Events Recommendation Framework: A Ranking Algorithm Approach Based on KNN Concept

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***Abstract**: With VIT, Vellore's huge community of clubs and chapters, there are events being hosted almost every day ranging in various domains of interests. In such a vast community, students often find it difficult to decide what all events are of their interests. In this project, we plan to make an Event Recommendation Framework. Event recommendation is an essential means to enable people to find attractive upcoming events that suit their interests. We are keen to make a model that will recommend students of VIT the events they should attend based on their interests and past experiences. We formalize group recommendation as a ranking problem using the concept of KNN and propose an event recommendation framework based ranking technique. The existing algorithms for creating an Event Recommender are often seen to have use item- based approach for suggesting future events. Item-based methods might sometimes recommend obvious items, or items which are not novel from previous user experiences. Also, it has been observed that LSA has an overall negative effect on the item-based recommendations. We propose a model that would rectify the disadvantages that have often been seen while making a recommender system using algorithms like SVM Model, Linear Regression, etc.*

***Keywords:** Event Recommendation, Ranking Algorithm, KNN concept, Recommender Framework, Item-based, User-based*

1. Introduction

Data mining, also known as knowledge discovery in data (KDD), is the process of uncovering patterns and other valuable information from large data sets. This concept has improved organizational decision-making through insightful data analyses. The data mining process involves a number of steps from data collection to visualization to extract valuable information from large data sets. Data mining usually consists of four main steps: setting objectives, data gathering and preparation, applying data mining algorithms, and evaluating results.

By using the techniques of Data Mining, chiefly KNN concept, we have devised an Event Recommender Project for the students of VIT, Vellore that would suggest them various clubs and chapters' events that they could attend based on their interests and past attendance. We plan to make a ranking algorithm that revises the drawbacks faced by the classical SVM model by using the KNN Concept. We are constructing an Event Recommendation Model that works on a Learning Algorithm derived through KNN and would rectify the problems otherwise faced in the Event Recommenders.

Equations Support Vector Machine is a machine learning methodology which assists in classifying various features under appropriate labels. An SVM algorithm constructs a model that allots the data from the testing set into apposite labels using the training dataset. As there are only two required categories of output, it can also be termed as a Binary linear classifier [6, 11, 14, 19]. A hyperplane or set of hyperplanes are constructed in a high- or infinite dimensional space by Support Vector Machine, which can be used for classification, regression, or other tasks. Examples are plotted into space in such a method that the examples belonging to different classes are separated by an apparent gap. These separated spaces can be termed as hyperplanes. Each hyperplane contains examples of same category or labels.
But SVM is not suitable for classification of large data sets, because the training complexity of SVM is highly dependent on the size of data set. SVM does not perform very well when the data set has more noise. As the support vector classifier works by putting data points, above and below the classifying hyperplane there is no probabilistic explanation for the classification. Also, the standard

recommendation engine use item-based approach. Item- based methods might sometimes recommend obvious items, or items which are not novel from previous user experiences. Also, LSA has an overall negative effect on the item-based recommendations.

2. Literature Survey

• **Machine learning: Supervised methods, SVM and kNN Danilo Bzdok, Martin Krzywinski, Naomi Altman**

Danilo Bzdok, Martin Krzywinski, Naomi Altman. Machine learning: Supervised methods, SVM and kNN. Nature Methods, Nature Publishing Group, 2018, pp.1-6. ffhal- 01657491f

In contrast, kNN is a nonparametric concept because it avoids a priori assumptions about the shape of the class boundary and can thus adapt more closely to nonlinear boundaries as the amount of training data increases. kNN has higher variance than linear SVM but it has the advantage of producing classification fits that adapt to any boundary. Even though the true class boundary is unknown in most real-world applications, kNN has been shown to approach the theoretically optimal classification boundary as the training set increases to massive data.

• **Adaptive KNN based Recommender System through Mining of User Preferences**

Subramaniyaswamy, V., Logesh, R. Adaptive KNN based Recommender System through Mining of User Preferences. Wireless Pers Commun

In this paper, we present a new recommendation approach to address the problems such as scalability, sparsity, and cold-start in a collective way. The prediction models are induced by data mining algorithms by correlating the user preferences and features of items for user modeling. We have proposed a new variant of KNN algorithm as Adaptive KNN for the collaborative filtering based recommender system.

• **KNN-Based Clustering for Improving Social Recommender Systems**

Pan R., Dolog P., Xu G. (2013) KNN-Based Clustering for Improving Social Recommender Systems. In: Cao L., Zeng Y., Symeonidis A.L., Gorodetsky V.I., Yu P.S., Singh M.P. (eds) Agents and Data Mining Interaction. ADMI 2012

In this paper we propose a KNN based approach for ranking tag neighbors for tag selection. We study the approach in comparison to several baselines by using two datasets in different domains. We show, that in both cases the approach outperforms the compared approaches.

Hybrid Recommender Systems: Survey and Experiments

Burke, R. Hybrid Recommender Systems: Survey and Experiments. User Model User- Adap Inter 12

A variety of techniques have been proposed for performing recommendation, including content-based, collaborative, knowledge-based and other techniques. To improve performance, these methods have sometimes been combined in hybrid recommenders. This paper surveys the landscape of actual and possible hybrid recommenders, and introduces a novel hybrid, EntreeC, a system that combines knowledge-based recommendation and collaborative filtering to recommend events.

• **A Collaborative and Content Based Event Recommendation System Integrated with Data Collection Scrapers and Services at a Social Networking Site**

M. Kayaalp, T. Ozyer and S. T. Ozyer, "A Collaborative and Content Based Event Recommendation System Integrated with Data Collection Scrapers and Services at a Social Networking Site," 2009 International Conference on Advances in Social Network Analysis and Mining, 2009

There are many activities that people prefer/opt out attending and these events are announced for attracting people. An intelligent recommendation system can be used in a social networking site in order to recommend people according to content and collaboration assessment. This study is an effort to recommend events to users within a social networking site. It can be any networking environment. We have used social environment that has been designed as a facebook application.

• **A user-centric evaluation of recommender algorithms for an event recommendation system**
Proceedings of the RecSys 2011 : Workshop on Human Decision Making in Recommender Systems (Decisions@RecSys'11) and User-Centric Evaluation of Recommender Systems and Their Interfaces - 2 (UCERSTI 2) affiliated with the 5th ACM Conference on Recommender Systems (RecSys 2011).

• **Integrating Knowledge-based and Collaborative-filtering Recommender Systems**
Robin Burke, Recommender.com, Inc. and Information and Computer Science University of California, Irvine
Knowledge-based and collaborative-filtering recommender systems facilitate electronic commerce by helping users find appropriate products from large catalogs. This paper discusses the strengths of both techniques and introduces the possibility of a hybrid recommender system that combines the two approaches. An approach is suggested in which knowledge-based techniques are used to bootstrap the collaborative filtering engine while its data pool is small, and the collaborative filter is used as a postfilter for the knowledge-based recommender.

• **Personalized recommendation system K- neighbor optimization**
The User-based collaborative filtering algorithm is one of the most successful recommendation algorithms, and its biggest advantage is the characteristic property does not require analysis of the project, there is no special requirements on the recommendation system that can handle unstructured projects. Predicting movie ratings using KNN Moa Andersson and Lisa Tran The implementation of the user-based KNN was applied to different sets of ratings, both taken from the same source as this study. However, they also used a different approach to KNN than this study did. The results show that for the MAE the baseline method was 17.2% bigger than KNN for the 100K dataset and 21% bigger for the 1M dataset. For RMSE the baseline method was 10,7% bigger for the 100K dataset and 15% bigger for the 1M dataset. [9]

• Results from the KNN algorithm:
MAE: 0.8059 (on 100 000 ratings)
RMSE: 1.0157 (on 100 000 ratings)
MAE: 0.7707 (on 1 million ratings)
RMSE: 0.9677 (on 1 million ratings)

• Results from the baseline method:
MAE: 0.94439 (on 100 000 ratings)
RMSE: 1.1248 (on 100 000 ratings)
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MAE: 0.9337 (on 1 million ratings)
RMSE: 1.1169 (on 1 million ratings)

• **User-Based Collaborative Filtering for Tourist Attraction Recommendations**
Z. Jia, Y. Yang, W. Gao and X. Chen, "User-Based Collaborative Filtering for Tourist Attraction Recommendations," 2015 IEEE International Conference on Computational Intelligence & Communication Technology, 2015
A user-based tourist attraction recommender system is developed in this paper. The recommender system is constructed as an online application which is capable of generating a personalized list of preference attractions for the tourist. Modern technologies of classical recommender system, such as collaborative filtering are considered to be effectively adopted in the tourism domain. On the basis of collaborative filtering principle, the recommendation process of tourist attractions divided into three steps, representation of user (tourist) information, generation of neighbor users (tourists) and the generation of attraction recommendations.

• Simple social-aware user similarity for a KNN-based recommender system
Proceedings of the 2nd Challenge on Context-Aware Movie Recommendation October 2011
We ran some variations of a traditional user-based neighbourhood recommender system based on two simple ideas: (1) Force the inclusion of household members into the neighbourhood of the user and (2) increase the similarity of users that use the system if they use the system at similar time slots. The approaches are evaluated using the MAP, P@5, P@10 and AUC metrics. Results show that a small improvement is achieved on of the chosen metrics when comparing the social and time strategies to a traditional KNN approach.

• A Hybrid Recommender System Based on User-Recommender Interaction
Heng-Ru Zhang, Fan Min, Xu He, Yuan-Yuan Xu, "A Hybrid Recommender System Based on User-Recommender Interaction", Mathematical Problems in Engineering, vol. 2015, Article ID 145636, 11 pages, 2015.
Recommender systems are used to make recommendations about products, information, or services for users. Most existing recommender systems implicitly assume one particular type of user behaviour. However, they seldom consider user-recommender interactive scenarios in real-world environments. In this paper, we propose a hybrid recommender system based on user-recommender interaction and evaluate its performance with recall and diversity metrics. First, we define the user-recommender interaction. The recommender system accepts user request, recommends N items to the user, and records user choice. If some of these items favour the user, she will select one to browse and continue to use recommender system, until none of the recommended items favours her. Second, we propose a hybrid recommender system combining random and k-nearest neighbour algorithms. Third, we redefine the recall and diversity metrics based on the new scenario to evaluate the recommender system.

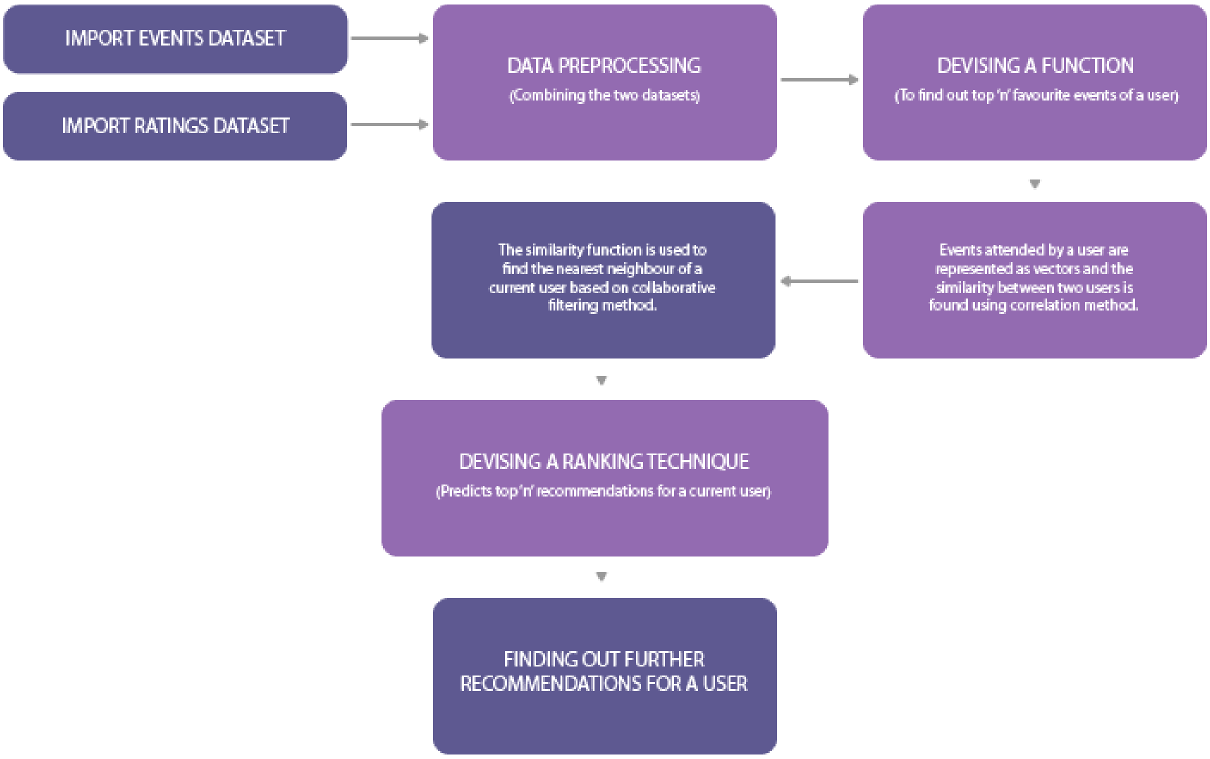
• Movie Recommender System Using K-Means Clustering AND K-Nearest Neighbour
R. Ahuja, A. Solanki and A. Nayyar, "Movie Recommender System Using K-Means Clustering AND K-Nearest Neighbour," 2019 9th International Conference on Cloud Computing, Data Science & Engineering (Confluence), 2019
In this research work a movie recommender system is built using the K-Means Clustering and K-Nearest Neighbour algorithms. The movie lens dataset is taken from Kaggle. The system is implemented in python programming language. The proposed work deals with the introduction of various concepts related to machine learning and recommendation system. In this work, various tools and techniques have been used to build recommender systems.
Various algorithms such as K-Means Clustering, KNN, Collaborative Filtering, Content- Based Filtering have been described in detail.

• An Approach for Recommender System by Combining Collaborative Filtering with User Demographics and Items Genres
Tiwari, Saurabh Kumar, and Shailendra Kumar Shrivastava. "An approach for recommender system by combining collaborative filtering with user demographics and items genres." International Journal of Computer Applications 128.13 (2015)
Collaborative filtering techniques play a vital role in designing the recommendation systems. The collaborative filtering technique-based recommender system may suffer with cold start problem i.e., new user problem and new item problem and scalability issues.

• Semantic and Rule Based Event-driven Services-Oriented Agricultural Recommendation System
Z. Laliwala, V. Sorathia and S. Chaudhary, "Semantic and Rule Based Event-driven Services-Oriented Agricultural Recommendation System," 26th IEEE International Conference on Distributed Computing Systems Workshops (ICDCSW'06), 2006
In this paper, we propose a semantic and rule-based event-driven Services- Oriented Architecture to facilitate the seamless and meaningful information integration and interoperation of distributed and

heterogeneous web hosted AIS services to deliver personalized recommendation driven by real-time events and user preferences.

3. Flowchart



4. Dataset Description

The dataset used for this project has been trained oneself by taking into consideration variousevents that have been attended by students of VIT. It contains the Event_ID, Event Name andthe various domains to which an event belongs. The dataset contains more than 18000 ratingsacross 2000 events ranging over 119 users. We are going to build a recommendation engine which will suggest events for a user which he hasn't attended yet based on the events which he has already rated.

5. Proposed Model

We propose a model that would rectify the disadvantages that have often been seen while making a recommender system using algorithms like SVM Model, Linear Regression, etc. We plan to make a ranking algorithm that revises the drawbacks faced by the classical SVM model by using the KNN Concept. We are constructing an Event Recommendation Model that works on a Learning Algorithm derived through KNN.

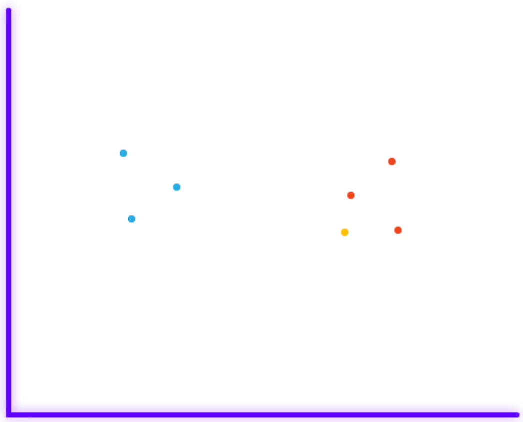
Our Proposed ranking Algorithm uses the KNN concept because our algorithm stores the training dataset and learns from it only at the time of making real time predictions. This makes the KNN – based Ranking Algorithm much faster than the algorithms that required prior training (e.g. SVM, Linear Regression).

If training data is much larger than number of features (m>>n), then KNN method is better to use than the SVM Algorithm. KNN can find very complex patterns.

Also, our proposed ranking algorithm is user-based instead of the classical item-based collaborative filtering because performance of user-based recommenders keeps improving as neighbourhood sizes are increased. Latent Semantic Analysis (LSA) has a beneficial effect on user-based recommendations. There's greater diversity in user-based recommenders and they are context-independent as well as easy to implement.

Principle Used:
K-Nearest Neighbour algorithm, or better known as KNN algorithm assumes that every data point falling in near to each other is falling in the same class. In other words, it classifies a new data point based on similarity.
Consider the following figure. Let us say we have plotted data points from our training set on a two-dimensional feature space. As shown, we have a total of 6 data points (3 red and 3 blue). Red data points belong to 'class1' and blue data points belong to 'class2'. And yellow data point in a feature space represents the new point for which a class is to be predicted.
Obviously, we say it belongs to 'class1' (red points), since its nearest neighbours belong to that class

Yes, this is the principle behind K Nearest Neighbours. Here, nearest neighbours are those data points that have minimum distance in feature space from our new data point. And K is the number of such data points we consider in our implementation of the algorithm. Therefore, distance metric and K value are two important considerations while using the KNN algorithm. For predicting class/ continuous value for a new data point, it considers all the data points in the training dataset. Finds new data point's 'K' Nearest Neighbours (Data points) from feature space and their class labels or continuous values.
For classification, a class label assigned to the majority of K Nearest Neighbours from the training dataset is considered as a predicted class for the new data point.



Data Preparations Required:
Data Scaling: To locate the data point in multidimensional feature space, it would be helpful if all features are on the same scale. Hence normalization or standardization of data will help.

Dimensionality Reduction: KNN may not work well if there are too many features. Hence dimensionality reduction techniques like feature selection, principal component analysis can be implemented.

Missing value treatment: If out of M features one feature data is missing for a particular example in the training set, then we cannot locate or calculate distance from that point. Therefore, deleting that row or imputation is required.

6. Empirical Analysis

The dataset used for this project has been trained oneself by taking into consideration various events that have been attended by students of VIT. It contains the Event_ID, Event Name andthe various domains to which an event belongs. The dataset contains more than 18000 ratingsacross 2000 events ranging over 119 users. We are going to build a recommendation engine which will suggest events for a user which he hasn't attended yet based on the events which he has already rated.

As shown in Table 1, there are three users rating on five events in the toy example. The rating range is from 1 to 5, where 1 indicates that the user does not like the event at all, and 5 shows that the user enjoyed it; while the question mark means that the event hasn't been rated by the user.

Name	Avengers	Star wars	Thor	Spider-man	Iron Man
Alex	4	2	?	5	4
Bob	5	3	4	?	3
Tom	3	?	4	4	3

Table 1: User-Event rating example

The objective of the recommender systems is to recommend top-N events to a specific user.

User-Based Collaborative Filtering

Step 1: Calculate the similarity between Alex and all other users

The calculation for the similarity between Alex and Bob can be derived from Formula 1 by putting the corresponding values into the formula as follows: sim (Alex, Bob) = (4 * 5 + 2 * 3 + 4 * 3) / [sqrt(4^2+ 2^2+ 4^2) * sqrt(5^2 + 3^2 + 3^2)] = 0.97. The similarity value between Alex and Tom can be obtained by following the same way, which is 1.

$$sim(x,y) = \cos(\vec{x},\vec{y}) = \frac{\vec{x}\cdot\vec{y}}{||\vec{x}||_2 \times ||\vec{y}||_2} = \frac{\sum_{s\in S_{xy}} r_{x,s} r_{y,s}}{\sqrt{\sum_{s\in S_{xy}} r_{x,s}^2}\sqrt{\sum_{s\in S_{xy}} r_{y,s}^2}}, \tag{13}$$

Formula 1: Calculate the similarity between user x and y based the ratings of all events by user x and y

Step 2: Predict the ratings of events that are rated by Alex

In this example, Formula 2-(b) is used as the prediction function. First of all, k value needs to be calculated by injecting the similarity values calculated at Step 1, which is k = 1/(0.97+1) = 0.51. Now, the event Thor unrated by Alex can be worked out by the following calculation: R(Alex, Thor) = k * [sim(Alex, Bob) * R(Bob, Thor)+ sim(Alex, Tom) * R(Tom, Thor)]= 0.51 * (0.97 * 4 + 1 * 4) = 4.02. The final table with the ratings on all events from Alex is shown in Table 2.

$$\begin{aligned}
&\text{(a) } r_{c,s} = \frac{1}{N}\sum_{c'\in\hat{C}} r_{c',s},\\
&\text{(b) } r_{c,s} = k\sum_{c'\in\hat{C}} sim(c,c') \times r_{c',s}, \qquad\qquad (10)\\
&\text{(c) } r_{c,s} = \bar{r}_c + k\sum_{c'\in\hat{C}} sim(c,c') \times (r_{c',s} - \bar{r}_{c'}),
\end{aligned}$$

where multiplier k serves as a normalizing factor and is usually selected as $k = 1/\sum_{c'\in\hat{C}} |sim(c,c')|$, and where the average rating of user c, $\bar{r}_c$, in (10c) is defined as[1]

Formula 2: Rating prediction formula for UBCF

Name	Avengers	Star wars	Thor	Spider-man	Iron Man
Alex	4	2	*4.02*	5	4

Table 2: Alex's ratings after the prediction

<u>Step 3</u>: Select top-2 rated events
Since the ratings of events that are not rated by Alex have been predicted, it is straightforward to find the top-2 events, which are Spider-man and Thor.

Item-Based Collaborative Filtering

<u>Step 1</u>: transpose the user-item matrix to the item-user matrix
As the item similarity is required by IBCF, the item-user matrix shown in Table 3, transposed from the corresponding user-item matrix, makes it more clear by viewing each row as an item vector during the similarity calculation.

	Alex	Bob	Tom
Avengers	4	5	3
Star wars	2	3	?
Thor	?	4	4
Spider-man	5	?	4
Iron Man	4	3	3

Table 3: Transposed item-user table from user-item table

<u>Step 2</u>: Calculate the similarity between any two items and fill up the item-item similarity matrix

First of all, an example of calculating the item similarity between Avenger and Star wars is demonstrated here. According to Formula 3, the specific calculation of the similarity between Avenger and Star wars is as follows: sim(Avengers, Star wars) = (4 * 2 + 5 * 3) / [sqrt(4^2 + 5^2) * sqrt(2^2 + 3^2)] = 0.99624059. By following the similar way, the item-item similarity matrix can be filled as Table 4, where 0 means the similarity between the two events cannot be calculated due to data sparsity.

$$sim(i,j) = \cos(\vec{i},\vec{j}) = \frac{\vec{i}\cdot\vec{j}}{||\vec{i}||_2 * ||\vec{j}||_2}$$

Formula 3: Cosine similarity used for calculating item similarity

	Avengers	Star wars	Thor	Spider-man	Iron Man
Avengers					
Star wars	0.99624059				
Thor	0.9701425	0			
Spider-man	0.99951208	0	0		
Iron Man	0.9701425	0.94299033	1	0.99951208	

Table 4: Item-item similarity matrix

<u>Step 3</u>: Predict the ratings of events that are rated by Alex

After successfully building the item-item similarity matrix, the calculation of the rating of events that are not rated by Alex can be done by injecting the values to Formula 4: R(Alex, Thor) = (sim(Thor,Avengers) * R(Alex,Avengers) + sim(Thor, Iron man) * R(Alex, Iron man)) / (sim(Thor, Avengers) + sim(Thor, Iron man)) = 4.

$$P_{u,i} = \frac{\sum_{\text{all similar items, N}} (s_{i,N} * R_{u,N})}{\sum_{\text{all similar items, N}} (|s_{i,N}|)}$$

Formula 4: Prediction formula for IBCF

<u>Step 4:</u> Select top-2 rated events for Alex

The final predicted rating of the event Thor rated by Alex is listed in Table 5 along with the other ratings made by Alex. It is obvious that three events tie for second place, so the top-2 rated events by Alex is comprised of Spider-man and one of the three tied events — Avengers, Thor and Iron man.

Name	Avengers	Star wars	Thor	Spider-man	Iron Man
Alex	4	2	*4*	5	4

Table 5: Alex's ratings after predictions by IBCF

Computational Cost Comparison

The computational cost for UBCF in the worst case is O(NM) because it requires examining N customers and up to M items for each customer; However, due to the sparsity of the user- item matrix, the actual computational cost would be close to O(N + M) because for most customers, they only rated a small number of events which results in a computational cost of O(N), and for a handful customers who rated a significant amount of events, the computational cost is close to O(M).

In terms of the computational cost for IBCF, there are two parts — building the item-item similarity matrix and predicting the ratings. For building the item-item matrix, $O(N^2M)$ is required in the worst Case, and O(NM) is the computational cost in reality due to the sparsity in the user-item matrix. In regard to the prediction, the computational cost only depends on the events that the user has rated, which is usually very little.

By comparing the computational cost of these two methods, it seems that IBCF requires more expensive computational cost, but building the item-item similarity matrix are calculated offline and the online prediction needs very little computational cost.

7. Results

The project comprised of a self- made dataset by taking into consideration variousevents that have been attended by students of VIT. The dataset contains more than 18000 ratings across 2000 events ranging over 119 users. Through the analysis, we have revised the drawbacks faced by the classical SVM model. Our Proposed ranking Algorithm uses the KNN concept because our algorithm stores the training dataset and learns from it only at the time of making real time predictions. This makes the KNN – based Ranking Algorithm much faster than the algorithms that required prior training (e.g. SVM, Linear Regression). Moreover, in this project, the ranking algorithm is user-based instead of the classical item-based collaborative filtering because performance of user-based recommenders keeps improving as neighbourhood sizes are increased. The main steps involved in the project have been described through proposed model and empirical analysis.

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