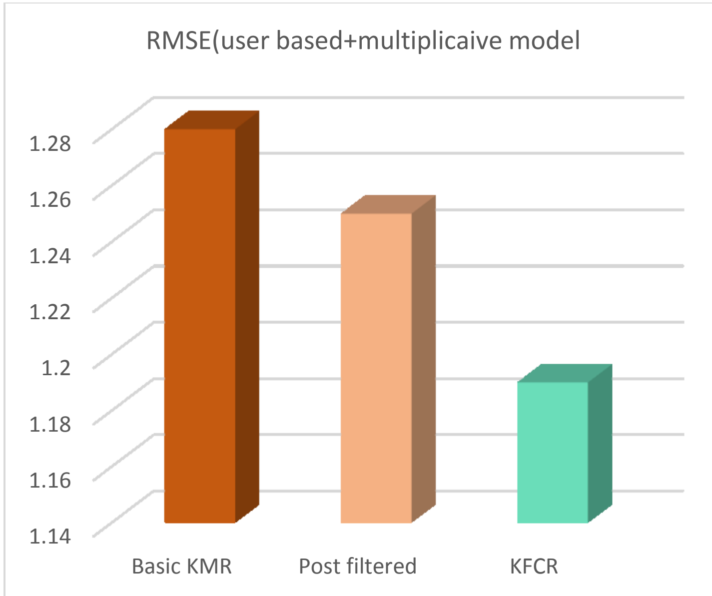

Figure 11 Comparison of Basic KMR, Post-filtered KFCR and Proposed KFCR in term of RMSE for user based multiplicative model

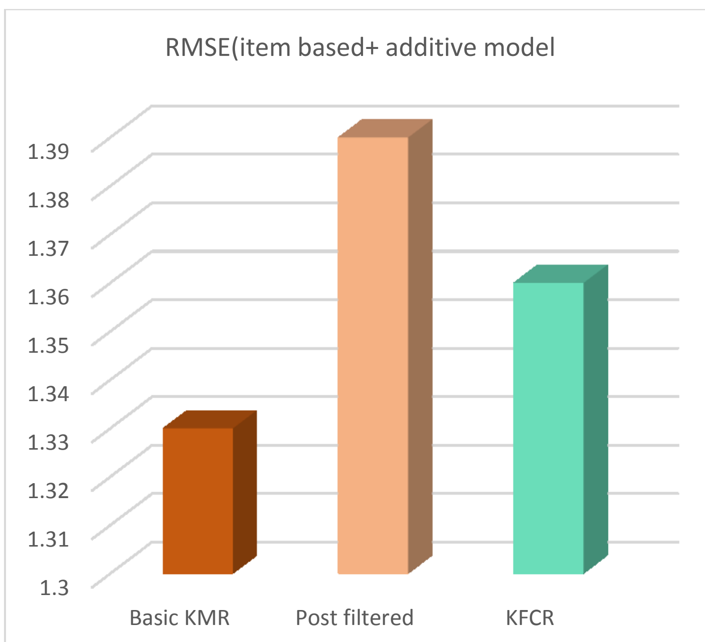

Figure 12 Comparison of Basic KMR, Post-filtered KFCR and Proposed KFCR in term of RMSE for item based additive model

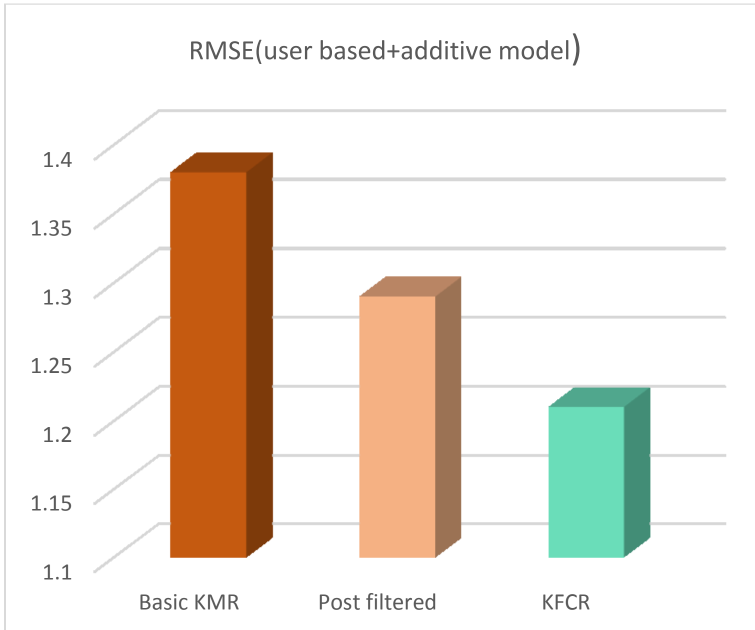

Figure 13 Comparison of Basic KMR, Post-filtered KFCR and Proposed KFCR in term of RMSE for user based additive model

4.3 SUMMARY

The proposed framework a combined the user and item's contextual information such as weather, location, height, weight, mood, etc to generate recommendation on user * item* context 3D matrix. these contexts integrated both linearly and non-linearly through additive model and multiplicative model. The assessment showed that item based multiplicative model showed better performance in term of RMSE and F1 score 1.01 and 0.42 respectively. Moreover, the performance of the proposed model also crosschecked with the basic KMR and post filtered technique, which revealed better performance of the proposed model than both mentioned more common used recommendations algorithms.

CHAPTER 5

CONCLUSION AND FUTURE WORK

5.1 INTRODUCTION

In the pervious chapter we discussed in detail the Introduction of the background of this work, the literature conducted, the brief but explanatory methodology followed conducting this research, then the overall performance of the proposed work in term of RMSE and F1 score. In this chapter we are able to conclude our work and also to discuss the future that can be done to further improve the recommendation process in the field of fashion industry.

This work focused on proposing scalable recommender system for fashion industry by introducing a novel context aware recommender system called Kernel Fashion Context Aware Recommender system **KFCR.** This work is incorporating contextual information like weather, height, etc related to user's or item's related information to the basic KMR. This chapter concludes the overall framework and assessment along with future work discussion for the researchers to enhance performance of recommendation systems.

5.2 CONCLUSION

In this paper, the exposed work aims at developing a new scalable kernel mapping context-aware Fashion recommender System, called KFCR to help online shops to create a more personalized customer experience, generating relevant prediction with maximum accuracy regarding the tastes. Throughout this paper, we've demonstrated experimentally, over the RentTheRunway dataset, that including context to a basic rating-based recommender system model can enhance radically the performance of this latter, in the field of fashion. The proposed model works on the basic of basic Kernel mapping recommender system which recommend item only based on user and item rating 2D matrix, The proposed framework also combined the user and item's contextual information such as weather, location, height, weight, mood, etc to generate recommendation on user * item* context 3D matrix. these contexts integrated both linearly and non-linearly through additive model and multiplicative model. The assessment showed that item based multiplicative model showed better performance in term of RMSE and F1 score 1.01 and 0.42 respectively. Moreover, the performance of the proposed model also cross checked with the basic KMR and post filtered technique, which revealed better performance of the proposed model than both of the mentioned more common used recommendations algorithms.

5.3 FUTURE WORK

Normally recommendation in online product needs just user and item rating matrix to generate recommendations based on the same user or for the same item, but in the fashion context only rating may not always be the best choice to generate recommendations because the outfit mostly depends on the choice of the users, their mood, situation and the color and height etc of the user. Therefore, contextual information plays a pivotal role in recommendation in fashion industry to generate a perfectly match outfit according to the mood, choice of the user and the situation, our work mainly focused on the contextual recommender system, which a good performance in recommendation system for fashion industry. But the selection of contextual information is still not standardized, it means there is no specified way to select contextual information for specific user or item, so suitable context selection is still a huge challenge in contextual recommender system. So contextual selection procedure and standard is a huge problem that needs to be addressed in the future to further improve the performance of contextual recommender system. Secondly user item rating matrix still can not be trusted completely as there rating could be fake or generated unauthentically, so generating a real rating matrix can also improve the recommendation process, we are planning generate a real rating data set a standardized contextual selection process to accurately generate the recommendation in fashion industry.

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