Product recommendation approaches: Collaborative filtering via customer lifetime value and customer demands

Ya-Yueh Shih
https://dl.acm.org/profile/81100194056
Department of Information Management, Chung Hua University, Taiwan

Duen-Ren Liu
https://scholar.google.com/citations?user=pQ7QfRsAAAAJ&hl=zh-TW
Institute of Information Management, National Chiao Tung University, Taiwan

Recommendation systems allow companies to develop individual marketing strategies and provide support in communicating with customers for e-commerce. Recommendation systems are widely used and widely accepted to recommend products for online stores, generate playlists for video and music services, promote social media content and web content advocates.

There are a variety of recommendation methods, including content-based filtering (CBF), WRFM-based method, collaborative filtering (CF), and hybrid methods. The CF method usually uses pre-purchase preferences to determine recommendations for targeted customers based on the opinions of other similar users. The CF method predicts user preferences on items in a word-of-mouth manner. Amazon.com uses collaborative filtering to create book recommendations for customers. The content-based filtering (CBF) offers a different approach to collaborative filtering and provides recommendations by matching customer profiles (e.g., interests) with content features (e.g., product attributes).

Typical KNN-based collaborative filtering finds the k most similar customers are selected as the k-nearest neighbours of customer u. The products then are sorted based on frequency count. The N most frequent products that have not yet been purchased by target customer u are recommended to target customer u.

$$Corr_P(c_i,c_j) = \frac{\sum_{s\in I}\left(r_{c_i,s}-\bar{r}_{c_i}\right)\left(r_{c_j,s}-\bar{r}_{c_j}\right)}{\sqrt{\sum_{s\in I}\left(r_{c_i,s}-\bar{r}_{c_i}\right)^2\sum_{s\in I}\left(r_{c_j,s}-\bar{r}_{c_j}\right)^2}}$$

The WRFM-based collaborative filtering approach makes recommendations based on the weighted customer lifetime value (CLV) - Recency, Frequency, and Money. This method mainly integrated AHP, clustering, and association rule mining techniques for product recommendation. The preference-based CF method is similar to the WRFM-based CF method, except that clustering is performed based on purchase preferences. A hybrid method that groups customers by considering both the WRFM values and purchase preferences can improve the quality of recommendations.

$$Corr_{WRFM}(c_i,c_j) = \frac{\sum_{s\in V}\left(WRFM_{c_i,s}-\overline{WRFM}_{c_i}\right)\left(WRFM_{c_j,s}-\overline{WRFM}_{c_j}\right)}{\sqrt{\sum_{s\in V}\left(WRFM_{c_i,s}-\overline{WRFM}_{c_i}\right)^2\sum_{s\in V}\left(WRFM_{c_j,s}-\overline{WRFM}_{c_j}\right)^2}}$$

Hybrid methods have been suggested to overcome the challenges of CF and CBF methods. This work proposes several hybrid recommendation methods that include collaborative filtering, WRFM-based method, and extended preferences. Customer demands are determined by simple statistics that calculate the frequency count of each product item purchased by customers in each industry. If the frequency count of a product item purchased in an industry is greater than a given threshold h, then customers in such industries tend to have a demand for the item. Limited to available content information, in which product features are not provided in the data set, customer demands are integrated with purchase preferences to reduce the sparsity of customer item matrix.

The proposed methods use customer requirements (demands) to adjust the ranking of recommended products to improve recommendation quality. This work describes the availability of customer requirements in each industry. A hybrid approach that integrates WRFM-based CF with customer demands, called WRFMCD. The WRFMCD approach first establishes a customer-WRFM and customer demand matrix. Subsequently, the WRFM-based and the customer-demand correlation coefficients are computed using the Pearson correlation coefficient, respectively.

$$Corr_{WRFMCD}(c_i,c_j) = w_{WRFM}\times corr_{WRFM}(c_i,c_j) + w_{cd}\times corr_{cd}(c_i,c_j)$$

After all, K-means clustering is used to collect customers with the same CLV and customer demands based on weight coefficients. Finally, the association rule mining approach is applied to extract recommendation rules from each group derived from K-means clustering. Candidate products are sorted by their associated confidence values, and the top-N highest-ranked candidate products are recommended to users.

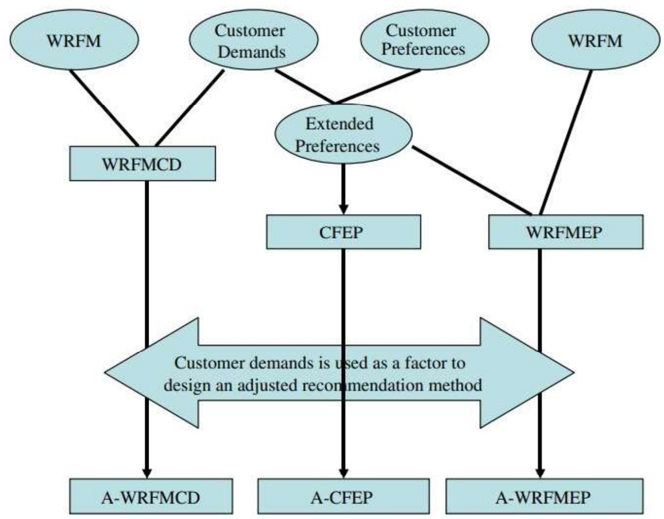

Figure 1: Flow-Chart

Besides, the acquisition of extended preferences by combining purchase preferences with customer requirements is also presented. This work proposes another hybrid approach, which is the WRFMEP method, by which customers are clustered by integrating the dimensions of customer lifetime value and extended preferences. This method adopts relative weighting to adjust the importance of customer lifetime value and extended preferences in clustering.

$$Corr_{WRFMEP}(c_i,c_j) = w_{WRFM}\times corr_{WRFM}(c_i,c_j) + w_{ep}\times corr_{ep}(c_i,c_j)$$

The association rule mining approach is then applied to extract recommendation rules from each group derived by K-means clustering. Test results show that the proposed methods work better than a few other recommended methods.

[1] Recommendation systems,
`https://youtu.be/jhFFOmvPne4`

[2] WRFM-based CF method,
`https://youtu.be/fdUofaT8gUw`

[3] Maciej Kula, Basics of Hybrid method
`https://youtu.be/EgE0DUrYmo8`

[4] Rayan Gillard, Hybrid methods
`https://youtu.be/5VylUiV5zsc`

[5] Edureka!, Recommendation Rule set 1
`https://youtu.be/guVvtZ7ZClw`

[6] Augmented Startups, Recommendation Rule set 2
`https://youtu.be/WGlMlS_Yydk`