A Combined Neural Price-Aware Collaborative Filtering and Clustering Approach for User Segmentation Based on Willingness to Pay

Aakash Swami
TCS Research
India

Tirumala V
TCS Research
India

ABSTRACT

For Businesses, a key strategy for delivering value and maximizing revenue is user segmentation. User segmentation allows businesses to understand their users better and adapt their offerings and marketing efforts to specific segments. Segmenting users based on their willingness to pay is a specific type of user segmentation that focuses exclusively on the price sensitivity aspect of user behavior and is crucial in developing successful pricing strategies. Increasing data has enabled leveraging Artificial Intelligence to create better segmentation approaches. We propose a novel approach that uses a combination of neural price-aware collaborative filtering and clustering techniques to segment users based on their Willingness to pay using user purchase data. Neural price-aware collaborative filtering is an extension to neural collaborative filtering (2017) that takes price into consideration and models user, item, and price interaction using a Multilayer Perceptron based neural network. It learns similarities between users based on the user's purchase behavior for a given item at a given price. Using user purchase data results in segmentation that is based on the revealed preferences of the users. We synthetically generate user purchase data and consider two scenarios based on whether the user's purchase data contains the user's interaction with a single item or multiple items. The formed segments are analyzed by visualizing segments in 2D space, comparing the distribution of price in one segment to another, and comparing the purchases of users within a segment to validate our proposed approach.

CCS CONCEPTS

• **Information systems → Users and interactive retrieval; Collaborative filtering**; • **Computing methodologies → Machine learning; Unsupervised learning**;

KEYWORDS

User segmentation, Willingness to pay, User purchase behavior, Artificial Intelligence, Collaborative filtering

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1 INTRODUCTION

The importance of user segmentation is widely acknowledged [1]-[3]. User segmentation can benefit in increasing business revenue by providing users with the right offers, improving user satisfaction by making marketing efforts segment-oriented, etc. While user segmentation considers a wide range of factors such as geographic, demographic, psychological, and behavioral[4], user segmentation based on willingness to pay (WTP) is a specific type of user segmentation that focuses exclusively on the price sensitivity aspect of user behavior and is crucial in developing a successful pricing and revenue strategy for a product or service. The paper aims to propose a novel approach for user segmentation based on their WTP using user purchase data.

Bolton and Myers [5] stated that user price sensitivity is a crucial basis for user segmentation and specific attention needs to be paid to price-based user segmentation. The existing works on WTP-based user segmentation are limited and differ based on whether it uses user stated preference data[6] or revealed preference data[9]. Works[6],[7] that use user stated preferences data are limited in the sense that user stated preference does not necessarily require respondents to purchase the product, and thus can deviate from the user's actual WTP[8], which reflects their revealed preferences. The works [9] that use user revealed preference data are limited in a way that they need well-defined item and user attributes, which might sometimes be difficult to gather due to security and privacy issues [10]. In addition, none of these existing works [6],[7],[9] takes into account the joint purchase behavior of the user on multiple items. For example, in a hotel or airline ancillary purchase scenario, the user is typically exposed to multiple items at the same time and the user purchases one or more of them based on the joint preference for multiple items and prices. Taking into account the user's joint purchase behavior on multiple items can help in better segmentation. The proposed approach addresses the limitations in the existing works by using user purchase data that correspond to revealed preference data, considering joint purchasing decisions/behavior on multiple items when segmenting, and using the collaborative filtering technique that does not require well-defined item and user attributes.

Collaborative filtering[11] in the recommendation system uses user interactions to find similar patterns or information of the users. Among collaborative filtering techniques based on neural networks, neural collaborative filtering (NCF) was proposed by He et al. [12], where the dot product was replaced by a Multilayer Perceptron (MLP) based neural network to bring non-linear interaction between user and items. The paper however only considered user-item interaction without considering price. The proposed novel approach of user segmentation based on WTP uses a combination of neural price-aware collaborative filtering and clustering techniques to segment users based on their WTP using user purchase data.

The neural price-aware collaborative filtering brings user, item, and price interaction using an MLP-based neural network and learns similarities between users based on the user's purchase behavior for a given item at a given price. We use synthetically generated user purchase data in the form of user, item, price, and binary purchase decisions (purchased or not purchased) for user segmentation based on WTP and consider two scenarios based on whether user purchase data contains the user's interaction with a single item or multiple items. The data contains user interactions with an item at different price points. The formed segments are analyzed by visualizing segments in 2D space, comparing the distribution of price in one segment to another, and comparing the purchases of users within a segment to validate our proposed approach. It is seen that the approach can effectively segment users based on their WTP. The segments are formed not only based on the price at which the item is purchased by a user but the price at which the item is not purchased by a user is also considered. When user purchase data contains the user's interaction with multiple items, it is seen that the segmentation is based on the user's joint purchasing decisions on all items. The rest of the paper is organized as follows: related works in section 2, describing the proposed approach in section 3, then describing data generation in section 4, the parameter setting in section 5, the results in section 6, followed by the conclusion in section 7.

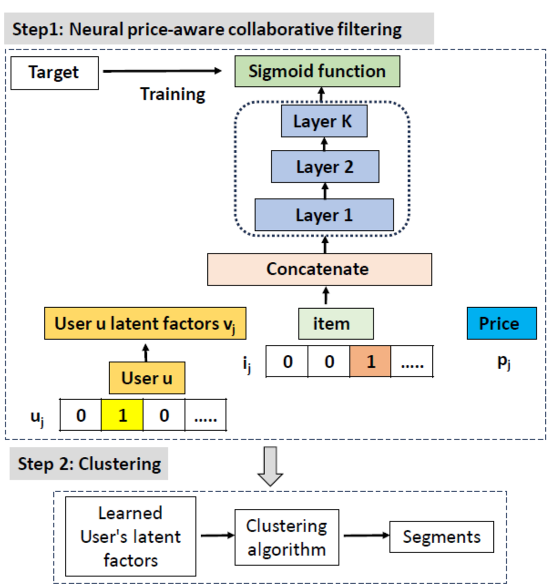

Figure 1: Proposed approach

2 RELATED WORKS

Behera, L et al. [13] did a thorough literature review in the area of user segmentation and also highlighted the growing establishment of machine learning techniques in this field. Most of these literatures that uses the data-driven approach for user segmentation [14]-[17] considers users' demographic, geographic, or behavioral attributes, and the kind of literature that considers the price sensitivity aspect of user behavior is scant. Lorenzo and Nicolau [6] found the tourist segment from individual tourist price sensitivity to tourism activities. To understand tourism preference they carried out a stated preference experiment where tourists were asked to choose one of the two tourist cards at a certain price. The methodology consists of, first estimating individual tourist price sensitivity parameters using a mixed logit model, then applying the clustering technique to the matrix of the parameter of each tourist. Thus segmenting tourists using individual price sensitivities to tourism activities. The paper however used stated preference data. The stated preference which corresponds to hypothetical WTP, can deviate from their actual WTP[8], which reflects their revealed preferences. Arevalillo[9] proposed a machine learning approach that uses a combination of a classification tree, random forest, and model-based recursive partitioning to generate customer segments based on their differential price sensitivity characterized by item and user attributes. However, the approach uses well-defined product characteristics and customer attributes and is not based on collaborative filtering[11] which is the base of our work. Breidert, C. et al. [18] highlighted that the data used to measure WTP based on revealed preferences can be market data or experimental data. In this paper, we use user purchase data in the form of user, item, price, and binary purchase decision for user segmentation based on WTP. Data containing user, item, price, and binary purchase decision can be found in various platforms like E-commerce Websites platform, A/B Testing platforms, Hotel and Travel Booking Platforms, etc.

3 PROPOSED APPROACH

In this section, we describe the proposed approach. The proposed approach is divided into 2 steps as shown in Figure 1. In the first step, the neural price-aware collaborative filtering is used to learn the user latent factors using user purchase data in the form of user, item, price, and binary purchase decision data. These user latent factors represent a user. To learn these user latent factors user, item, and price interaction is bought using an MLP-based neural network model which captures the nonlinear interaction between user, item, and price. The target is whether the item at that particular price is purchased by the user or not. When training, the model learns the latent factors for the users to best explain their purchase behavior. Consequently, latent factors of users with similar purchase behavior will be close together. In the second step, the users are then clustered using the learned latent factors. These clusters refer to the segments formed comprising users having similar WTP. The details of the two steps are discussed below.

Step1:Neural price-aware collaborative filtering

Here we describe the neural price-aware collaborative filtering architecture. The lowest input layer is made up of two vectors u_j of size M and i_j of size N that, respectively, characterize user u and item i for the j-th sample. These vectors represent user and item

identities via hot encoding. Here, M is the total number of users, and N is the total number of items. The latent factor matrix for users is denoted by $P \in R^{MXL}$ where L is the number of the latent factor used to represent a user.
The MLP model equations are:

$$\begin{aligned} v_j &= P^T u_j \\ x_j &= [v_j \; i_j \; p_j] \\ c_1 &= a_1(W_1^T x_j + b_1) \\ c_2 &= a_2(W_2^T c_1 + b_2) \\ &\ldots\ldots \\ \hat{y}_j &= a_k(W_k^T c_{(k-1)} + b_k) \end{aligned} \tag{1}$$

Here p_j represents the price of item i for the j-th sample and v_j represents the latent factors of user u_j. We have represented items by one-hot encoding assuming that there is no relationship between items. The a_k, W_k, and b_k denote respectively the activation function, weights, and bias term for the k-th layer. The last activation function a_k is the sigmoid function. The $\hat{y}_j$ represents the predicted purchase probability of item i at a particular price p by a user u for the j-th sample. We used binary cross-entropy loss, also known as log loss as the loss function. The equation is as shown below:

$$Log\ loss = -\frac{1}{n}\sum_{j=1}^{n}(y_j \log(\hat{y}_j) + (1 - y_j)\log(1 - \hat{y}_j)) \tag{2}$$

Here y_j represents the target for the j-th sample and n is the total number of samples. The loss function is optimized using the Adaptive Moment Estimation (Adam) [19] optimization technique. The neural price-aware collaborative filtering is trained to learn the weights of the MLP and the user latent factor matrix P. The user latent factors are learned such that the closeness of latent factors represents closeness between users based on their purchase decisions for a given item at a given offer price.

Step2:Clustering

The second step is to cluster the users using the learned user's latent factors into segments. Among different clustering algorithms available [20] we have used K-means in our work. The K-means clustering algorithm [20] is a centroid-based clustering algorithm having the goal of identifying the K number of groups in the dataset.

4 DATA GENERATION

To validate our proposed approach we generate two synthetic data as per the two scenarios considered. In the first scenario, we consider that user purchase data contains the user's interaction with only a single item, and in the second scenario, we consider that the user purchase data contains the user's interaction with multiple items. Let's say we have 3 items i.e. item 0, item 1, and item 2. In scenario 1, we consider item 0 and around 1000 users while in scenario 2 we consider three items i.e. item 0, item 1, and item 2, and around 1000 users. To generate data a given user is shown an item/items (as per scenario) at a given offer price, and based on the user's WTP, the user decides to purchase it or not. The typical distribution of the price of an item is multimodal[21]. We take the price for all three items as following a bimodal distribution with two distinct peaks as shown in Table 1. Each user WTP for an item/items is sampled from the above-mentioned distributions for items adding diversity in the data since each user will have a different WTP for item/items. The range of offer prices for items is fixed such that it includes the lower and upper bound of WTP. A sample generated data for scenarios 1 and 2 is shown in Table 2. Here '1' and '0' under the 'Purchase decision' column are used to represent the item purchased and not purchased respectively. It is to be noted that we excluded users who made purchase decisions '1' or '0' at all price points since we cannot infer WTP for these users.

Table 1: Items distribution

Item	1^{st} peak	2^{nd} peak
Item 0	$\mathcal{N}(40, 5)$	$\mathcal{N}(60, 5)$
Item 1	$\mathcal{N}(80, 5)$	$\mathcal{N}(100, 5)$
Item 2	$\mathcal{N}(100, 5)$	$\mathcal{N}(120, 5)$

Table 2: Sample data: scenario 1 and scenario 2

Scenario 1				Scenario 2			
User	Item Shown	Offer price	Purchase decision	User	Item Shown	Offer price	Purchase decision
User 0	Item 0	35.55	1	User 0	Item 0	31.02	1
User 0	Item 0	67.87	0	User 0	Item 1	78.36	0
User 1	Item 0	68.88	0	User 0	Item 2	89.79	1
User 1	Item 0	31.51	1	User 1	Item 0	73.87	0
...	...	...	...	User 1	Item 1	66.12	1
...	...	...	...	User 1	Item 2	113.06	1
...	...	...	...	...	...	...	...

5 PARAMETER SETTING

The problem is cast as unsupervised learning using unlabeled data and we implement our proposed approach based on Keras[22]. The architecture of the MLP layers is $64- > 32- > 16$ and the number of latent factors used to represent a user is 32. The number of training epochs is 2000 for both scenarios and the learning rate is 0.001.

6 RESULT

In this section, we discuss the results to answer the following research questions. These questions aim to validate our proposed approach.

RQ1 What is the quality of the segments formed?

RQ2 Is our proposed approach able to segment users based on WTP ?

RQ3 Do the segments have users having similar purchase behavior for a given item at a given price ?

In what follows we answer the above three research questions:

Quality of segments formed(RQ1)

To access the quality of segments we first apply t-SNE on the learned user's latent factor to transform it into 2D space. The T-distributed Stochastic Neighbor Embedding(t-SNE) is a machine learning algorithm and it is often used to transform high-dimensional data in a low-dimensional space[23]. Then we calculate the silhouette score that measures how similar a user is to its own segment compared to other segments. The silhouette score is widely used by various researchers [24], [25] as a metric to assess the quality of segments.

The result is shown in Figures 2 and 3 for scenarios 1 and 2 respectively. The users are labeled based on the segment they belong highlighted in different colors. The closeness of the user's latent factors represents that users are similar in their purchase decision for a given item at the given offer price. The silhouette score is 0.48 with 4 segments and 0.61 with 7 segments for scenarios 1 and 2 respectively indicating appreciable segmenting.

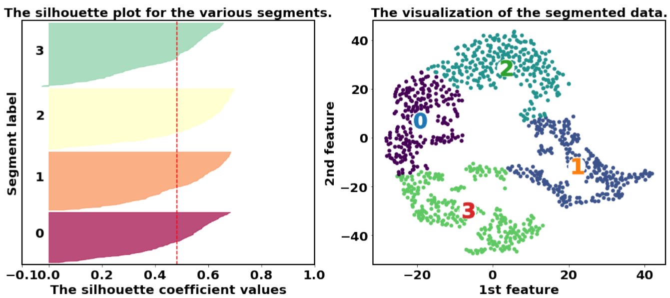

Figure 2: Silhouette analysis and segments: scenario 1

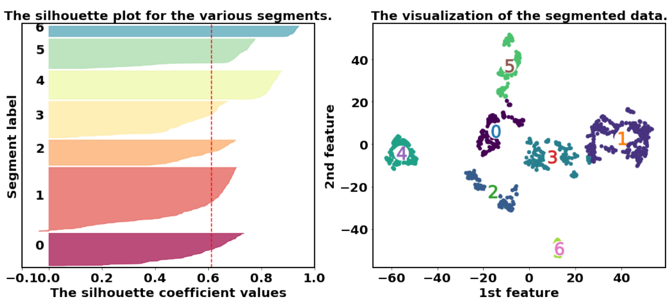

Figure 3: Silhouette analysis and segments: scenario 2

Comparing segment-specific WTP(RQ2)

To validate whether the proposed approach is able to segment users based on WTP we tried to measure the segment-specific WTP and later compare it between segments. To do so we calculate the mean and standard deviation(Stdev) of the prices at which a particular item is purchased within a segment denoted as "Mean:P" and "Stdev:P" respectively as also used by [26]. The [26] segmented users based on their purchasing portfolios and calculated the mean of expenditure in a segment to compare different segments. The mean will provide insight into the segment-specific WTP and the Stdev will provide insight into the quality of the segment because users making similar purchase decisions around similar prices will be clustered together leading to less Stdev. We too calculate the mean and standard deviation of the prices at which a particular item is not purchased within a segment denoted as "Mean: NP" and "Stdev: NP" respectively. This will provide additional insight into the segments formed.

Table 3 shows the mean and Stdev of the segments formed using the proposed approach for scenario 1. In scenario 1 we observe that:

Table 3: Segment-specific WTP: scenario 1

Segment	Item	Mean:P	Stdev:P	Mean: NP	Stdev: NP
0	0	41.22	2.83	72.87	5
1	0	36.9	4.74	52.09	6.57
2	0	33.33	2.28	68.9	7.24
3	0	52.9	4.86	69.56	6.2

Table 4: Segment-specific WTP: scenario 2

Segment	Item	Mean:P	Stdev:P	Mean:NP	Stdev:NP
0	0	42.67	9.4	71.95	6.33
0	1	75.65	12.44	97.9	12.62
0	2	101.48	12.84	108.16	4
1	0	64.18	3.57	63.41	10.6
1	1	77.68	11.65	106.1	11.03
1	2	92.08	10.01	122.28	12.11
2	0	35.1	0	53.7	9.93
2	1	80.6	11.34	77.14	0
2	2	100.01	11.3	135.1	3.15
3	0	42.79	9.98	69.93	8.9
3	1	72.67	8.24	99.14	11.49
3	2	99.91	11.95	124.33	11.36
4	0	43.16	9.13	78.21	1.96
4	1	63.37	1.33	103.65	11.83
4	2	0	0	124.35	11.45
5	0	43.33	9.27	0	0
5	1	80.27	10.47	110.74	6.98
5	2	89.09	5.72	119.86	11.54
6	0	42.95	8.77	0	0
6	1	67.15	5.01	0	0
6	2	0	0	130.56	7.47

- The segments formed have users with different WTPs. This is inferred from that WTP for item 0 is different between segments for example in segment 0 the "Mean:P" is 41.22 and in segment 2 the "Mean:P" is 33.33.
- The segmentation is not only based on the price at which the item is purchased by a user but also based on the price at which the item is not purchased by a user. This is evident from the fact that even though "Mean:P" is nearly the same between segments 1 and 2 i.e. 36.9 and 33.33 respectively, the "Mean: NP" is 52.09 in segment 1 and 68.9 in segment 2.

Table 4 shows the mean and Stdev of the segments formed using the proposed approach for scenario 2. We observe that:

- Similar to scenario 1, segmentation in scenario 2 is also not only based on the price at which the item is purchased by a user but also based on the price at which the item is not purchased by a user.
- Segmentation is based on the user's joint purchasing decisions on all items. This is evident from the fact that even though "Mean:P" for item 0 is nearly the same between segments 0 and 4 i.e. 42.67 and 43.16 respectively, the mean is different for item 1 and item 2.

Tables 3 and 4 show that the Stdev varies across segments. To measure the quality of overall segmentation, we calculate the Mean Stdev by taking the mean of Stdev across all segments. The mean Stdev is calculated for both settings i.e. considering the price at which an item is purchased and the price at which the item is not purchased, denoted by "Mean Stdev: Purchased" and "Mean Stdev: Not Purchased" respectively. For scenario 1 the "Mean Stdev: Purchased" is 3.68 and "Mean Stdev: Not Purchased" is 6.25. For scenario 2 the "Mean Stdev: Purchased" is 9.02 and "Mean Stdev: Not Purchased" is 8.99. The mean Stdev is appreciably lower and will further decrease with an increasing number of segments.

User's purchase behavior for a given item at a given price within a segment (RQ3)

To better realize user segmentation using the proposed approach we compare the purchases of the user within a segment. For this, first, we took user ID 150 from scenario 1 and user ID 92 from scenario 2 and identified the segment they belong to. Then we compare the purchases of nearby clustered users in the found segment. The result is shown in Figure 4. It is seen that the nearby clustered users are the ones having similar purchase decisions for a given item at a given offer price.

In one scenario, the proposed approach can also be applied to price

	User	Item shown	Offer price	Purchase decision
	150	0	65.35	1
		0	78.99	0
Similar Users	427	0	66.36	1
		0	77.98	0
	269	0	73.43	0
		0	58.28	1
	312	0	60.81	1
		0	72.42	0
	141	0	61.31	1
		0	74.95	0
	...	...	...	...

(a) Scenario 1

	User	Item shown	Offer price	Purchase decision
	92	0	77.96	0
		2	97.14	1
		1	63.67	1
Similar Users	253	1	62.45	1
		0	75.92	0
		2	94.69	1
	383	2	92.24	1
		1	64.9	1
		0	78.98	0
	...	...	...	...

(b) Scenario 2

Figure 4: Purchases of the users within a segment

unseen items for a user, as the user WTP for items not seen by the user can be estimated based on the segment the user belongs to. To understand this say user 1 interacted with item 1 and item 2 and user 2 interacted with item 2 and item 3. Say user 1 and user 2 purchase behavior for item 2 is similar. Because in segmentation the users are clustered based on purchase behavior around similar price points for an item, user 1 and user 2 will belong to the same segment. Thus, we can price item 3 for user 1 based on user 2 purchase behavior and similarly can price item 1 for user 2 based on user 1 purchase behavior. However, the scenario requires experimentation before reaching any conclusion.

7 CONCLUSION

In this paper, we demonstrated a novel approach for user segmentation based on WTP, using a combination of neural price-aware collaborative filtering and clustering techniques. We observe that the segments are not only formed based on the price at which the item is purchased by a user but the price at which the item is not purchased by a user is also considered. Also, in case the user purchase data contains user interaction with multiple items, the user's joint purchasing decisions on all items are considered while segmenting. The work can be extended to experimenting on real-world datasets and other different user purchase scenarios. The proposed approach can be used to create user segments based on WTP in various business domains, enabling them to create more personalized pricing and marketing strategies, leading to increased revenue and user satisfaction.

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