User Preference based Cross Domain Recommender System

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Major Project

Submitted in partial fulfillment of the requirements

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Prepared By

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Certificate

This is to certify that the Major Project Report entitled "**User Preference based Cross Domain Recommender System"** submitted by **Bhoomi D. Khanderia (Roll No: 12MCEC36)**, towards the partial fulfillment of the requirements for the degree of Master of Technology in Computer Science and Engineering of Nirma University, Ahmedabad is the record of work carried out by her under my supervision and guidance. In my opinion, the submitted work has reached a level required for being accepted for examination. The results embodied in this major project, to the best of my knowledge, haven't been submitted to any other university or institution for award of any degree or diploma.

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Annexure VI

Undertaking for Originality of the Work

I, **Bhoomi D. Khanderia**, Roll. No. **12MCEC36**, give undertaking that the Major Project entitled "**User Preference based Cross Domain Recommender System**" submitted by me, towards the partial fulfillment of the requirements for the degree of Master of Technology in **Computer Science & Engineering** of Nirma University, Ahmedabad, is the original work carried out by me and I give assurance that no attempt of plagiarism has been made. I understand that in the event of any similarity found subsequently with any published work or any dissertation work elsewhere; it will result in severe disciplinary action.

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- Bhoomi D. Khanderia

Abstract

Recommender systems have developed with the advent of technology. With the increasing amount of data on web, it has become difficult to provide quick and user satisfactory recommendations. Inspite of the recommendation systems having achieved tremendous success in various domains, however improvement is still required in cross-domain recommendation field. On account of the increase in volume of music data stored online, opportunities have opened up to implement music recommender systems among users. It is always a difficult task to recommend appropriate music to the users. It becomes easier to recommend music if certain context based information is provided. This leads to cross domain recommendation system.

Cross Domain Recommendation System recommends two different items from two different domain. This dissertation focusses basically on cross domain recommendation comprising of selecting two things at a time from two separate domains and recommending them together. The system will suggest music tracks to the user on the basis of the place along with consideration of user's preference of music tracks. Hence, the combination of Place-Music pair is recommended by using different approaches using the tags attached to music tracks and places by the users.

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Chapter 1

Introduction

The concept of big data is prevalent from the early days of computing. The volume of the data that is in the range of exabytes and beyond is called Big Data. Traditional database methods and tools cannot process this huge amount of data efficiently. Various aspects of big data are volume, variety, velocity, value, and complexity. Hence, the need for processing and analyzing the large amount of data for decision making has also been increased. Processing huge amount of data require more time which consequently delays quick recommendations. Combining variety of data and generating relevance among data using Collaborative Filtering, Filtering uncorrelated data, enhancing recommendation system, etc [1] are major issues related to Big Data. Due to large amount of data, there is a need to enhance recommender systems to cope up with the 3V's - Volume, Variety and Velocity of Big Data.

Recommender System works on the principle of collecting information on the preferences provided by the users for a specific set of things which may include domains like music, books, restaurants etc. Recommender Systems can acquire the information explicitly by gathering feedback from the users or implicitly by monitoring user activities. Recommender Systems can also use attributes of the user like sex, age, etc. or different sources to provide the user with recommendations. Recommender System takes into consideration various evaluation parameters such as precision, accuracy, dispersity, stability etc. in the recommendations. Collaborative Filtering methods has a major part in the recommendation proceseses, although it is commonly used along with other Filtering techniques.

Recommender Systems are available in different domains like Music, Movies, Restaurants etc. Music Recommender System is also one of the evolving system. Inspite of the increase in amount of digital music data, it has become extremely difficult to manage and search music tracks. Music information retrieval (MIR) techniques have been researched and implemented successfully in the last decade. But as the music recommender system is still is in preliminary level, there is a scope of research and development. The two broadly utilized techniques proposed for music recommendation are Collaborative Filtering and content-based recommendations.

Context based music recommender systems can suggest music tracks based on contextual conditions, such as user temperament or location. This probably influences the preference of the user at a particular period of time. The system considers a particular type of cross domain recommendation task to select music track that matches a particular place. To address this problem the system uses tags attached by the users to Music as well as Places.

Chapter 2

Recommendation Systems

In the area of recommendation system(RS) mostly research is done in the domain of movies. But, a huge volume of literature for RS is focused on various domains, like e-learning, e-commerce, music, books, documents, various market applications as well as others. With constant development in the field of RS, the importance of hybrid recommendation techniques that merges with different techniques to overcome short comings of a single technique has increased .

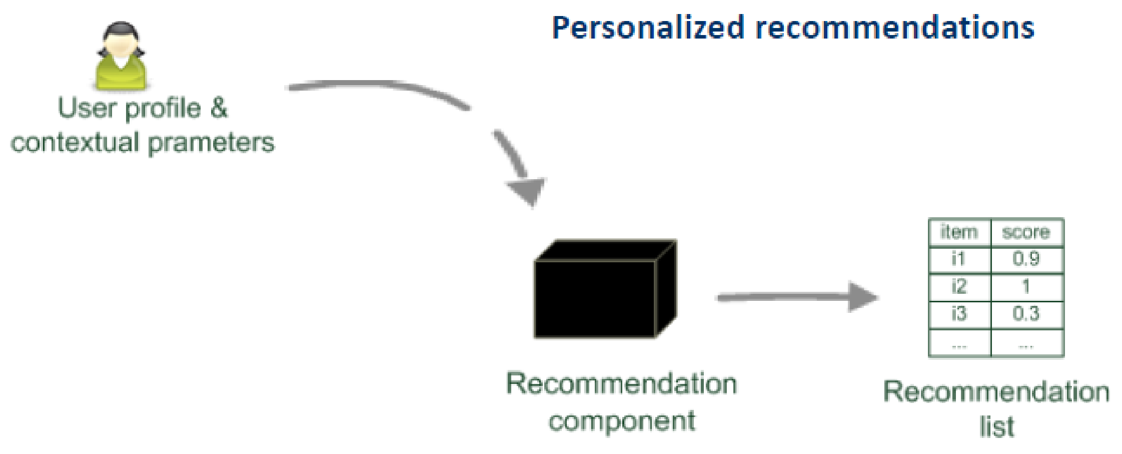

Figure 2.1: Personalized Recommendations[11]

2.1 Recommender Systems Foundations

The process for generating recommendations is based on the following factors:[2]

- The type of information available in the dataset.
- The type of algorithm that is used.
- The model that is chosen whether it is memory-based or model-based.
- The techniques that are employed. For example: fuzzy models, probabilistic approaches, genetic algorithms, nearest neighbors algorithm etc.
- The level of the sparsity in the database and the scalability that is desired.
- Performance of the system in terms of time and the amount of memory that is being consumed.
- The target sought is considered that is, predictions and top N recommendations as well as
- The nature of the results required are made looking into accuracy, correctness, and so on.

2.2 Filtering Algorithms

Filtering Algorithms characterizes internal function for recommender systems. The following are the types of filtering algorithms[2]:

2.2.1 Demographic Filtering

Demographic Filtering algorithm works by considering various personal attributes like age, nationality, gender etc..

2.2.2 Collaborative Filtering

Collaborative Filtering is based on allowing users to give ratings about various items in a domain for example books, videos, songs, films, etc. in a way such that when satisfactory amount of data is saved on the system, recommendations are made to user on the basis of the information provided by such users who have the most in common with them. As mentioned above, user ratings can also be obtained implicitly. The most commonly used algorithm for Collaborative Filtering is the k Nearest Neighbours (kNN). In the user to user version, the following 3 tasks for making recommendations for a user are executed by the KNN:

1. Determine k users neighbors corresponding to an active user A;

2. An aggregation approach is then implemented using the ratings of items in the neighbourhood that are not rated by A; and

3. Further, after extracting the predictions obtained from step 2, the top N recommendations are selected.

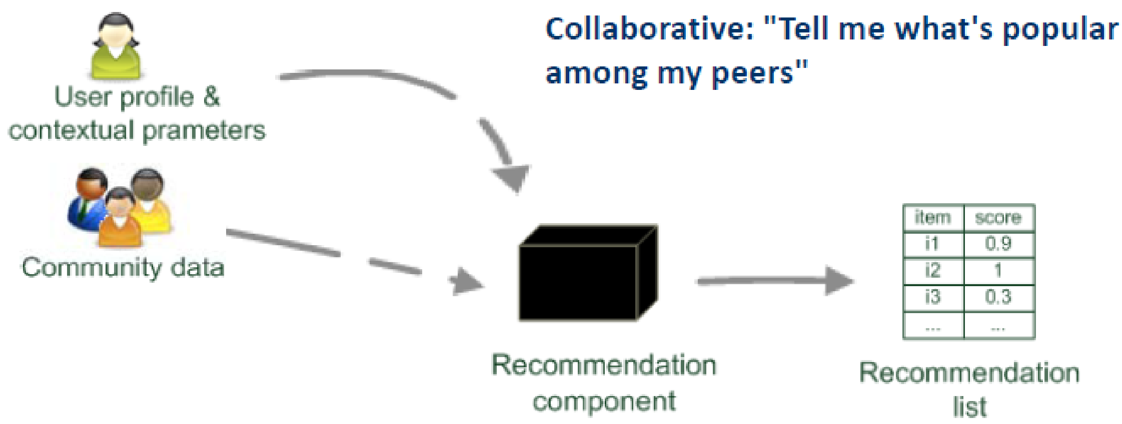

Figure 2.2: Collaborative Filtering[11]

2.2.3 Content-based Filtering

This method makes recommendations based on the selection of items that were made by the users previously (e.g. in a RS, if mystery books have been purchased by the user in the past, the RS will give recommendation for a newly released mystery book that the user has still not purchased). This method can also generate recommendations by using the data from objects that are used for recommendation; and hence, certain information can be analyzed, like music, images, etc. On the basis of this analysis, a similarity can be obtained between objects for recommending items that are almost same to the other

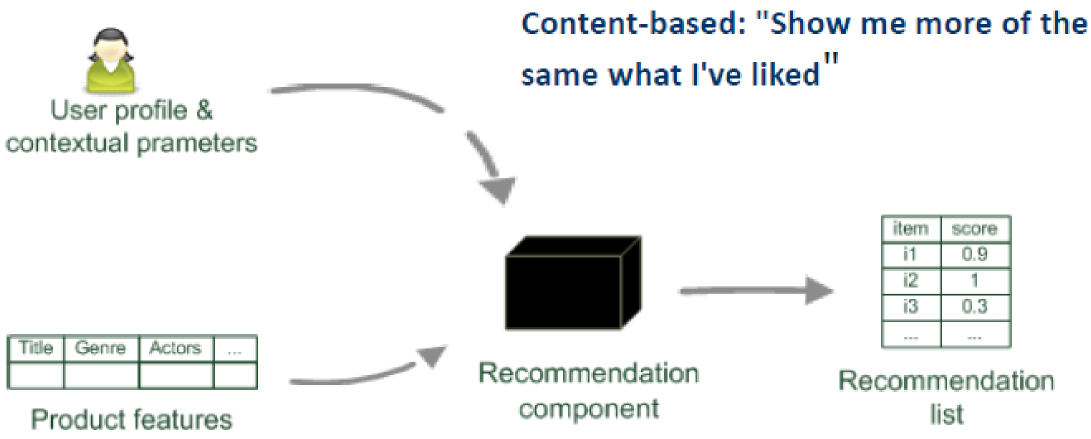

Figure 2.3: Content-based Filtering[11]

items which a user has seen, bought and ranked positively. The pure Content-based filtering has several shortcomings:
(a) It becomes extremely difficult to generate the attributes for items belonging to domains like music, videos, etc.
(b) Content-based Filtering generates recommmendations for the similar types of items and hence an overspecialization problem occurs.
(c) In this method, users do not rate the items so it becomes difficult to get proper feedback from the users as a result of which it is impossible to know whether the recommendation is correct or not.
Due to all these problems, it is not to find a good Content-based Filtering implementation. It is generally more acceptable to use the hybrid Content-based Filtering/Collaborative Filtering. The problems of Content-based Filterings are solved by Collaborative Filtering because Collaborative Filtering method can function in any domain; it can acquire feedback from users and hence it is not much affected by the problem of overspecialization. Content-based Filtering adds the certain qualities to Collaborative Filtering approach: it improves the predictions obtained, large amount of information is used to generate predictions, which ultimately reduces the impact from the problems like cold-start and other sparsity problems. Recommendation methods are generally dicided into following two categories:

- **Memory-based methods:** Methods which act on the matrix of ratings provided by the users for items and which uses any rating that is generated before the referral process are called memory based methods. These methods generally obtains the distance between 2 users or 2 items using similarity metrics which are based on the ratios(users or items).

- **Model-based methods:** Model-based methods are the methods that use RS information for creating a model that is used to generate the recommendations. Generally a model-based method is considered when any new information from any user outdates the model. The most widely used models include fuzzy systems, genetic algorithms and matrix factorization.

2.2.4 Hybrid Filtering

Hybrid Filtering generally uses a combination of two different techniques like demographic filtering with Colaborative Filtering or Content-based filtering with Demographic filtering to combine advantages of each of the above mentioned techniques. Hybrid filtering is generally based on various methods like genetic algorithms, neural networks, Bayesian networks etc.

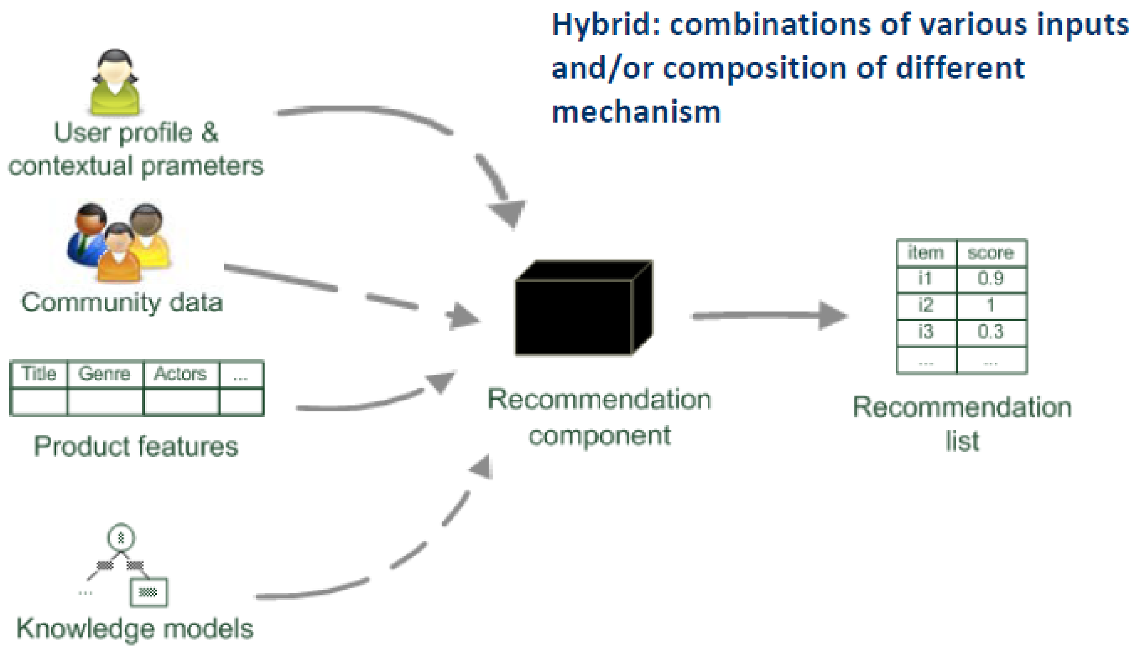

Figure 2.4: Hybrid Filtering[11]

2.2.5 Context-aware recommender systems:

Recommender Systems that focusses on contextual information like location, time, etc. are called Context-aware recommender systems. The context based information that is used in this type of recommender system can be obtained implicitly or explicitly by mining the data or using hybrid filtering techniques. At present, many mobile applications use location information as such information enables geographic Recommender System that can be considered as location-aware Recommender System. For geographic Recommender System, recommendations are generally obtained by taking into consideration the location of the user that obtains the recommendation.

2.2.6 Location-aware Recommender Systems:

With the increase in use of mobile devices has increased to a great extent, location-aware systems have become more popular. These type of Recommender Systems has the tendency towards their consolidation as web 3.0 services which normally leads to location-aware Collaborative Filtering and location-aware Recommender System, that may be called geographic Collaborative Filtering and geographic Recommender System.

Certain Recommender Systems are available like Location-aware, Mood based, Personalized Receommender Systems, etc. In this dissertation we are working on mainly two domains: Music and Places, and recommend a music-place pair to the user using the similarity computed for tags attached to both music tracks and places.

2.3 Music Recommendation Systems

With the increased use of internet in the past decades, most of the multimedia information such as music, books, movies etc. can be retrieved from the internet. It was observed that people listen to music more than they are engaged in any other activities and it has become one of the important aspects of their lives which inspired the researchers to carry out research in the domain of music.

As the amount of music content stored online has gradually increased so much that the problem managing and organizing the music has become a point of major concern. The principle assignment of music recommender is to give users to channel out and uncover songs according to their taste. A music recommender framework ought to have the capacity to discover users' preferences and thus produce playlists in like manner which will help to total the users who are intrigued by music. With the development in the

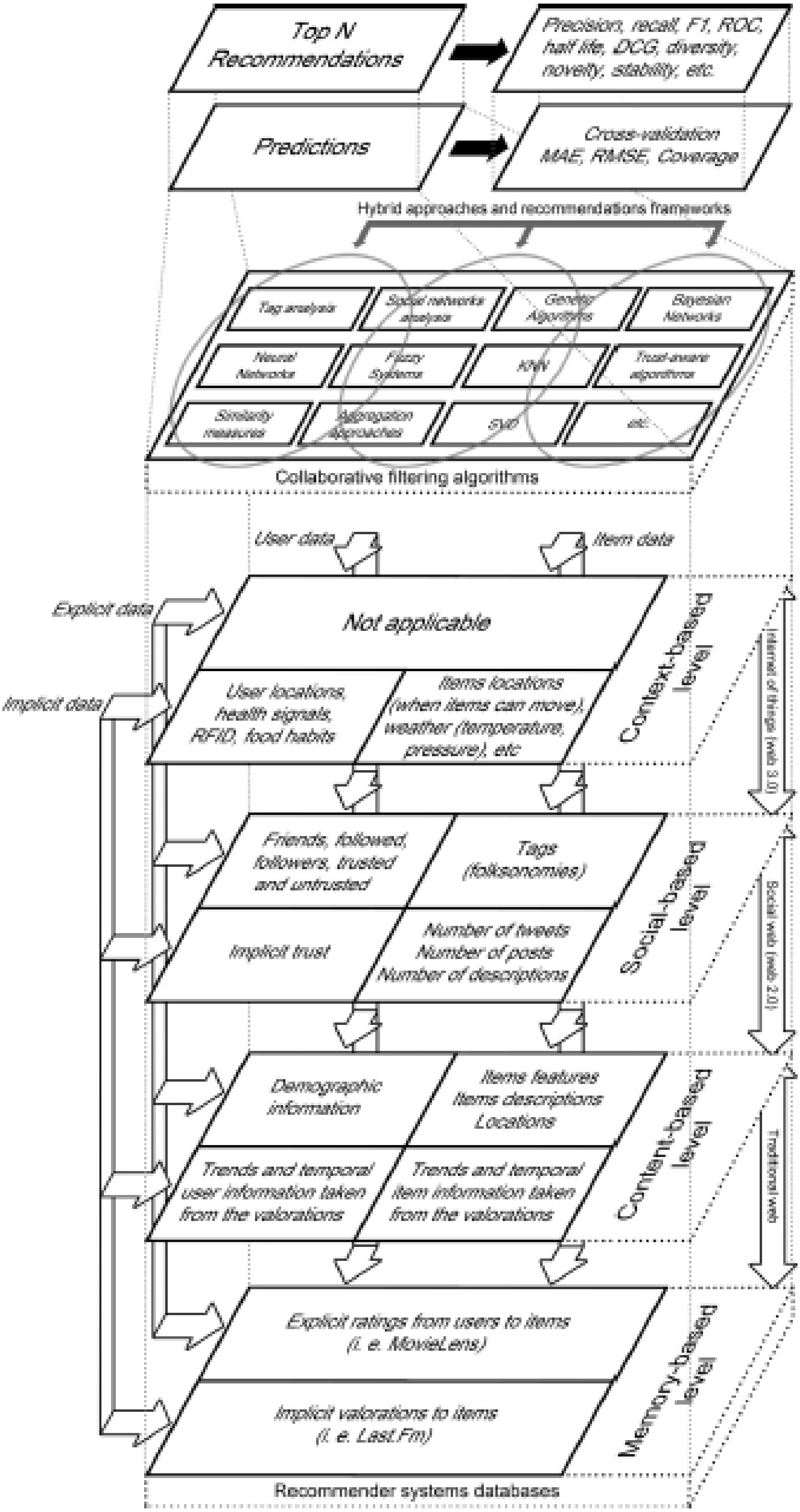

Figure 2.5: Recommendation Systems' Taxonomy[2]

domain of Music recommender system, the idea of understanding and modelling users' preferences has become a major concern.

2.3.1 Components in Music Recommender System

Typically, a music recommender system consists of 3 components -items, users and item-user matching algorithms.[3]

- **User Modelling:**

  User Modelling is one of the key elements of music recommender system. A music recommender framework ought to have the capacity to help users. This component models the difference in the profile of users like there may be difference in location, age, their preferences of music, etc. Various factors like life styles, sex, interests may affect the music choices of users.

  - **First Step - User Profile Modelling** The profile of user generated can be categorised into 3 main domains as shown in Table 2.1.

Data type	**Example**
Demographic	Sex, marital status, age etc.
Geographic	Location, Nationality, city etc.
Psychographic	Stable: lifestyle, interests, personality etc., Fluid: attitude, mood, opinions etc.

Table 2.1: User profile classification

  - **Second Step - User Listening Experience Modelling:**

    On the premise of the profundity of learning of users in Music domain, their expectations may differ. The different types of listeners can be catogorized into four groups: savent, enthusiasts, casuals, indifferents.

- **Item Profiling**

  Music item is the second component of recommender systems. In 2005 Music metadata was classified by Pachet [4] into 3 categories: acoustic metadata (AM), editorial metadata (EM) and cultural metadata (CM).

– **Editorial metadata:**

  A single expert or group of experts provide the metadata. This information is truly acquired by the supervisor which can additionally be seen as the data gave by them. This data consists of information like composer, genre, title etc.

– **Cultural metadata:**

  The analysis of corpora of text based information provides metadata, generaly from the Internet or other sources. The data thus obtained results from the examination of rising examples, acquaintanceship or classifications from archives. For instance: Similarity between music items.

– **Acoustic metadata:** It consists of the metadata that is retrieved from an analysis of the audio signal. The metadata thus obtained should be without any reference to a text based or prescribed information. Examples of acoustic metadata are tempo, pitch, beat, mood etc.

Metadata information retrieval mainly uses Editorial metadata while Context-based information retrieval generally uses cultural metadata. Almost all the music recommendation systems use acoustic metadata for music discovery which is better known as content-based information retrieval.

2.4 Cross Domain Recommender System

In the era of explosive information, recommendation systems have gradually become an indispensable part of network applications. However, most of the efforts and achievements only focus on within-one-domain recommendation up to now. For cross-domain recommendation problem, there still exists huge potential both in academic and in business. Now a days attempts are made which combines information from various domains which introduces the concept of cross-domain recommender systems. These cross-domain recommender frameworks can reuse the information about the users from one domain in an-other domain, e.g., books, to give suggestions in an alternate domain, e.g., movies. Cross-domain recommendation can bring many benefits to both users and websites. In traditional recommendation systems, when users are browsing resources from one domain, the recommended list is only generated from this domain. So, why not recommend a classic movie Forest Gump when the user is browsing inspirational books? Why not recommend a science fiction when the users preference to sci-fi movie is known? In this way, user experience improves by providing more diversified and serendipitous recommendations. In addition, as websites already have users preference information in original domains, cross domain recommendation systems can be used to quickly open up new areas in business, saving precious time and money. Meanwhile, cold-start problem or data sparseness problem in the target domain can be also solved by cross-domain recommendations[16].

As shown in Figure 2.6, an example is considered where Alice is a user in a movie recommender system/domain, and Bob is a user in a book recommender domain, the problem is to predict Alices rating on Movie2 and Bobs rating on Book1 (or in other words, whether the movie recommender system should recommend Movie2 to Alice and whether the book recommender system should recommend Book1 to Bob). As can be

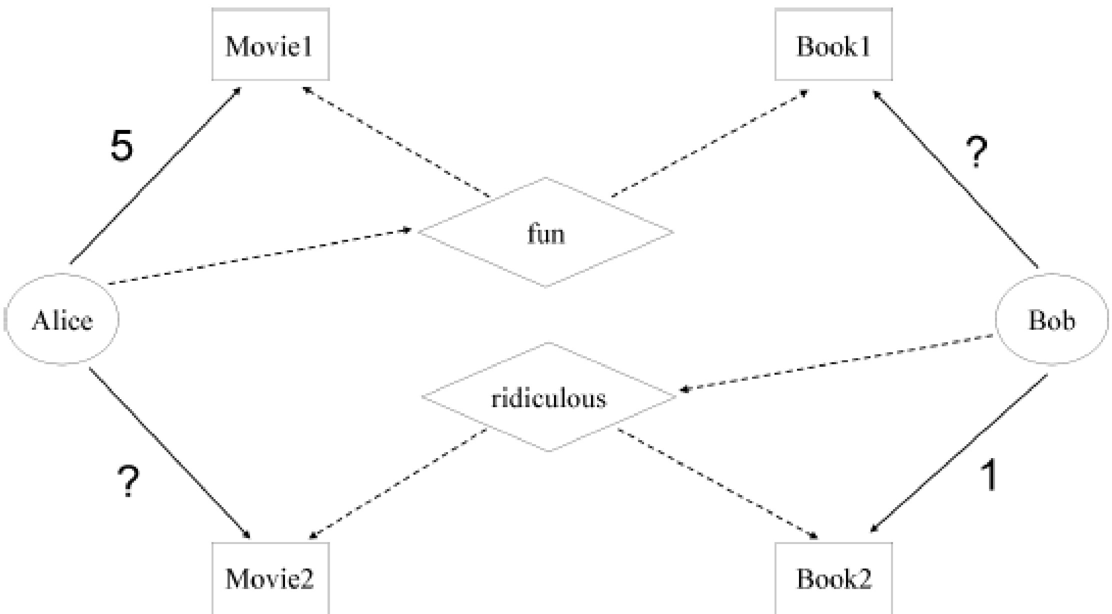

Figure 2.6: A toy example of two recommender domains with common tags[10]

seen, Alice rated the Movie1 with the highest rating, and she also tagged Movie1 with fun. From this observation, we may infer that an item tagged by fun tend to be favored by users. Based on this inference, we can infer that in the book domain, Bob might also be in favor of Book1, which is tagged with fun by some other users. According to the same reasoning, we can infer that Movie2 may not be a good recommendation for Alice. Although this toy example in Figure 2 is much simplified from real systems, it still demonstrates that there is great potential of mutually benefitting different recommender domains from the common tags.

Even though numerous methods have been developed for traditional single-domain recommendation, most of these methods cannot be directly applied to solve cross-domain recommendation problem. Traditional single-domain recommendation methods infer users preferences based on behavior information from the same domain. On the contrary in case of cross domain, behavior information in the target domain is unknown or little, information from other domains is used to make recommendation. In a word, whether known information and inference information are from the same domain is the main difference between traditional recommendation and cross-domain recommendation.

For cross-domain recommendation, if we can use behavior information in the source domain to deduce users behavior information in the target domain, then the known information and inference information are from the same domain, and the cross-domain issues are transferred to single domain issues, the various methods in traditional single domain can be directly used. Therefore, the main challenge for such recommender system is how to build bridge to connect different domains. The Domains are not mutually inclusive in general, each involving a particular type of resource, (for example, books, movies). The task of extracting common characteristics from various resources is difficult to build the bridge among different domains. Here we use user-generated-tags. Systems which use user-generated-tags are called folksonomy.

A folksonomy is a system that collaboratively creates and manages tags to annotate resources characteristics. It is widely used in various kinds of online applications, and becomes the symbol of Web 2.0 services. Instead of selecting specific resources as features, tags in folksonomies have more advantages for solving cross-domain recommendation problem:

1. Different domains have different resources, but share many tags with similar meaning. For example, love can be used as a tag for both a love story and a romantic

movie. Therefore, it is easy to use tags as bridge to link domains.

2. Tags have better understanding of users preferences. If we know users favorite tags, we can directly get what factors are key to influence users preferences.

3. Tags can alleviate sparsity problem. For example, there are hundreds of thousands of resources in one domain in ecommerce websites, the matrix to describe relationships between users and resources is very sparse, but the number of tags in one domain will not exceed tens of thousands. If we use tags instead of resources to show what the users may like, the problem of matrix sparsity is eased by conversion from resources to tags.

Inspired by these thoughts, a framework for cross-domain recommendation in folksonomies has been proposed: Here it is intended to recommend music tracks according to the places using user generated tags.

Chapter 3

Literature Survey

3.1 General

Big Data is an emerging area which has brought many challenges to be worked on like loss of useful data, poor recommendations due to unavailability of useful data, etc. There are certain problems faced while recommending items to the users. The main problem faced is the recommended list is not as per the users' preference, so sometimes it may happen that the user is not satisfied with the provided recommendation. Wei Fan and

Albert Bifet provided a wide overview of Big Data, its present status, controversy, and a forecast to the future[1]. Further, they described major challenges prevalent in Big Data management and analytics, that arise from the large, diverse and evolving data. Various problems like visualization, hidden big data led to poor recommendation which sheds light on improving recommendation.

3.2 Recommender System Survey

J. Bobadilla., A. Gutierrez, A. Hernando, F. Ortega, presented complete overview of the Recommendation Systems[2]. Initially, Recommender System were based on content-based, demographic and collaborative filtering but at present, social information is being incorporated in RS. It is expected that in near future, RS will be using local, implicit and personal information from the Internet of things. They provided the concept of recommender systems along with their evaluation parameters as well as collaborative filtering methods and algorithms; along with the evolution of RS, an original classification for recommender systems and further identified areas of future implementation. They also described shortcomings of all the methods and have proposed solutions to it. Their future research is based on the advancement of the existing methods and algorithms so that the predictions and recommendations provided by the recommender systems can be improved.

Providing correct recommendations to the users has always been a difficult task. Music recommendation system is also such a system wherein providing appropriate music to the people is always a difficult task.

Yading Song, Simon Dixon, Marcus Pearce provided a general framework and state-of-art approaches in recommending music[3]. It was found that there are 2 widely used algorithms: collaborative filtering (CF) and content-based model (CBM) that perform well. They further described that as a result of the bad experience in finding songs in long tail and the powerful emotional meanings in music, two approaches: context-based model and emotion-based model, have become popular. Three key components in music recommender - item profiling, user modelling and match algorithms have been discussed by them. Six recommendation models and four potential issues have also been discussed towards user experience. The modelling of a personalised music RS is difficult, and it becomes a challenge to understand the needs of the users and to meet requirements of the users. Their future research is focused on usercentric music recommender systems.

Yajie Hu, Mitsunori Ogihara presented an approach for recommending suitable songs from a collection of songs[8]. The system's goal is to recommend songs that have been favored by the user, are recently heard by the user, and should also fit the users listening pattern. They have analyzed users listening pattern so that the estimation of the level of interest of the user in the next song can be predicted. Their future research will concentrate on mixing music recommendation in a local device and an online server data so that the issue of cold start can be removed and hence new preferred songs can be obtained.

3.3 Cross Domain Recommender System

Ying Guo and Xi Chen [16] displayed a novel system for cross-domain recommendation in folksonomies: CRF is proposed. The thought of CRF is producing users tag-profile in the target area, taking into account the correspondence of tags between different areas. At that point the cross-domain issue is moved into traditional single domain recommendation issue. CRF is focused around folksonomy, so it might be broadly utilized within different provisions of Web 2.0. Further it was demonstrated that CRF is more exact than one-domain recommendation algorithms to unravel cold start issue in the target domain. Their future work includes evaluatation of more realizations of CRF. For example, other classical single domain recommendation algorithms can be used. In addition, CRF on data can be tested from more than two domains and further consider the evaluation methodology. Trying CRF in other research fields, such as cross-domain research collaboration can also be a promising direction.

Anant Gupta, Kuldeep Singh presented the idea of a personalized location based restaurant recommendation system that studies the users behavioral pattern of visiting restaurant using a Machine Learning algorithm[6]. Various issues like Cold Start, Unclassified Restaurants and Constant User Participation and their solutions were presented. Their Future work includes extra features to the mobile app like voice-based notifications and results, number of people already present at the venue, online reservation of restaurants. They further expect to integrate Facebook places to get users past visits data. More current information of recommended restaurants can also be searched online to lookout for offers and discounts. Locating the users friends, if nearby, and providing recommendations for same venues can also be added to the application.

Marius Kaminskas, Francesco Ricci presented a specific sort of cross domain personalization errand comprising of selecting at the same time two things in two separate domains and prescribing them together in light of the fact that they fit the users preferences and additionally they fit well together[7]. They proposed a specific sort of context aware recommendation task selecting music substance that fits a place of interest(POI). [5]. To address this issue they have used enthusiastic tags annexed by the users' populace to both music and POIs. Additionally, Jaccard similarity measure was showed to set up the matching supported by the greater part of the users. Future work incorporates utilizing ontology to match music and considering users' inclination. Further they exhibited some customized proposals for places of interests (POIs). Their future work included settling a portion of the constraints of the current approach and performing a more wide user study with more users, reconsidered POIs and more music tracks.

In this disseration, it is intended to provide recommendation for two different items from two different domains, particularly Music tracks and Places are the two domains considered here from which pairs are recommended using tags attached to both the domains considering user's preference.

Chapter 4

System Description

Cross Domain recommendaton is a new approach for recommending two different items from two different domains. A specific sort of cross domain personalization undertaking including selecting at the same time two things in two different domains and recommending them together has been addressed here in light of the fact that they fit the users inclination and additionally they fit well together. It is indicated here that when a few recommendations are provided for places, the users fulfillment for these Places might be expanded by giving music tracks that match the user's profile and are moreover matching the Places. Here it is planned to recommend music tracks as indicated by the places, the user satisfaction could be expanded by giving a musical soundtrack matching to the places of interest using the tags given by the users to both music tracks and places.

It is aimed to recommend a music track focused around the place using distinctive methodologies. Figure 4.1 shows the logical architechture of the system. This architechture uses profile data for giving recommendations and additionally computing music-to-place similarity for consolidating music and place in a joined recommendation. This architechture consists of: the user profile, the place profile, the music profile and the recommendation algorithm that comprises of Place ranking, music filtering and music-to-Place similarity computation. The system consists of:

- The user profile holds the essential music and sightseeing preferences of the user. The sightseeing preferences are used for ranking the Places. The user choices may be any mix of: history, nature, and so forth. The objects incorporate castles,

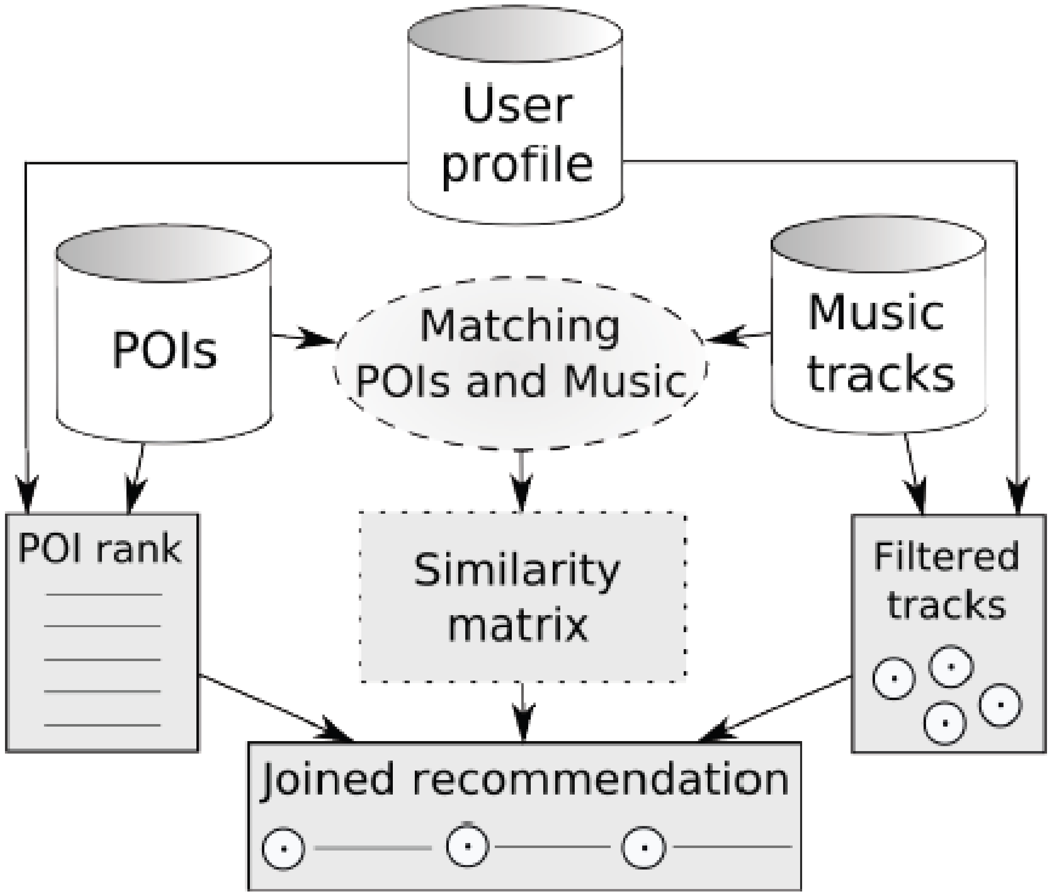

Figure 4.1: System Architecture[7]

churches, monuments, nature objects and museums. An alternate part of the user profile holds the user's favored music genre; and the database recognized here holds music tracks fitting in with distinctive genres.

- The music profile contains the information related to tracks like its title, description,genre and the list of tags describing the music track. These music items contain tags assigned to them by the users.

- The places are portrayed by a place profile comprising of : the name of the place, its description, a set of tags given to the places by the users, and the types of the places like history , nature and so forth. An example of music and place profile is shown in figure 4.1.

Music profile	**Place profile**
Name: Wagner - Tristan und Isolde	Name: Festenstein Castle Ruins
Genre: Classical	Type: Art, Architecture, History
Description: Tristan and Isolde is an opera in three acts by Richard Wagner to a German libretto by the composer,based largely on the romance by Gottfried von Strazburg...	Description: he ruins of Festenstein castle stand bold, forbidding and seemingly inaccessible on a jag in a rock face overlooking the wild ravine beneath the hamlet of Gaid in the municipality of Eppan. Its date of construction is unknown but it is mentioned in a document dating from around 1220..
Tags: Bright(1), Calm(1), Cold(1), Colorful(1), Dark(2), Fast(1), Gentle(1),...	Tags: Big(2), Cold(1), Dark(1), Happy(1), Mysterious(5), Narrow(1),...

Table 4.1: Example of Music and Place Profile

Chapter 5

Proposed Methodology

For the task of recommending music as per place, the database provided by the author[5] has been used which consists of 75 music tracks of 4 different genres (Classical, Romantic, Baroque, Soundtrack), and 50 places of 14 different categories (Castle, Museum, Monument, Church, etc.) in the city named Bolzano and the areas surrounding it. There in total 46 tags attached to places and music tracks. The dataset consists of total 119 users who provided these tags to both music tracks and places.

To recommend the place-music track pair, three different approaches have been proposed. Initially, the places are filtered as per user's preferred sight seeing category. As per the user's preferred genre, music tracks are then filtered.

The different approaches used for recommendation are as follows:

5.1 Approach 1

In this approach, we appoint to each of the N places (retrieved from the user's preferred sight seeing category) one music track picked randomly from the set of filtered tracks. Thus the picked music is favored by the user yet it is not adjusted to the place.

Herein, the favoured genre of the user is "Classical" and place category is "Castle".

Place	Music Track
Castel Boymont	Mozart - The Marriage of Figaro
Freudenstein Castle	Mozart - Symphony No. 40
Castel Montan	Mozart - Rondo Alla Turca
Roncolo Castle	Haydn - Emporors Hymn

Table 5.1: Place-Music Pair recommended using approach 1

5.2 Approach 2

In this methodology, after getting the list of Places as per user's desired category, we dole out the best matching music track from the list of filtered tracks to each of the Places in the list. The Music-to-Place similarity computation is carried out by utilizing the idea of Jaccard Similarity. Hence, the order of recommended Places is same as the one obtained from the first approach, just the recommended music is distinct.

The Jaccard similarity:

$jaccardSim(u, v) = \frac{\sum_{y \epsilon X_u \bigcap X_v} logp(y)}{\sum_{y \epsilon X_u \bigcup X_v} logp(y)}$

Here,

- 'u' represents place,
- 'v' represents music track,
- 'y' represents a tag,
- 'X_u/y' represents the set of tags which do not have null frequency in the tag-profile of the item u/v.
- 'p(y)' represents the fraction of items (both music tracks and Places) denoted with y.

5.3 Approach 3

In this approach, music track is not simply assigned to the existing list of Places, but instead the Place rank is combined together with the music-to-Place similarity score to generate create an alternate ranking for the pairs of Places and music tracks. This is how

Place	Music Track
Castel Boymont	Mozart - Violin Concerto No. 5 in A
Freudenstein Castle	Haydn - Emporors Hymn
Castel Montan	Mozart - Horn Concerto No. 3 in E flat
Roncolo Castle	Mozart - Horn Concerto No. 3 in E flat

Table 5.2: Place-Music Pair recommended using approach 2

the top N pairs are recommended. The intersection of the bags userTags(tags entered by the user to that particular place) and Placetags(total tags assigned to all the places by all the users) is calculated and afterwards the cardinality of the union is put away as the score of Place. The Place-music pair score is processed utilizing the accompanying mathematical statement:

score = (0.7 X Place-pers) + (0.3 X similarity)

Here Place-pers is the Place score that is looked for from the Place ranking calculation and similarity is the Music-to-Place similarity computed using Jaccard similarity.

Place	Music	Score
Roncolo Castle	Mozart - Horn Concerto No. 3 in E flat	0.384999
Freudenstein Castle	Haydn - Emporors Hymn, from String Quartet in C	0.295882
Castel Montan	Mozart - Horn Concerto No. 3 in E flat	0.199999
Castel Boymont	Mozart - Violin Concerto No. 5 in A	0.187125

Table 5.3: Place-Music Pair recommended using approach 3

Chapter 6

Evaluation and Results

In order to evaluate the approaches used, a user feedback was taken. Comparison of the number of times every recommendation calculation was favored by the users while providing feedback has been made. The user interaction with the feedback method consists of 3 main parts: user registration, checking the two most comparative recommended things and henceforth giving a criticism, i.e., picking the favored itinerary. Figure 6.4 shows amount of selection probability of the three given approaches where the different genre like classical,romantic, baroque or soundtrack music was the favoured genre of the user. The likelihood of selection is figured as the proportion of times a schedule with a soundtrack created by one strategy was chosen over the aggregate number of times it was offered in one of the two recommended agendas in the recommendation process.

Taking into consideration all the session data it has been observed that both the approaches that is Approach 2: Place rank + matching and Approach 3: music similarity rank methodologies are supported more than the recommendations where music is doled out to Place arbitrarily. It backs the truth that the procedure of music matching to Place is helpful and it has the ability to produce more satisfying recommendations. Everytime the music preferred was from the user's preferred category of music tracks.

The analysis of results when gathered independently for every music genre, it indicated that classical music audience members supported the recommendation techniques with matching concept, while soundtrack music mates did not show any slant among the distinctive methodologies. This unmistakably demonstrates that on occasion even a direct approach of designating a music track could be suitable for certain sort. The results got from the client reaction demonstrate that the practicality of the two proposed procedures

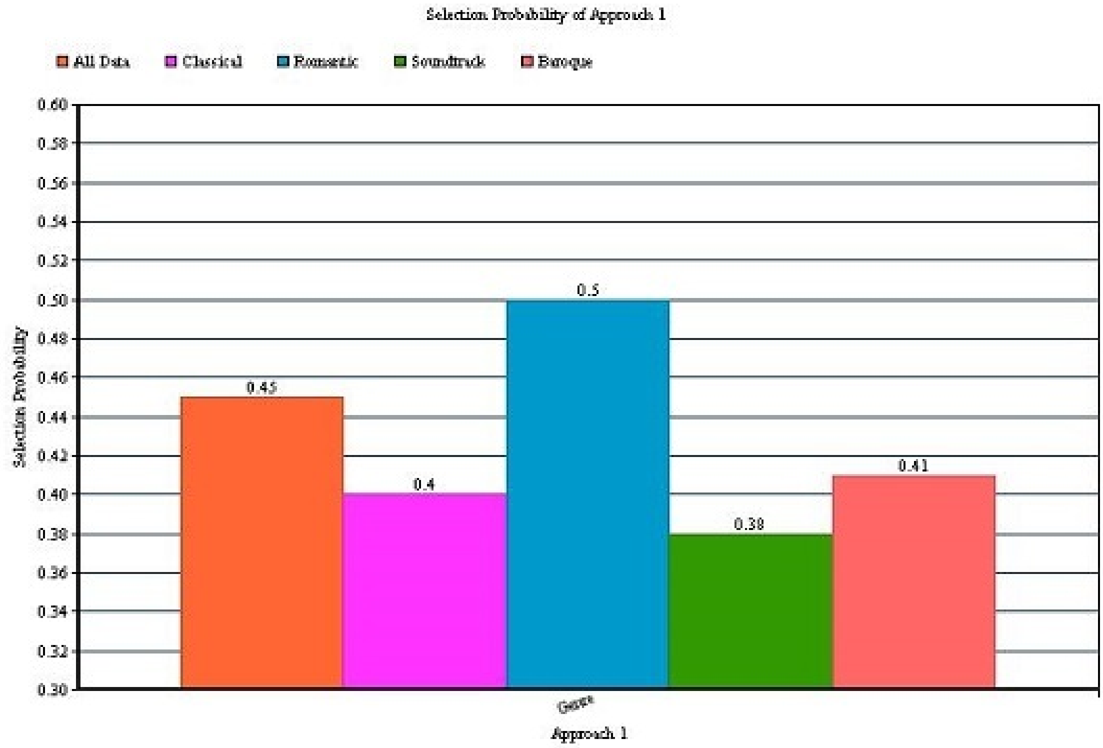

Figure 6.1: Selection Probability of Approach 1

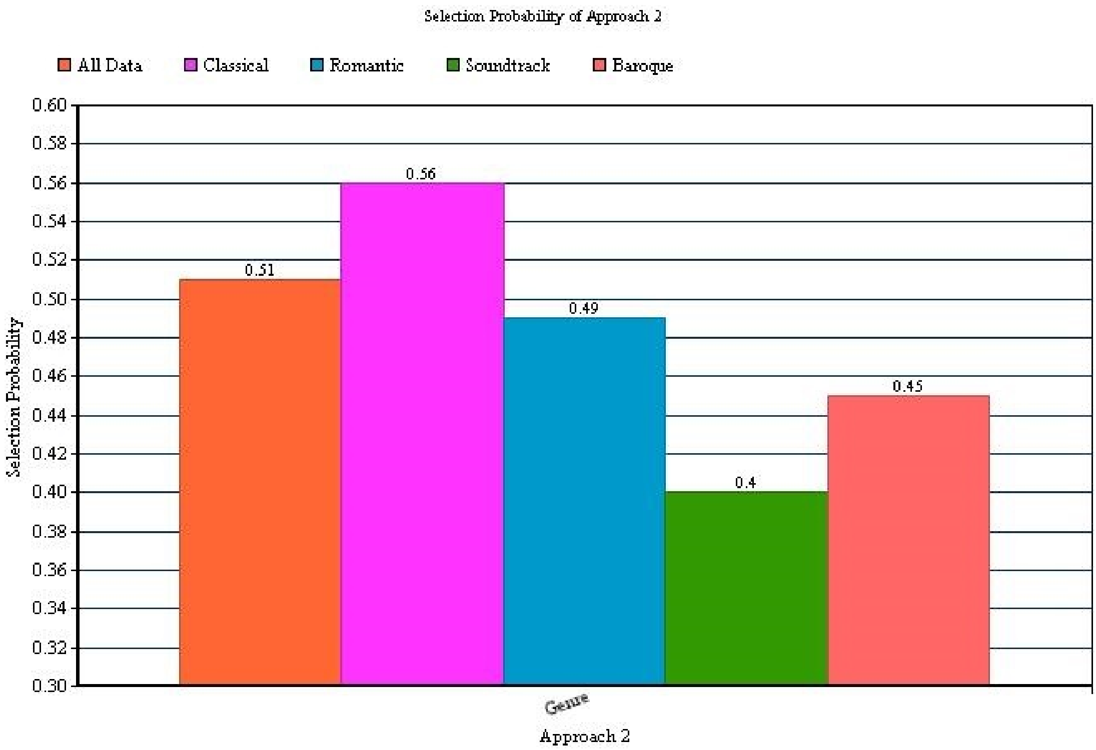

Figure 6.2: Selection Probability of Approach 2

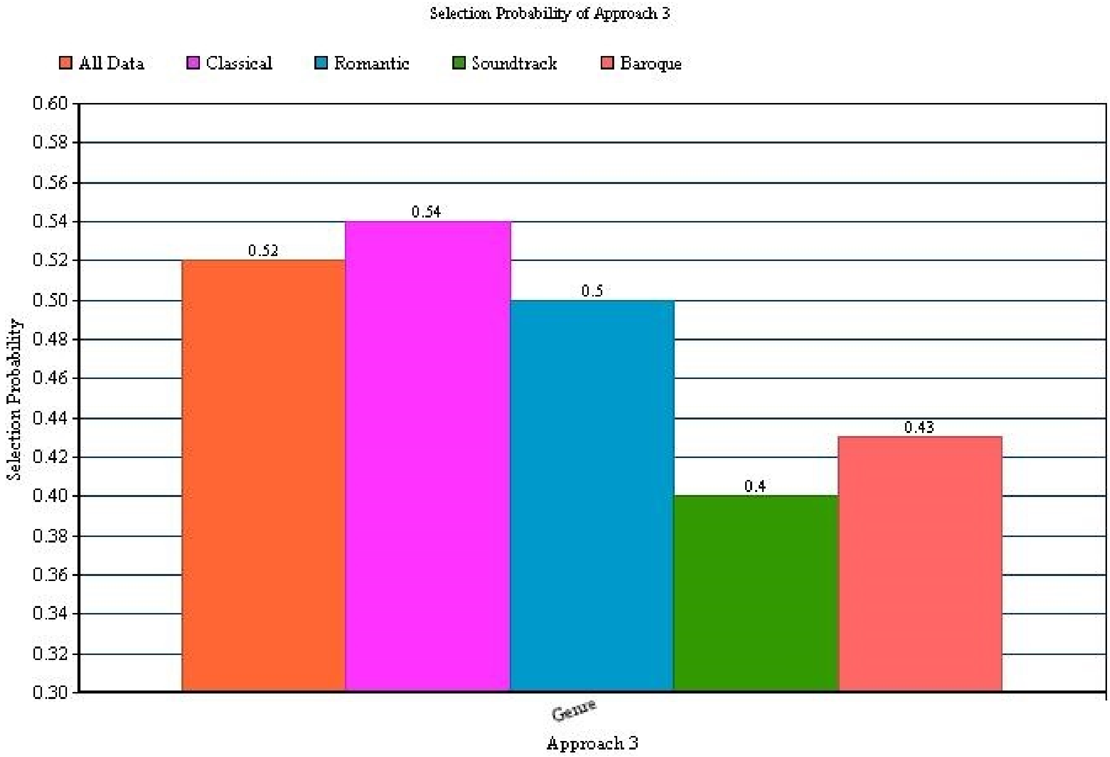

Figure 6.3: Selection Probability of Approach 3

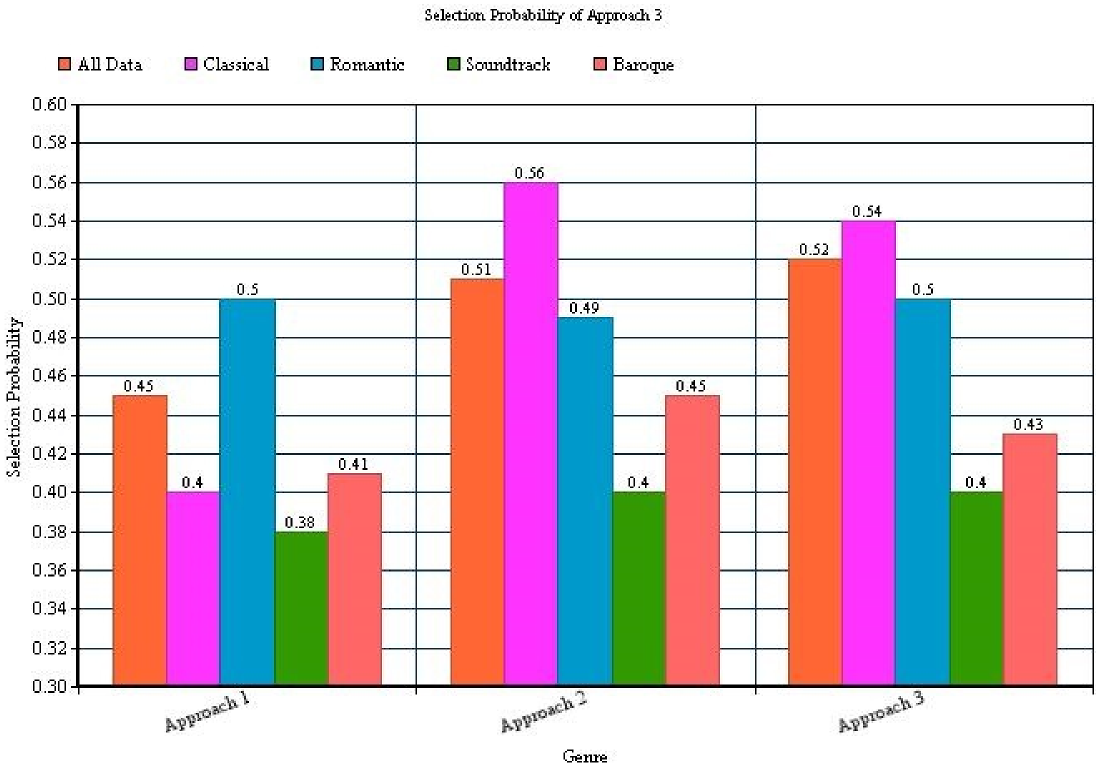

Figure 6.4: Selection Probability of all the Approaches

for matching music with Place relies on the genre of music favoured by the system users.

Chapter 7

Conclusion and Future Work

In this system, the Place-Music track pairs are recommended using different approaches - by randomly assigning a music track to a place, calculating Jaccard Similarity and then assigning the best matching Music track to the place and then combining the Place rank and similarity score and then the score is obtained on the basis of which the recommendation is done.

From the experimantal results it can be concluded that:

For a specific Place, user's experience of using the system can be expanded by recommending music tracks that match with the user's profile and the Places.

The evaluation results showed that users prefered more the approach of matching place to music rather than the approach where the track is assigned randomly.

Thus, it might be found that music matching has positive effect on user satisfaction and decision making with the joined music and Place recommendations. The results got likewise show that execution of the different methodologies depend on the type of genre that is favored by the users.

Further, it also showed that recommendations where classical music was selected gave better results for the music-to-Place matching techniques as contrasted with the users' who favored soundtrack genre.

Future works includes testing the same approach on larger dataset. Further recommendations can be provided for more than two domains using the same approach.

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