Neural Network Feature Selection Based on Collaborative Filtering Recommender Systems for User Classification

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Abstract

In today's competitive markets, it is crucial to render personalized assistance tailored to unique individual's needs. To accomplish this goal, a recommender system represents a noteworthy progression in collaborative filtering recommender systems. This shift highlights a broader research focus that extends beyond algorithms to encompass a diverse array of questions related to the functionality of the recommender. The identification accuracy must be assessed as a function of how well the suggested approach fits with a user's wants and needs, particularly in the context of collaborative constraint-based functions. The next phase of research must focus on defining parameters for assessment which may be used to compare the performance of constraint-based algorithms across a wide variety of diverse issues. It is currently necessary to design, or at criteria for assessment for constraint-based algorithms. We have addressed key research challenges related to the following topics: constraint-aware machine learning, understanding parameters in solution spaces, metrics for assessing constraint-based systems, algorithm selection, machine learning considerations, and investigating constraint-based platforms, and elucidations.

Keywords: Recommendation system; Neural Network; Users Classifications; Collaborative Filtering; Personalization

1. Introduction

The role of the recommendation system is significant in the newest technology which is applied in different sectors such as healthcare, tourism, marketing, media, and education [1][2][3]. Collaborative filtering-based recommendation technique, demographic-based recommendation analysis systems, content-based recommender systems, utility-based recommendation systems, hybrid recommendation technology, and knowledge-based recommender platforms represent categories that have evolved over decades [4][5]. Current research extends beyond simple evaluations of efficacy and classification accuracy, as highlighted by recent studies [6][7][8]. Nevertheless, the most prominent applications that have gained significant traction are those relying on collaborative filtering for recommendations [9][10][11]. In this paper, various collaborative filtering techniques are explored.

Collaborative filtering approaches analyze feedback from individuals to produce individual suggestions for others who have comparable preferences [12]. By considering the individual's prior interactions with various objects, the collaborative filtering algorithm determines recommendations. For instance, this system can identify individuals who align with a customer's preferences and suggest products that have been rated highly by those individuals. The collaborative filtering-based approach relies on matrices (second-order tensors) to depict the connections between individuals and products.

Figure 1 shows the architecture of typical Social Networking, which includes the user, the location, and content layers. An individual might use the data from each level individually to benefit from predictions. Nevertheless, in a higher-level scenario, we can additionally make utilize of the primary relationship among organizations, which cuts across multiple layers and includes individual, location, and content [6][13]. Although numerous times the

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information's findings are ternary method for a recommendation that were initially built to work with a matrix are unable to be used.

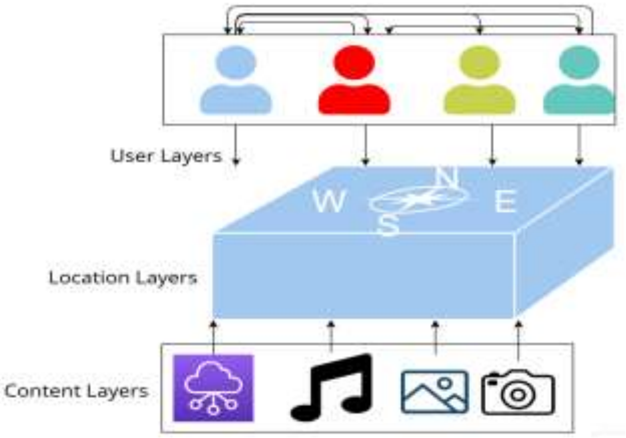

Figure 1: The typical social networking architecture

To take advantage of factor fundamental semantic structure, matrix factoring methods can be used in recommendation systems (see Figure 2), including the processing of natural languages, algorithms for image processing, machine learning, which have previously employed the concept of developing low-rank matrix estimates. The fundamental concept of matrix factorization transforms the problem into a third-order tensor completion problem.

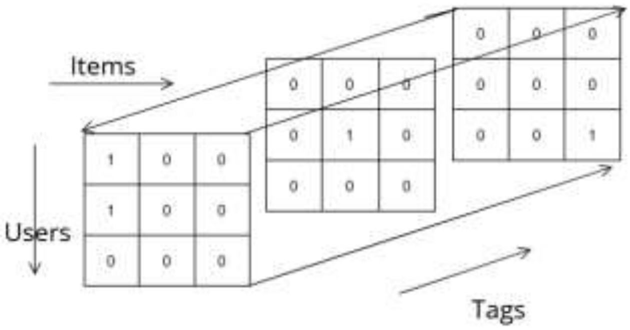

Figure 2: Representation of positive feedback from users

Artificial intelligence and machine learning are frequently employed in recommendation systems considering artificial intelligence can evaluate a set of data to identify individual trends that enable the algorithm to identify the customer's needs. Recommendation networks are a group of machine learning algorithms that present customers with extremely relevant information. As a result, the individual using it develops a relationship of confidence with the system [14]. This is significant maintaining satisfied customers is crucial for all businesses such as Netflix, Amazon, and even social networking websites like Instagram are instances [15]. These sites employ machine learning and artificial intelligence to recommend better products and services.

On the other hand, recommender system also serves as information fusion. In addition to message-passing outcomes, Graph regularized Multilayer Concept Factorization (GMCF) uses node-matching outcomes to collect node-level matching details while producing the merged node representations. The node-merging function has the input as the node ni, message carrying results mi, and node-matching results vi and the output is the fused node. From testing, it is evident that recurrent neural networks give the best results. Therefore, a gated recurrent unit (GRU) is used in this model for the fusing function. The fused node representation is GRU’s final output hidden layer.

With regards of neural network collaborative filtering, the embedding layer positioned above the input layer plays a critical role as a fully connected layer, transforming sparse data representations into dense vectors. These resulting item embeddings and user embeddings can be likened to hidden vectors within a broader hidden vector model [16]. These embeddings are subsequently transmitted to a neural collaborative filtering layers (a multi-layer neural architecture) facilitating the prediction of scores. Each neural collaborative filtering layer can be customized

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to discern specific underlying patterns within user-item interactions [17]. The overall capacity of this framework is contingent upon the dimension of the final hidden layer [18][19].

2. Methods and Materials

2.1 Background and Related Works

This recommender system introduces two distinct profiles, one housing the consumer's personal information and the other holding their social connection details. By harnessing social records like social tagging, bookmarking, co-authoring, and trust indicators, this system offers valuable insights for machines with limited information, enabling them to identify similar customers [20][21]. Collaborative filtering, a key component of social recommendation systems, is primarily categorized into basic categories [16]. Further divisions emerge in the form of matrix factorization, which is based on the comprehensive recommendation engine, and matrix factorization, which is primarily grounded in the complete recommendation system [19][22].

The most recent studies on RS has covered a wide range of approaches, including conventional Matrix Factorization [23][24] and extending to sophisticated Deep Neural Networks. This phase comprises four crucial scenarios, each of which plays a central role within the proposed framework. These scenarios encompass registration, social login, user guidance for those who opt not to log in, and context [15]. In the registration process, users express their interest in the system by completing the registration form. Conversely, social login offers users the option to access the system using their social network accounts, such as Google, Twitter, and Facebook using their existing login details, rather than creating a new system-specific login account. In the realm of social recommendations, this phenomenon is referred to as the "user usage pattern". It hinges on the passive observation of user actions, with the application implicitly carrying out this analysis [25]. In a recommender system, all of this occurs seamlessly without requiring direct user input, operating in the background [21].

The identified indicators encompass various user actions, which encompass actions like copying and pasting text from the webpage, searching for specific content on the webpage, adding or removing items from the shopping cart (relevant for e-commerce applications). These actions also encompass actions such as saving or printing a webpage. Navigation indicators include parameters like browsing frequency, duration, clicks on webpages or links, mouse movements, scrolling, and so on. In addition, the contextual aspect involves personalized and dynamic browsing routes. The filtering technique incorporates and processes all the modules constituting the user's profile [26][27]. This profile comprises three primary modules: the collaborative module, the content-based module, and the demographic module. Within the collaborative module, there is rating data related to the referenced articles. The content-based modules focus on characterizing the features of destinations or activities that users have shown interest [13]. These features are identified through keyword vectors, either automatically generated during the session or manually assigned during registration [28]. For instance, in the travel planning process, after assessing the degree of gratitude, the system considers its context, selects items that are considered relevant to the user, and uses operations research techniques in the form of a journey to correlate these recommendations [22][28]. This process results in a list of items associated with their relevance to the specific user. In the travel planning phase, after assessing the relevance level, the system takes the user's context into consideration. Identifies items deemed suitable for the user, and employs operations research techniques to optimize travel recommendations. Figure 3 shows the demographic module contains the user's demographic information, which can be provided to the user during registration or extracted from social login data.

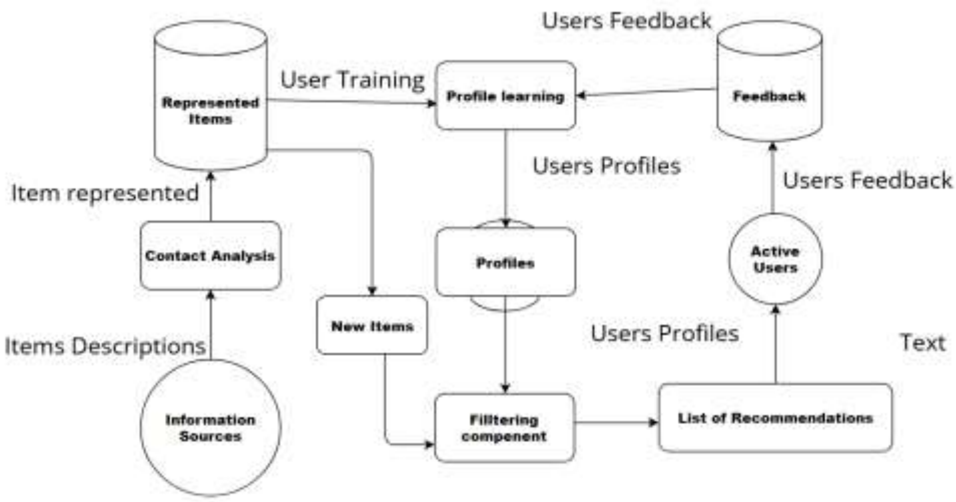

Figure 3: Collaborative module based on recommender system

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Content-based recommendations are built upon a user's historical preferences and their individual profile, with a focus on item attributes. To illustrate, when a user demonstrates interest in an item with particular characteristics and price range, they are more inclined to receive suggestions for similar items [17] [29]. The user's profile generally encompasses details about their past preferences and aversions [13]. The profiling process in a content-based recommender system is akin to a binary classification problem, a well-established Profiling in a content-based recommender system can be likened to a binary classification task, a widely explored domain within machine learning and data mining [27]. Frequently employed algorithms encompass naïve Bayes, nearest neighbour methods, and decision trees. Within this framework, the recommendation process entails sifting through and aligning items with the user's profile, leveraging analyzed features to present matching items while filtering out those the user usually dislikes. The effectiveness of the item representation and user profile plays a pivotal role in determining the relevance of the recommendation [30]. Several considerations go into creating a carefully chosen list of suggested products. Factors such as user popularity overall, recency, and frequency of recommendations are considered throughout the ranking process. Interestingly, the ranking model has a more straightforward architecture than the retrieval model [21]. This model uses a multi-layer perceptron to lessen the difference between the anticipated and actual ranks after obtaining the embedded versions of user_id and movie_title as input. A detailed illustration of the rankings algorithm's construction is provided in Figure 4.

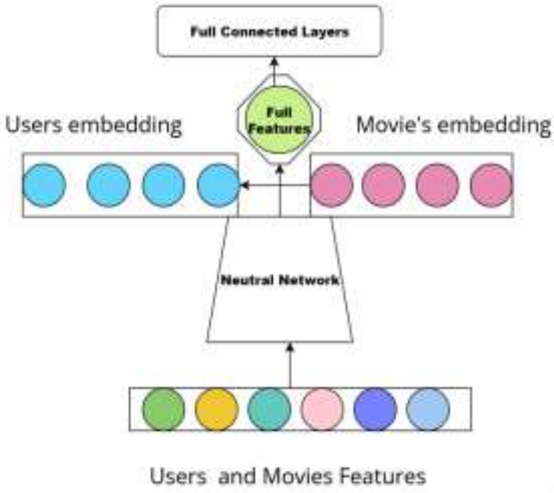

Figure 4: The rankings algorithm

This approach offers various advantages, chief among them being user autonomy, by utilizing item representation to address data sparsity issues [22]. It additionally successfully addresses the issues of users being recommended new products, which fixes the cold-start issue with new items. Another notable feature of content-based recommender systems is their capacity to provide lucid and understandable justifications for the recommendations they provide [18][20].

2.2 Proposed Collaborative Filtering Algorithm

Figure 5 depicts the methodology used to create the collaborative filtering algorithm.

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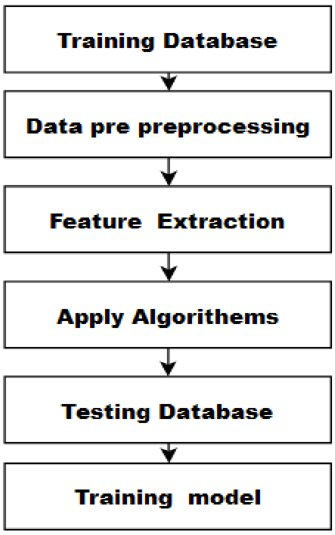

Figure 5: Methodology adopted for applying the algorithm for analysing social data

Data Collection : This method has several advantages, the most important of which is that it is user-independent because it depends on item visualizations, which makes it resistant to problems with data sparsity. It also does a great job at recommending new products to users, which helps to mitigate the problem of cold-starting new stuff. Especially noteworthy are content-based recommender systems, which excel at providing clear and understandable justifications for their recommendations challenging to retrieve info. Since incomplete data doesn't follow any set patterns, it is possible to obtain pertinent information from any incident by using certain keywords.
Data Preprosessing: Three categories of data are subjected to this process: text, location, and keywords. Expansion of contractions, removal of accented letters, lowercase text conversion, removal of digits, tokenization of the text, and finally, lemmatization and terminating words are all steps in the data cleansing process.
Feature Extraction: We employed the Term Frequency-Inverse Document Frequency (TF-IDF) method for text-to-word vector conversion. Consequently, we were left with an equation of parameters m*n, where 'm' represents the number of samples in the collected data, while 'n' is the number of different Machine Learning Algorithms used for Tweet categorization.
Apply Algorithm - Matrix Factorization: Matrix factorization is a widely used algorithm in this context. It uses a set of concealed attributes that describe every single thing or user and visualizations a mixture of into a common latent space [13]. As such, the relationship between a user and an item can be expressed as the inner product of their individual latent vectors. Although MF is a useful technique for collaborative filtering, it is commonly recognized that its efficiency may be compromised by the overly simple selection of the interaction function that is, the inner product [23], [29]. It is well known that improving the communication functioning by including item and user bias factors can improve the predictive accuracy of MF, particularly for rating predictions based on clarified inputs.
This approach has certain drawbacks even though it offers an easy and fast method to generate recommendations for improvement. Traditional algorithmic factorization techniques are limited by their linearity, making it difficult to understand complex customer and product relationships [21]. Relying on dot-products for computations and sharing the same hidden space between goods and individuals makes it challenging to depict the relationship between new and current users without disrupting pre-existing relationships [20]. Extending the hidden space's dimensions can lead to longer training times and overfitting but can also make interactions more complex. The idea is to use Deep Neural Networks to get around these limitations by substituting non-linear functions for linear ones, improving the model's capacity to recognize intricate patterns.

2.2.1 Neural Collaborative Filtering

The fully connected layer above the input layer, which known as the embedding layer transforms sparse data into dense vectors. Within a hidden vector model, these dense vectors—also called item embeddings—encapsulate latent features of items (the same applies to users) [31]. The neural collaborative filtering layers are a multi-layer neural architecture that receives these items and user-embedded data and processes them to produce predicted outcomes scores [31]. Customizing each neural collaborative filtering layer to identify distinct fundamental trends

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in user-item interactions is possible. The size of the last invisible layer establishes the framework's overall capacity [31].

2.2.2 Generalized Matrix Factorization (GMF)

Because the item ID or user ID is encoded once at the input layer, the outcome's embedding of a vector can be thought of as the underlying vector for the item or the user. The element-wise products of the hiding transmission mechanisms for the item and the user are calculated in the first neural collaborative filtering layer. The result is then passed to the second layer [17]. The outcome from the layer immediately prior is processed using the outcome of this layer's weights in the next layer, and the resultant terms are subjected to an activation procedure [32].

2.2.3 Singular Value Decomposition (SVD)

Singular Value Decomposition (SVD) is a fundamental idea in linear programming that is applied to the factorization of real and complex matrices. The mathematical characterization of SVD and its connection to the mitigating factors fragmentation technique are covered in this section. The relationship between SVD and the concept of the eigenvalue fragmentation technique arises from a specific case in the latter, which we will discuss in more detail later [24]. It is important to note that this relationship only holds when matrix A is positively determined and symmetric (A ⇐⇒ A = A ∧ ∀e ∈ E, e > 0). then SVD and eigenvalue decomposition is shown in Equation (1).

$$\mathcal{A} = \mathcal{u}\mathbb{S}\mathcal{SUT} = \mathcal{CAe} - 1 \qquad (1)$$

with U = E and S = Λ.

In case that matrix A is a nonsquare matrix and its factorization can be written as A = U SV, then there are two other matrices M1 = A. A and M2 = A A and their factorization, which is of special interest:

$$\mathcal{M}1 = \text{ÅtÅ} \;\; \mathcal{M}1 = (\upsilon SVt)(USVt) \qquad (2)$$

$$M1 = (USVt)(USVt)M1 = VSt, ISVt \qquad (3)$$

where M1 is, U is user unitary and S is S-orthogonal. Finally, the V is unitary

It is important to note that SVD can be used to figure out the SVD factorizations for both matrix data (M1 and M2) by applying it to the original matrix A. This process also represents the eigenvalue decomposition of these matrices, where the eigenvalues Λ equal S^2, because they are naturally symmetric and positive definite. As an example, consider the following computation of the SVD decomposition for the M1 matrix (Equation 4).

$$M1 = \mathcal{ATA} = \mathcal{VS}2\mathcal{VT} \qquad (4)$$

With matrices A and A known, the S matrix has the eigenvalues of A on its diagonal. As a result, we can use Equation 5 to calculate matrix V. Now that matrix U has been computed, as indicated by Equation 4 we have all the parts needed to apply the SVD algorithm to matrix A. First, we take a matrix A with dimensions of n × m and apply SVD to it (this is our example's training data). This gives us the decomposition that is shown in Equation 5. The next section provides illustrations of the matrices in our particular example (Equation 6).

$$\mathcal{An}\;x = \mathcal{u}\mathfrak{R}n\;.\mathfrak{S}\mathfrak{n}\;x\;\mathfrak{M}.\;V\;m\;\mathcal{X}\;m$$

$$A\,n\,X\,m \begin{matrix} 4 & 1 & 1 & 4 \\ 1 & 4 & 1 & 0 \\ 2 & 1 & 4 & 5 \end{matrix} = \text{Un X n} \begin{bmatrix} 0 & 61 & 0.28 \\ 0.28 & 0.75 & 0.13 \\ 0.75 & 0.15 & 0.65 \end{bmatrix} \text{ X Sn X m} \begin{pmatrix} 8.88 & 0.00 & 0.00 \\ \vdots\, 0.00 & 3.02 & \vdots\, 0.00 \\ 0.00 & 0.00 & .\,2.55 \end{pmatrix} \qquad (5)$$

Whereas An X m (initial matrix A), while Un X m is left singular factors of A. Sn X Sn X m is a single factor value A.

$$\mathcal{An} \times i \begin{matrix} 2.65 & 0.52 & 1.23 \\ 0.65 & 2.6 & 3.25 \\ 2.17 & 2.37 & 2.86 \end{matrix} = Un \times c \begin{Vmatrix} 0.30 & 0.99 \\ 0.75 & 015 \end{Vmatrix} \qquad (6)$$

This technique, referred to as most-frequent item recommendation, involves sorting items by their frequency in the target user's neighbourhood and recommending the top N items. Alternatively, a method known as highest

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predicted rated item recommendation (HPR) utilizes predicted values to rank items, aiming to recommend those likely to receive higher user ratings based on mean absolute error (MAE) considerations. HPR performs well when combined with SVD but performs poorly with classic collaborative filtering algorithms. Another approach is the highest sum of rating item recommendation (HSR), where items in the neighbourhood have their positive ratings summed, and the top N items with the highest sum are recommended. HSR combines frequency, like MF, and actual ratings, favouring items that frequently occur in the neighbourhood and are highly rated.

3. Result and Discussion

It demonstrates that enhancing online platform categorization through the use of Neural Collaborative Filtering (NSF) and conjunction in the DSV examination will raise the precision of categorization if feature factors with attributes are attentively chosen. the (SDV) determined in NSF methods According to Figure 6, showed 90.35% and 93.81% for the SDV and NSA approaches, respectively.
After conducting a simulation process and examining the outcomes of various machine learning classifier algorithms, it was observed that logistic regression demonstrated strong accuracy when using the TF-IDF word embedding technique. Our results, which represent an average of five runs, are displayed in Figure 6. In this experiment, eight algorithms were employed, namely logistic regression.

Class No	Percentage %	Recall %	Features (SDV)
1	98.82	100.00	94.64
2	87.06	100.00	91.74
3	60.83	100.00	100.00
4	90.01	100.00	94.64
5	89.82	100.00	91.74
6	97.06	100.00	100.00
7	90.83	100.00	94.64
8	69.44	100.00	91.74
9	89.82	100.00	67.07
10	71.60	100.00	94.64
11	90.83	75.05	91.74
12	67.07	99.01	100.00
13		98.52	94.64
14	79.05	98.02	91.74
15	72.05	99.01	99.01
16	98.02	72.12	94.64
Average	90.35	93.81	100.00

Figure 6: Simulation for SDV and NSF methods

We haven chosen to implement Gaussian naïve Bayes (GNB), K-nearest neighbour (KNN), decision tree SVM, nearest centroid, Multinomial Naïve Bayes (MNB), and random forest in the experimental evaluation. The results of these evaluations are presented in Figure 6. As demonstrated in Table 1 and illustrated in Figure 4, the output of the tensor reduction algorithm in the provided example is intriguing because it unveils a new connection among these entities. This fresh association involves u1, i2, and t2, and it is prominently indicated in the last row (boldfaced) in Table 1 and visually depicted by a dashed arrow line When we face the task of recommending an item i2 to user u1 for tag t2, the original tensor A lacks a direct indication for this. However, a closer examination of Table 1 and Table 2 reveals that the element within ˆA related to (u1, i2, r2) holds a value of 0.44, while there are no other elements associating u1 with different tags for i2. Consequently, we suggest item i2 to user u1 who has used the tag t2. The resulting ˆA tensor for this specific example is depicted in Figure 7.

Table 1: Associating Derivation of User-Item

Arrow line	User	Item	Tag	Weight
1	U1	i1	T1	0.75
2	U2	i1	T1	1.18
3	U2	i1	T2	.0.73
4	U3	i3	T3	1
5	U1	i2	T2	0.44

Table 2: The reconstruction error (Mean and Standard Deviation)

Experiments	n	U= 10	I=10	T=20
	0.004	0.34$\pm$ 0.0005	0.45 $\pm$ 0.006	0.22 $\pm$ 0.006

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	0.002	0.07 ± 0.004	0.04 ± 0.007	0.0003
	0.005		0	0
	0.006		0.1	0
	0.001		0	1
	0.03		0	1

Subsequently, we conducted a more in-depth analysis, the training data, which accounts for 70% of the original dataset, was divided into different subsets (25%, 50%, 75%, and 100%). These distinct subsets were utilized to train the algorithms and then tested on the same test data, constituting 30% of the original dataset as shown the experiment in Figure 7.

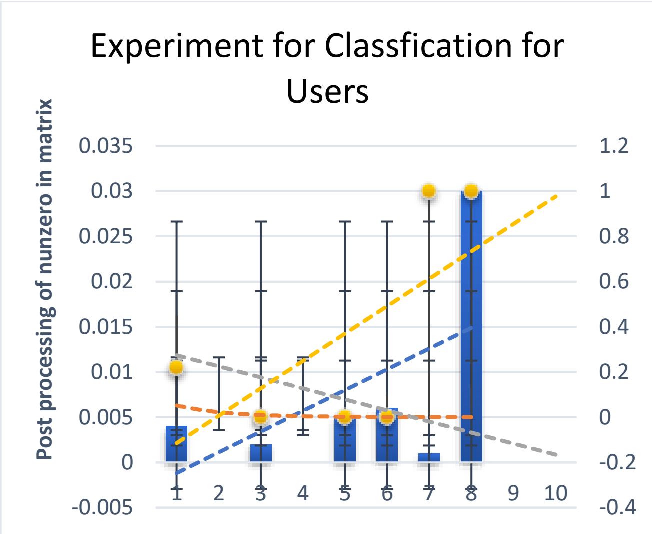

Figure 7: Post-processing step (An=20) with number of nonzero of Matrix

4. Conclusion

A vast amount of readily available online information, consumers often struggle to make well-informed decisions. Recommender systems have gained significant attention as a potential solution to the information overload challenge experienced by both knowledge workers and users. This increased interest has led to the development of various recommendation systems. It is important to note that no single approach universally excels consistently in all situations or for every individual, as numerous studies have confirmed. Machine learning and artificial intelligence-based recommender systems have emerged as a natural fit for addressing the issues faced by traditional recommendation systems. This paper discussed how techniques such as artificial neural networks, evolutionary algorithms and fuzzy logic can be harnessed to model efficient recommender systems. The intersection of machine learning and constraint solving is a dynamic field of study that calls for in-depth exploration. To encourage future works in this domain, we have deliberated on pertinent research subjects. These include algorithm selection, the development of evaluation metrics, considerate the learning configuration, integrating of machine learning technique into the testing of constraint-based systems, the concept of constraint-aware technique, and the provision of elaboration. In addition, we will perform more extensive experiments and compare it with other related works.

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