Machine Intelligence – Miniproject
BATCH - 7
LITERATURE SURVEY

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PAPER 1.

An Emotional Recommender System for music

https://sci-hub.se/https://ieeexplore.ieee.org/abstract/document/9204829

INTRODUCTION

This paper talks about how user personality can effectively provide more valuable information to significantly improve recommenders' performance, especially considering behavioral data captured from social network logs. In this work, we describe a novel music recommendation technique based on the identification of personality traits, moods and emotions of a single user, starting from solid psychological observations recognized by the analysis of user behavior within a social environment. In particular, users' personalities and moods have been embedded within a content-based filtering approach to obtain more accurate and dynamic results.

METHODOLOGY

To overcome the drawbacks, Content Bases Filtering and Collaborative Filtering are combined within hybrid approaches with different strategies here. There are straight correlations between personality and user's model in recommender systems. The recommendation framework follows three main steps, firstly recognizing the user's personality, then detecting the mood and lastly recommending content based on these (fig 1). The user's mood and personality are recognized and calculated by analyzing their Online Social Networks

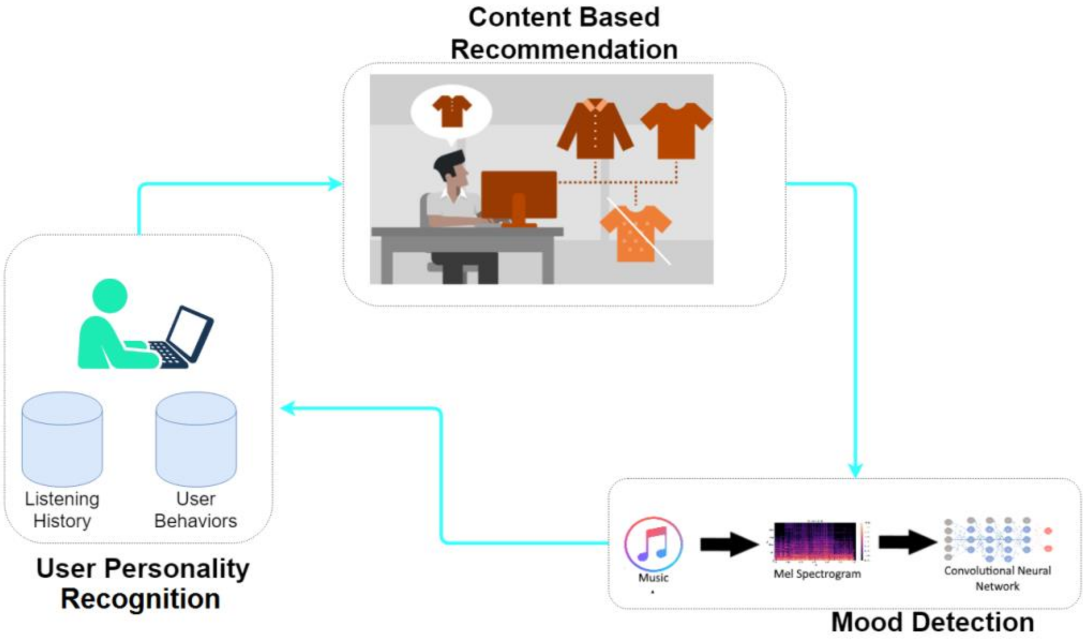

Fig. 1: Recommendation Process Workflow.

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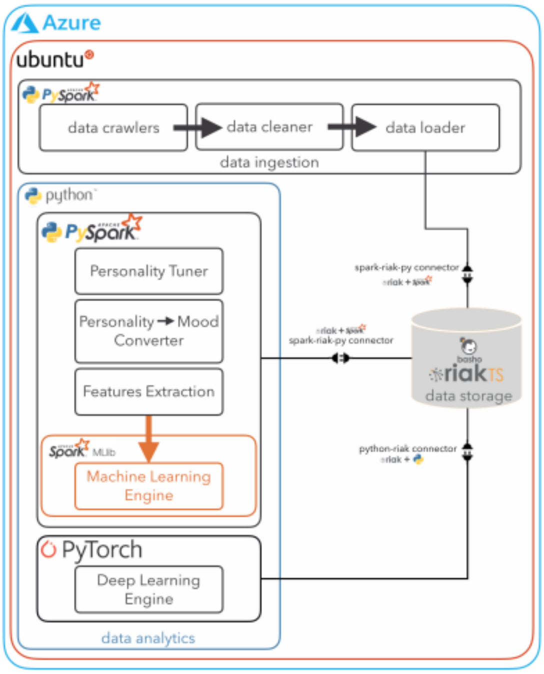


Fig. 3: Architecture of User Personality Recognition module.

CONCLUSION

A personality-based recommender system has been discussed and analyzed, using the Big Five psychological model and considering both user profile and mood for a content-based strategy. This work takes an enormous advantage of these two kinds of information to support in a very effective manner browsing of audio collections with respect to classical rating-based recommendation approaches. We can extend our experiments using different OSNs to better capture user personality and to compare our results with commercial techniques as those exploited by Spotify and Amazon music.

PAPER 2.

An emotion-aware music recommender system: bridging the user's interaction and music recommendation.

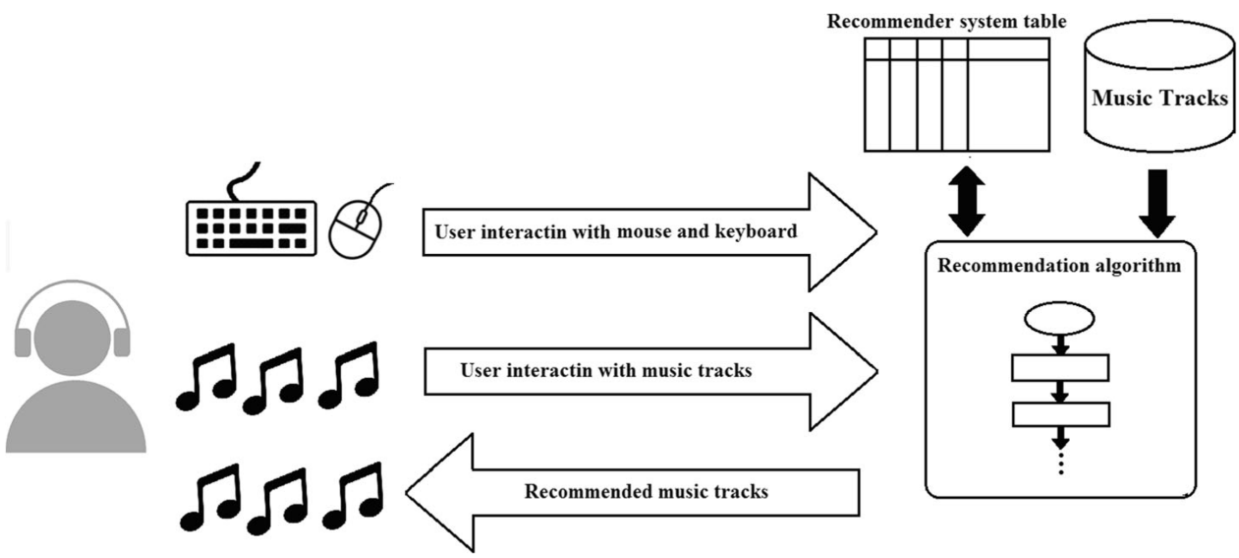
https://link.springer.com/article/10.1007/s11042-020-10386-7

INTRODUCTION

The user's current emotion is identified and considered in recommending music to them. In this study, a music recommender system is proposed to suggest music based on users' keystrokes and mouse click patterns. The music is recommended directly, without labeling the user's emotion, so that the error of estimating the user's emotion does not negatively affect the recommendation accuracy. This system is based on collaborative filtering. The results show that even though this system does not use any additional device, it is highly accurate compared to the other methods.

METHODOLOGY

Collecting data on mouse movement and keyboard usage patterns (when typing an arbitrary text) and using a variety of clustering algorithms (including KNN, KStar, random committee, random forest, and a new clustering algorithm called bounded K-means), the users'
emotions were categorized into five groups. These categories include happiness, inspiration, compassion, disgust, and fear. The best models could predict the user's emotion with an accuracy of more than 90%. The correlation between the user data (e.g., location, time of the day, music listening history, and emotion) and the music is calculated using the deep convolutional neural networks, and the weighted feature approaches. Then, the music's user ratings were calculated based on the term-frequency and inverse document frequency (TF-IDF) approach. Finally, music is recommended to users based on the estimated user ratings.



CONCLUSION

The user's interaction with the keyboard and mouse can reflect his emotions. In this study, a collaborative filtering recommender system has been proposed for recommending music to the user, which suggests music based on the user's keystrokes and mouse clicks patterns. Unlike the previous studies, the users' emotions are not labeled in this method. Still, the user's Interaction patterns are directly mapped to the user's favorite music to reduce the error and increase accuracy.

PAPER 3.

Music Genre Classification and Recommendation by Using Machine Learning Techniques

https://sci-hub.se/https://ieeexplore.ieee.org/abstract/document/8554016

INTRODUCTION

In this study, acoustic features of music have been extracted by using digital signal processing methods from raw music without considering the user's music profile or collaborative filtering. The features to be extracted from the music have been determined as zero crossing rate, spectral centroid, spectral contrast, spectral bandwidth, spectral roll-off and Mel-frequency Cepstral Coefficients-MFCC. Furthermore, the Convolutional Neural Network-CNN, which is one of the most useful methods of deep learning, has been used for music genre classification and music recommendation.

METHODOLOGY

Firstly, going about on choosing the dataset, then extracting the features in it - Digital signal processing– on the time domain and frequency domain. A few of the parameters used to extract features are Zero cross rate, spectral centroid, spectral contrast, spectral bandwidth, spectral roll-off, and Mel Frequency Coefficient of Cepstrum-MFCC.

The music genres are then classified using machine learning techniques like KNN, Naïve Bayes, Decision Trees, support vector machines, and random forests.

Deep learning techniques are used to further classify music by its genres. Convolutional neural networks are a tool, used to classify items that contain spatial neighborhoods.

CONCLUSION

This study aims to classify and recommend songs using acoustic features, extracted by digital signal processing methods and convolutional neural networks. Study has been conducted over two steps; determining how features that will be used in recommendation are obtained and developing a service that recommends songs to user requests. Firstly, feature extraction has been carried out by means of digital signal processing methods and then CNN has been trained as an alternative feature extraction. Then acoustic features of songs are used in classification to determine the best classification algorithm and the best recommendation results. According to the results summarized in previous tables, SVM achieved better classification results than other methods. In addition, changing the window size and window type caused very small performance changes.

PAPER 4.

Music Recommender System Based on Genre using Convolutional Recurrent Neural Networks

https://www.sciencedirect.com/science/article/pii/S1877050919310646?via%3Dihub

What this paper is about

1)To reach the objective, our research approach is based on comparing the similarity of features on audio signal. This approach can be considered as content-based music recommendation, where the recommendations is based on perceptual resemblance of what was previously heard by the user. This approach requires the definition of similarity metric, which used to measure the similarity between audio signals.

2)The main result of the study is that the accuracy of CRNNs is slightly higher than CNNs methods which combining frequency and time domains and using the same number of parameters.

3)These results are used in Mel-spectrograms for audio representation and CRNNs for feature extraction

What you can learn

1)When we viewed by the user's response based on the sequence of music recommendations, the first rank recommendation is not necessarily favoured by the user as a recommendation even though the music in other ranks is preferred.

2) Therefore, we can conclude that the second method which considering music genre information is better than the first method.

3) In addition, the calculation of feature vectors for the recommendation system takes 14 minutes for 726 audio data or about 1.2 seconds to create feature vector on one music.

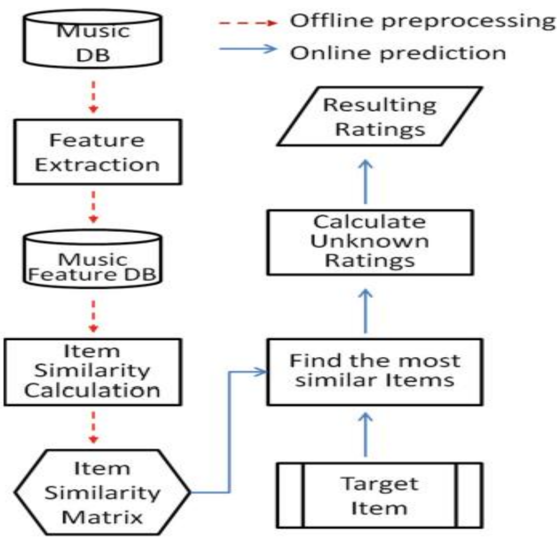
PAPER 5.

An Item-Based Music Recommender System Using Music Content Similarity

https://link.springer.com/chapter/10.1007/978-3-662-49390-8_17

- Aim – To provide user with the preferred music
- User interest for a music piece – item ,numeric rating from 1 to 5 (larger the score , higher the interest) – Rating matrix .
- Number of ratings = 0 (unknown ratings)- never rated by users
- Recommendation procedure – Rating prediction & Item Selection
- Rating Prediction – Predict the active user's unknown ratings for items
- Item Selection – Unrated items are sorted and top q unrated items are recommended
- Problems in Rating matrix – New item (items never rated by any users , making it difficult to predict as no related information) . Data Sparsity – rating density of the matrix is very low , info is insufficient)
- The paper proposes , integration of information of music content and ratings to improve quality of the rating prediction . Item based collaborative filtering – music content similarity instead of music rating similarity .
- Collaborative Filtering (CF) – predicts user preferences based on user ratings .
- Review of past CF's
  – Memory based CF -> infers unknown ratings using user/item similarity on ratings . Divided into User-based CF (item ratings predicted by most relevant users on similar ratings)and item based CF(predict item ratings by most relevant items on similar ratings)
  - Model Based CF – Model the behaviours by ML techniques . User's preferences that are hidden in the rating behaviours are implied , using SVM , Decision Tree, Bayesian (Classification) . Limitation – rating space

- PROPOSED METHOD – (problem – user & item similarities not robust enough)
  - Calculate the item similarities based on the music low level features fused with info of ratings .
  - Offline Pre processing phase -> Accelerate the online prediction . Features of all music items extracted . Item to item similarity matrix generated
  - Online prediction phase -Based on item-t -item similarity matrix , most similar items to target determined . Then , unknown ratings computed using item based CF



- Comparisons with Other Well-Known Methods in Terms of RMSE
- Comparisons with Other Well-Known Methods in Terms of Numbers of Un-Predicted Items

PAPER 6.

EMOTION BASED MUSIC RECOMMENDATION SYSTEM

OBJECTIVE

- To provide an interface between the music system.
- To provide a very good entertainment for the users.
- To implement the ideas of machine learning.
- To bridge gap between growing technologies and music techniques.

This project utilised pycharm is an analytical tool.

What this paper is about

☑ Multidisciplinary efforts such as emotion description, emotion detection/recognition, feature based classification, and inference-based recommendation are needed for the achievement in content based music recommendation system.

☑ The "arousal" and "valence" are the two main dimensions in Thayer's model.

☑ However, other emotions such as nervous and excited aren't considered.

What you can learn

☑ The facial expression is detected by programming interface with the RPI camera.

☑ In this project, we presented a model to recommend a music based om the emotion based detected from the facial expression. This project proposed designed & developed an emotion based music recommendation system using face recognition System.

☑ Thus the proposed system presents Face based emotion recognition system to detect the emotions and play music from the emotion detected.

PAPER 7.

Collaborative filtering : technology that focuses on the relationships between users and between items to make a prediction

Goal of the recommender system: compute a scoring function that aggregates the result of computing similarities between users and between items.

Two basic strategies of recommender systems are:

$ content filtering and

$ collaborative filtering.

II. THE GOALS OF RECOMMENDER SYSTEMS

to increase sales of products and profit.

. That is why the technical goals are following :

1. Relevance: Users are more likely to consume the products they find interesting.

2. Novelty: Recommender system should recommend to the target user things that he has not seen before.

3. Serendipity: This goal differs from novelty because the recommendations should be unexpected, surprising to user.

4. Diversity: If the recommendation contains very similar elements, it increases the risk that the target user might like no one of them. If the recommendation contains elements of different types there is a greater chance that the user might like at least one of these items.

III. COLLABORATIVE FILTERING

User-based approach of collaborative filtering based on the fact that the ratings provided by similar users to the target user A are used to make recommendations for A.

Item-based approach is based on the fact that some items are often got together. The target user A likes one item from the set of items. So we can recommend him to consume other items from this set.

Collaborative filtering can be considered as a generalization of the classification problem.

The missing class variable needs to be predicted from the feature variables values in the classification problem.

In collaborative filtering, any of the matrix entries may be missing and need to be predicted in a data-driven way from the observed entries in the remaining matrix. There is no demarcation between training and test rows and no demarcation between independent and dependent variables

Similarity measure

U = users I = set of item songs R = matrix of preference

s R = {rЧℓ} ∈ ℝ୨×ზ

Has information on U listened to song I.

Modern recommender systems use different similarity functions to compute similarity between users and between items: Euclidean distance, cosine metric, Pearson correlation, Manhattan distance and others. Cosine metric can be used for both approaches of collaborative filtering: user-based and item based.

PAPER 8.

Efficient music recommender system using context graph and particle swarm

. The most existing models only focus on explicit data like ratings and other user-item dimensions. A challenging problem in music recommendation is to model a variety of contextual information, such as feedback, time and location. In this article, we proposed a competent hybrid music recommender system (HMRS), which works on context and collaborative approaches.

The timestamp is extracted from users listening log to construct a decision context behavior that extracted various temporal features like a week, sessions(as morning, evening or night).

Used depthfirst-search (DFS) algorithm which traverses the whole graph through the paths in different contexts.

Bellman-Ford algorithm provides ranked list of recommended items with multi-layer context graph. Enhanced the process using particle swarm optimization (PSO) which produced highly optimized results.

Decision-context layer extracts accurate data from user's listening log, i.e., from user's history database. Two methods were employed in our proposed work that includes collaborative filtering and graph algorithms. In collaborative filtering, we found similarity score for items using Pearson correlation coefficient. It helps us in the search for the songs that are similar to other songs. Then a ranked list of songs is produced for a given user, and thus, songs of similar preferences are being recommended to the user. The next method that is purely graph based method is also employed in our proposed work. We use two graph algorithms, Depth-FirstSearch (DFS) algorithm for backtracking and Bellman-Ford algorithm. The intelligent optimization algorithm is implemented at last to produces optimized ranked list of recommended results with PSO.

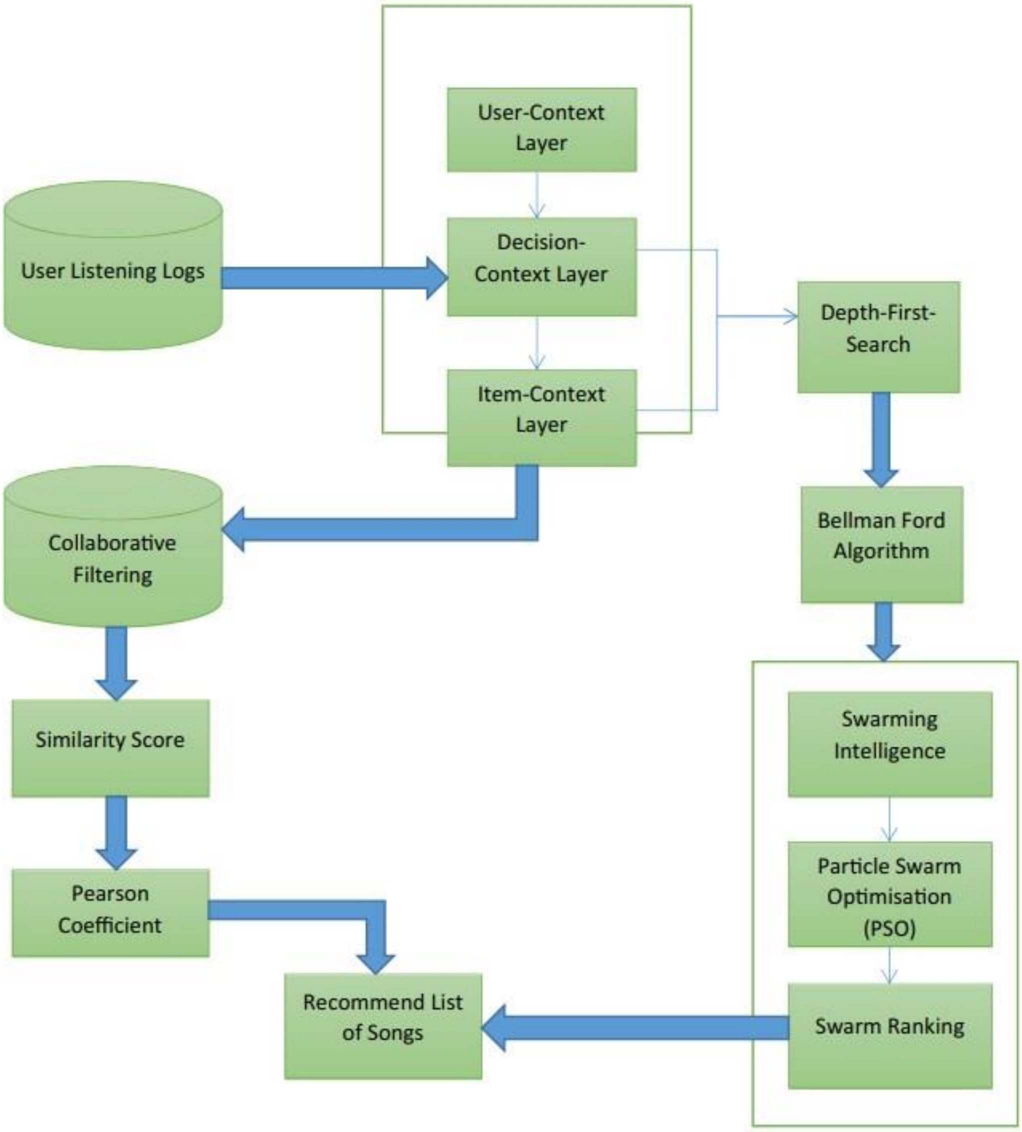


Fig. 1 System architecture of hybrid music recommendation system (HMRS)

Algorithm 1. Pseudocode of the hybrid music recommender system (HMRS)

```
Input: Set of users U for which we want to generate recommendations.
Output: Recommended songs for user
Construct Multi-layered context graph
    Initialize a directed graph G with User-Layer, Song-Layer and Decision layer
    Extract and add "user" nodes in graph
    for row in file f1:
            G.add_nodes_from (row, color = 'red')
    Extract and add "song" nodes in graph
    for row in file f2:
            G.add_nodes_from (row, color = 'blue')
    Extract and add "artist" nodes in graph
    for row in file f3:
            G.add_nodes_from (row, color = 'blue')
    Extract and add "weekday" nodes in graph
    for row in file f4:
            G.add_nodes_from (row, color = 'blue')
Perform a DFS search at each user node to find weekdays
def dfs_user (g2, start, path1 = []):
DFS at each weekday corresponding to given user to find artists.
for i, val in enumerate (days):
    def dfs_day (g1, start, path2 = []):
Bellmanford with negated edges to recommend favorite artist
def longest_path (g1):
    dist = {} # stores [node, distance] pair
Perform swarming to rank to evaluate results
    Extract k collaborative features (i.e., latent factors) I by factorizing matrix R.
    Apply Swarm Rank to learn a ranking function f (u; i), by optimizing
     return f (u; i)
    Extract k collaborative features (i.e., latent factors) I by factorizing matrix R.
    Apply Swarm Rank to learn a ranking function f (u; i), by optimizing
     return (u; i)
```

We constructed multi-layer context graph with implicit feedback data for our music recommendation system. A graph consists of three layers viz., User-context layer, Item context layer, and Decision-context layer. We considered all of the three types of contexts into recommender systems, and model the interactions between users and items in the corresponding decision context.

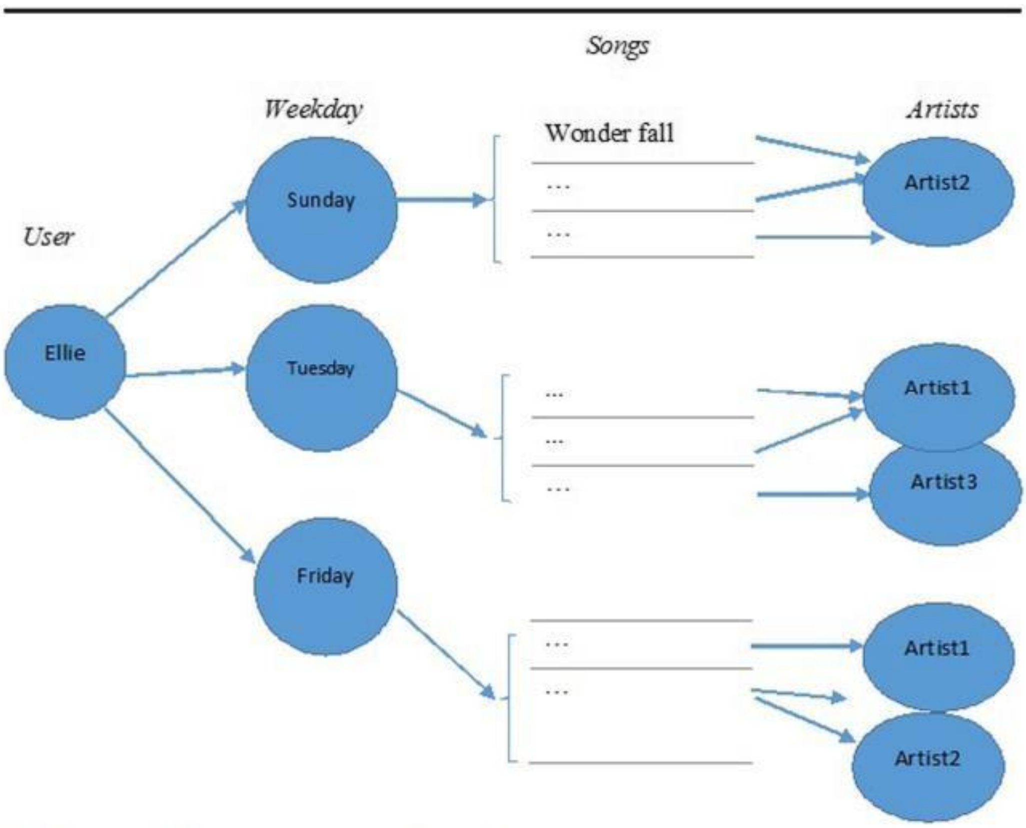


Fig. 2 An example of representation internal structure of proposed system

PAPER 9.

Improving Context-Aware Music Recommender Systems: Beyond the Pre-filtering Approach

Our experiments show that factorization machines are particularly capable of tackling the major issue of the pre-Flittering approach (i.e., splitting up the dataset). To foster reproducibility and repeatability.

. We consider the approach presented in this work as a contextual modelling approach as we do not filter the input or output data of the system.

It is widely agreed upon the fact that the user’s context improves personalized recommendations it is why we can see a shift from purely content- or CF-based approaches towards more user centric approaches incorporating the user’s context .

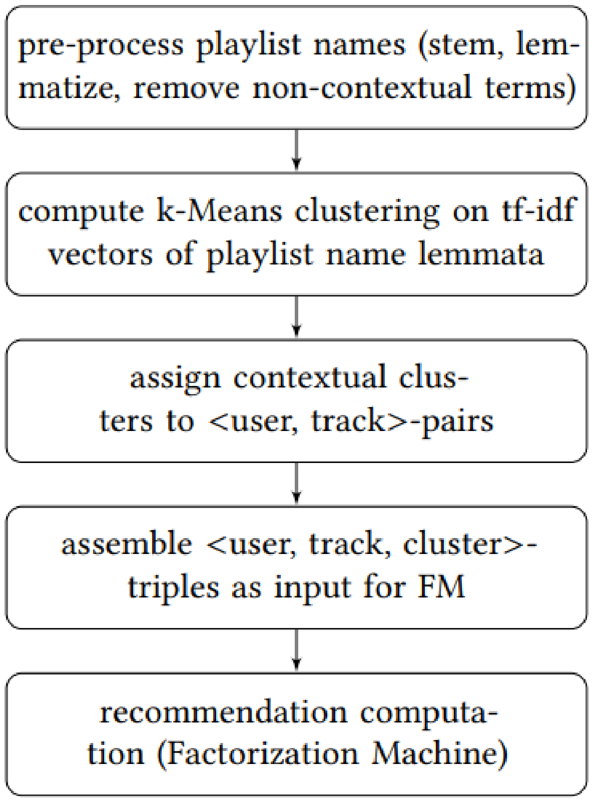


Figure 1: Pipeline for Computing Recommendations

Œe work presented in this paper builds upon this approach and aims to address the problems of the pre-filtering approach (as proposed by Pichl et al.) by using factorization machines. To the best of our knowledge, this is the first factorization machine based recommendation approach for integrating contextual clusters derived from playlist names into a music recommender system.

Based on the evaluation setup and measures described in the preceding section, we assess the performance of the following recommender systems: a pure CF-based recommender system (CF), context-aware CF with prefiltering (PR-CF) as proposed by Pichl et al. [27], a SVD-based recommender system (SVD), a context-aware SVD-based recommender system with pre-filtering (PR-SVD), a context-aware random forest classifier-based recommender system (RF) as well as our proposed context-aware FM-based recommender system (FM). As outlined in Section 4.2, we consider the first five recommender systems as baseline approaches to our FM-based recommender. Additionally, we compare all recommender system against the random baseline (RB).