Music Recommendation System Spotify - Collaborative Filtering

MUS-17

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Introduction Music recommendation has more and more become a worldwide recognition, especially with the technical approaches nowadays. Therefore, an ideal music recommender has to maximize the user's satisfaction but simultaneously "minimize the user's effort to start the recommender and providing feedback." The music recommender must recommend user's songs of his favourite list each time. [3]
In this paper Spotify will be the main example to show, because it uses various ways of recommendations and there are 100 million monthly active users with millions of songs and playlists. Spotify and other recommender often use three main services for recommendation and a feedback system. These will be shown in the following.

Methods of recommendation First of all there is the content-based recommendation, which works without user's evaluation or ratings. It uses machine language to acquire information and has several algorithms such as decision trees, neural networks or vector-based methods. The objects are defined by characteristics and related attributes. Knowledge-based recommendation uses demands and preferences of the user and decides predictions with functions and features of objects. The last method is collaborative filtering which has an own paragraph in the following. [1, 3]

Collaborative Filtering in Spotify Collaborative filtering is the most common method for recommender. It uses the K-nearest neighbour technique (KNN). The music taste of users calculates the distance between different users. The method searches for neighbour users who share similar interest in music and recommend the content based on these informations. Therefore, the recommender predicts users preferences with by user-item relationship. In daily life it can be compared to a friend's recommendation. Collaborative Filtering can further be divided into three types.
The memory-based filtering predicts items based on the complete collection of previous ratings, with algorithms such as the neighbourhood based filtering and item-based top-N recommendations, to find user groups with people with similar interests. The model-based method uses data mining or machine learning methods to train and model user's preferences. It then makes prediction for test based on the known model. The last method combines the both methods and is therefore called hybrid method, which outperforms both individual models. [1, 2, 3]

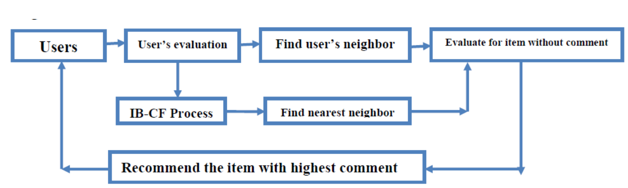

Figure 1: Collaborative Filtering Recommendation

[1]

In Figure 1, the produce of collaborative filtering is illustrated in a flowchart. It can be seen as a loop, where the user gets the recommended

item with the highest comment in result of user's evaluation and finding the neighbours. This circulation should run continuously to improve the recommendations, since it takes time. Based on the data and user's interests, neighbour user's are being searched who share the similar interests. The system then recommends the neighbour user's music to the user.
In Spotify the method is accomplished with the "discover weekly playlist". It gives more weight to company's playlists and those with more followers. Furthermore the playlist fills in blanks between listening habits and similar taste and uses "echo nest" for emerging genres. A taste profile is developed for each user with the individual taste in music. It is created based on the frequency of listening to a song, whether people skipped songs or not which works as thumbs up and down and with explorations and streams.

[5, 6]

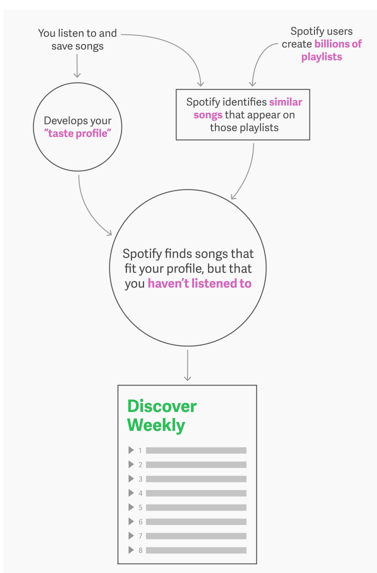

Figure 2: Discover Weekly Playlist Flow Chart
[6]

Approach of Collaborative Filtering The technical approach of collaborative filtering will be briefly explained with the equation below.

$$\min_{x_\star, y_\star} \sum_{u,i} c_{ui}(p_{ui} - x_u^T y_i)^2 + \lambda \left(\sum_u \|x_u\|^2 + \sum_i \|y_i\|^2 \right)$$

Figure 3: Minimize cost function
[4]

First of all the binary variable "Pui" represents the preference of user "u" to an item "i", where the user likes the item by consuming the item once, when "Pui" equals one. Otherwise the user never consumed the item before. There are different levels of confidence within items, but for easier illustration we use the binary variable. The next variable "Cui" measures the confidence depending on "Pui". The aim however is to find a vector "Xu" for user "u" and "Yi" for item "i" that will factor user preferences. The calculation is similar to the matrix factorization technique. The last term is for regularizing the model to avoid over fitting of training data. Each step of computation the value of the cost function is for sure getting lower.

$$x_u = (Y^T C^u Y + \lambda I)^{-1} Y^T C^u p(u)$$

Figure 4: Item vector
[4]

$$y_i = (X^T C^i X + \lambda I)^{-1} X^T C^i p(i)$$

Figure 5: User vector
[4]

This model leads to an alternating-least-squares optimization process, where the item and user vectors are initialized at the beginning. Then the item vectors are fixed and solved for optimal user vectors, by taking the derivate of the min function, setting equal zero and solving(figure 3). Analogous the user vectors are fixed and solved for optimal item vectors (figure 4). This procedure will be repeated until it converges.

[4]

Feedback system Briefly explained, the feedback system is loop (see the following figure), where the collected output information is sent back to the input and adjusts by the behaviours.

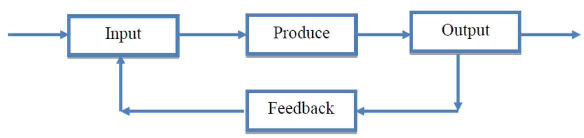

Figure 6: Theory of general feedback system
[1]

The process is called feedback control by error, because the system controls the behaviour and eliminates errors. As the name can tell, the system detects and analyses information after a learning research and reflects the given information. The main features of feedback shall contain to process information timely and accurately, be helpful for predicting and to control plans and management. So it refers to the output of the system but also returns to the input to change information to influence operations. Moreover the feedback system needs features such as targeted, timeliness and continuity, requirements e.g. true and accurate information and minimize time and last but not least development, where the system has to be sensitive, correct and strong.

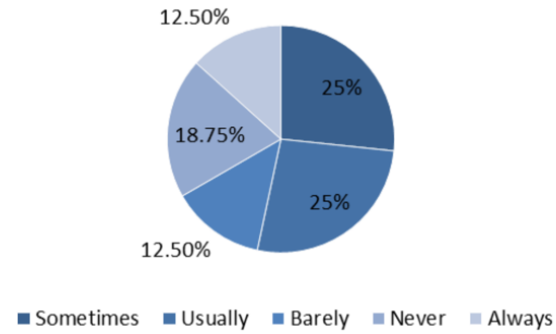

Figure 7: Frequency of pressing "like" when users find songs matching their tastes
[1]

At the moment, clicking "like" is widely accepted. The service for recommendation is based on the history of clicking "like" record. As shown in the figure above, 12.5 per cent never click "like". However less than a third have the habit to click "like" every time, and another 12.5 per cent want to adopt this habit.

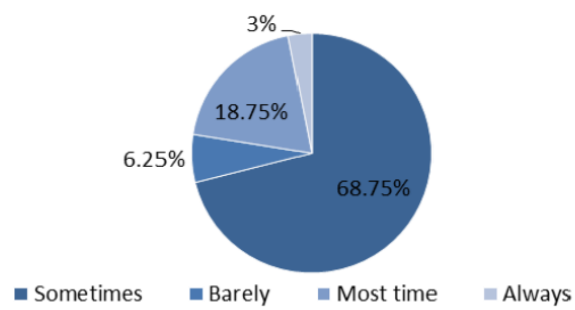

Figure 8: statistic to show whether the recommended music match the taste or not
[1]

In this figure, the question was whether the recommended music would match the taste of the users or not. And the majority of people did not get a customized recommendation while listening to music. Only less than 20 per cent are fully satisfied with the recommendation service. So there is still progress to make for the feedback system, but it is developing fast.

[1]

Conclusion Beginning with the disadvantages of Collaborative Filtering, a cold-start problem occurs when a new user or item enters the system with no ratings to recommend. If the user has an unusual taste the ratings are few and the user does not have many neighbours so the recommendations will be poor. The personalization would be weakened as a result of popular songs which will be recommended anyway. Besides with a lack of ratings or in the beginning without a big amount of data the predictions are poor. Lastly, a perfect recommender should not involve too much human effort, because users are not always willing to rate. The datas are not always representative due to ratings growing towards those who rate. As advantages, Collaborative Filtering evaluates information that is difficult to be analyzed. It also avoids low accuracy by matching items with neighbourhood users and provides the users with not similar recommendations but based on the user's taste.
To sum up the feedback system, the main disadvantage is the problem of time delay, if correct measures have to be taken. But in Spotify for example the service varies the recommended music based on different users' preference. Still, there need to be the right requirements, features and development for every feedback system.

[1, 2, 3]

References

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