An Automated Recommender System for Educational Institute in India

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Abstract

This study aims to suggest a recommender System for undergraduate students who desire to seek admission into engineering courses in different Indian Institute of Technology (IITs) in India. Initially, the focus is to purpose a recommender system for admission into the top 10 IIT on a pilot basis in four common branches such as Electrical Engineering, Computer Science and Engineering, Mechanical Engineering, Civil Engineering. Data were collected from different authentic sources from 2016 to 2018. A model was built to predict the ranks for 2019 for each branch of every IITs. This paper illustrates prediction using Time Series Forecasting and recommendation algorithm using classification techniques. A comparative study of Random Forest Classification and K-Nearest Neighbor classification has been done. Finally, the recommendation algorithm shown reliable results with high accuracy in prediction model. It can be diversify and implement other streams as part of future work.

Keywords: Recommender system, Random Forest Classification, K-Nearest Neighbor (KNN).

1. Introduction

As RS has emerged as a demanding tool a short time ago, it is extremely important to have a proper understanding of it. One must focus on few important aspects of recommender systems such as “building a recommender system”, different techniques to build or develop the recommender system such as DM, collaborative filtering, Content-Base filtering and Context-Aware methods. Different aspects that affect the RSD are the users, domains, and interfaces.

One more important aspect is to safeguard the privacy of the user during this decision making process. The recommender system is used in a wide variety of fields such as music, movies, education, social networks, mobile computing, healthcare, insurance, e-commerce applications and many more.

In the Internet era, the biggest problem for a person who wants to buy something online is not only how to get enough information to make a decision, but also how to make a right decision with that enormous information.

Recommender systems give a piece of guidance about the information, products or services that the user might be fascinated with. Those are quick-witted applications to serve the user in a decision-making process where they wish to pick one item between a potentially enormous set of substitute products and they are presumably between the most eminent applications having a notable smack on
the performance of e-commerce web sites and the sectors in prevalent.

In this paper the process of developing a recommender system for EI is being analyzed, the application domain of the Education Institutions is considered, algorithms are developed and architectures about recommender systems have been designed.

1.1. Recommender System

RS is a subspace of an information retrieval system that forecasts the "liking" or “rating” that a user would provide to a certain item. We can say it is a software tool/technique which suggests different products, services and information (which can be interpreted as items in short) based on the user’s interest to help the user for successful decision making. User preferences and constraints are two keywords that play a vital role in a recommender system. A recommender system is an independent area of research in the Mid-1990s after databases and search engines. Research regarding recommender systems has increased tremendously with the availability of information in the digital world. With the availability of so many choices for the user, the user is confused while choosing the right option or taking the right decision. The recommender system has evolved as a blend to the information overburden problem (IOP) helping the user in the right decision making. The recommender system deals with PR and NPR.

1.2. Approaches of RS

The RS can be classified based on the below techniques adopted for a recommendation. Figure 1 depicts the different types of recommendation systems. At a high level, the recommender systems can be classified as two types such as personalized and non-personalized.

The personalized recommender systems are again classified into various categories such as techniques of collaborative filtering (item and user-based), techniques of content-based filtering, Demographics techniques of filtering, KB and HRS. The Collaborative filtering technique is implemented through two mechanisms. One is UB and another is the IB recommendation. All the techniques are applied as per the need and based on the type of problems at hand.

1.3. Predictive Analysis

PA deals with the procedure of taking out useful information from the existing knowledge of data and predicts the future value by analyzing the previous value and trend. It may not result in actual value but can forecast what may happen in the future preserving the authenticity of the data. An analysis is done on the existing data especially with a large number of data and then optimization is done on the data. After that different model is applied a
nd implemented to forecast future data. Predictive analytics is defined as the branch of analytics which deals with the prediction of unknown future events. Figure 2. represents the high-level view of how predictive analytics works.

The basic functionality of predictive analytics is that it takes the historical data as input, uses the predictive algorithms and applies the models to train it. It tests the model with the new data and predicts future outcomes. Figure 3. highlights the trend of the plot of value and difficulty in descriptive, predictive and prescriptive analytics.

**Figure 2. Predictive Analytics**

![Predictive Analytics](image)

**Figure 3. Predictive Analytics value-difficulty plot**

### 1.4. Evaluation metrics for RS

The standards or the grades of the RS are classified into two groups.

1. Metrics for statistical accuracy
2. Metrics for decision support accuracy

The first one evaluates the accuracy of the RS filtering technique by comparing the forecast ratings in a straight line with the real rating. It is calculated by the formula:

\[
MAE = \frac{1}{N} \sum_{u,i} |P_{u,i} - R_{u,i}|
\]

Where \( N \) = Total rating on the group of items.
\( P_{u,i} \) = Predicted rating for a user on an item.
\( R_{u,i} \) = Real rating value of the user for an item.

RMSE is a measure of RS and it is calculated by the formula:

\[
RMSE = \sqrt{\frac{1}{N} \sum_{u,i} (P_{u,i} - R_{u,i})^2}
\]  

(2)

The Precision and Recall is the decision support accuracy matrix which is calculated by,

\[
\text{Precision} = \frac{\text{true positives}}{\text{true positives} + \text{false negatives}}
\]

(3)

\[
\text{Precision} = \frac{\text{true positives}}{\text{true positives} + \text{false positives}}
\]

(4)

In section 2 earlier literature and existing research have been highlighted and discussed as part of the literature survey. Section 3 defines the proposed methodology to achieve the recommending the educational institutes for the students based on the rank. It also describes the tools and techniques used to carry out this piece of work. Section 3 defines the problem statement and objective of the paper. Section 4 explains the stepwise procedure and implementation part. It describes the lab recommendation and software implementation of the proposed system. Section 5 explains the outcome of the implementation, analysis of the result, comparison of the result and accuracy of the result. Section 6 highlights the inference or conclusion of the present work.

### 2. Related Work

Though the work is done in this area is not very huge about the recommendation for educational institutes in India, still significant amount of research has been done in the field of recommendation techniques, course recommendation, student’s academic performance, an online recommendation for shopping, embedding emotional context in the recommendation and many more. F. Ricci, L. Rokach, and B Shapira-2007 [1] described the recommender system, its role in recent times, and various aspects of the recommendation system. It also highlights the various domains of recommendation systems, evaluation of its quality and applications of a recommender system.

Ken Goldberg and et al. Aug 2000 [2] proposed an innovation- the recommender system not only uses user's liking and attentiveness but also the user's emotional intellectual aspects.

Fuzheng Zhang and et al. 2016 [3] explored how to grip the assorted information based on knowledge to enhance the rank of the systems of recommendation. First, by
utilizing the knowledge base recommendation, they design 3 constituents to extract item semantic depictions from the textual content, constitutional content and optical content. It shows the joint learning of the latent constituents in collaborative filtering and also items semantic constituents from the filtering of knowledge base methods.

Ray and Sharma [4] suggested an RS method that assembles the approaches of collaborative filtering for the generation of courses that are elective as a recommendation. They assemble the utilization of both user and item base RS filtering techniques, which is applied to real-time data for the forecast of courses (elective). Outcomes are built on MAE, calculated for each elective course.

Arazy, Shapira [5] suggested an RS for course enrolment that is done online, which uses ancient data to manifest the factors which impact student’s choice of course selection of elective courses. They use the techniques of collaborative filtering and based on precision and recall performed the designed RS.

Osmanbegovic and Suljic [6] dispensed the techniques for data mining for modeling predictions of students based on their performance. Several data mining techniques were compared for the design of the prediction model, which in return calculate the student victory. By performing the survey during the semester the data was collected. The rate of success of students was calculated based on grades acquired by students in their end examinations.

William W. Guo [7] dispensed the neural network method by taking the use of methods of statistics. In this, the setting up of dynamic models techniques are incorporated which lend a hand in forecasting satisfaction of student course. Besides the entire model applied, MLP outperforms in the generation of near practical results.

Thilina Ranbaduge [8] proposed a model rely on the techniques of DM. The main aim of this article is to make a survey in the curriculum for the generation of approaches that can make predictions based on each student’s past performance in their academic curriculum. Al-Badarenah and Alsakran [9] presented a collaborative filtering RS using the technique of clustering for the generation of elective courses by making use of rules of association to suggest courses based on liking parameters. Cakmak [10] designed an RS technique that is used for the estimation of student course grades. They also increase the quality of result generation by implementing automated outlier removal.

Tran et al. [11] presented a model in educational scenarios on the calculation of student performance. They use the DM techniques and different regressions for the implementation of the suggested algorithm. They also implemented a combination of all the suggested techniques and based on the accuracy of the model they calculated the results.

Mueen et al. [12] hand over analysis for DM application methods for the prediction of the performances of the students. For this, they use the real-time data gathered from an undergraduate student.

Bienkowski et al. [13] dispensed amplified learning and teaching through educational DM along with learning analytics mock-up to predict the performance of the student based on different influencing factors to hold-up the online learning system.

Upendran and Chatterjee [14] designed a course RS that undertook students as the basis of their ancient performances and ability of learning. By using the data of the former student as the input they constructed the model. The main subsequent thing for the technique here is that if a student with certain expertise is capable of outright the course successfully then a new student with some expertise will also be capable of outright the course.

Castro and Vellido [15] come up with efficient and effective particulars about contemporary research and applications of DM in e-learning such as to know about the lack of success of the students, students’ performances based on classifications, e-learning counsel, clustering of students, etc.

Affendy et al. [16] put forward a model that relies on DM methods. Based on constituents that can affect the student’s overall grades, they use predictions for calculating their academic performance. The key purpose of this article is to provide a position to the affecting constituents to alert the students so that they are capable to keep up their grades.

Bydžovská [17] based on former achievements of similar students, presented a prediction model using collaborative filtering, regression, and classification techniques for forecasting concluding grades of students.

Ramesh et al. [18] presented statistical and DM methods. The main aim of this paper is to generate predictions of the student based on their performance in the academic curriculum. The influencing constituents that can affect student performance and their concluding grades also considered here.

Gaddam, poha, and Balagani [19] come up with a model for identifying anomalies by combining the k-mean clustering and ID3 tree classification. They also compare the performance of classification with the individual ID3 decision tree and K-mean clustering.

Mishra et al. [20] presented an analysis of methods and trends followed in PA in the domain of knowledge discovery. They made use of data of business intelligence for modeling and forecasting.

Felfernig et. al. [21] suggested the fundamental techniques in RS.

Zaiane [22] proposed the systems of web mining which described on-line learning exercises in course web pages, because of learners' history to intensify the course route and assist the process of online learning. By using association rule mining, they designed an RS agent.

3. Problem Statement

Despite many types of research around the field of academics and recommender systems, the research around the recommendation to choose the institutes in higher
education in India is very limited. Because of this, students who are seeking admissions into reputed institutions in India are still confused about making a decision on which institute to choose. With the progressing trend of fascination towards an engineering career, students and parents are having a keen desire to choose the IIT based on rank. Still, they are not very sure to choose the college and not getting confidence while seeking admissions into different colleges. This research fills the above gap and assists the students and guardians in choosing the college based on their ranks in JEE advance.

Here data (closing ranks of JEE advance) from different authentic sources are collected for the past three years such as 2016-2018. A model was built to predict the ranks for 2019 for each branch of every IIT. This paper illustrates prediction using Time Series Forecasting and recommendation using classification techniques. A comparative study of Random Forest Classification and KNN classification has been done. Finally, a recommendation is done based on the accuracy level.

4. Methodology

4.1 Data Set Description

As part of data collection, data for the past three years (2018, 2017 and 2016) have been collected for the top ten IITs from various authentic sources. Appendix 1 reveals the collected data where each data set contains the year, college name, branch, and rank for different IITs.

4.2 Feature Selection

College Name, Branch, Rank and Year are the different attributes or features selected for this work.

4.3 Data Pre-processing

Data from different sources are collected for the years 2016, 2017, and 2018. All the closing ranks for IIT JEE advances are collected for all the IITs in India. After analyzing the data, the top ten IITs are filtered based on the closing ranks of their different branches. Finally, four branches are filtered out to be the common branches (CSE, Electrical, Mechanical, and Civil). Data optimization is done by cleaning data set with missing value rows.

4.4 Methodology for Prediction

There exist many methodologies and statistical approaches, which can be applied to predict future rank based on historical data. The following approach is explored and analyzed to fit into our problem so that a clear idea of the methodology along with the efficiency and limitations were captured.

Time Series Forecasting

A time series is taken at successively uniformly distributed spaced tips in time. Hence it is an order of discrete-time data. The four main components of time series data are (1) Seasonal disparities that redo over a particular period such as day, week, month and season (2) current disparities that move up or down in a reasonably foreseeable pattern, (3) Cyclical disparities that coincide with business or economic boom-bust cycle and (4) Irregularity.

This method is the chosen method for our problem to predict the future year rank based on the past three years of historical data. As there is only one independent variable, time series forecasting is giving the best result while predicting future data. Figure 4. below shows a simple time series plot in R for ranks in different years (Table 2).

| S. No | CSE-IIT Bombay | Rank |
|-------|---------------|------|
| 1     | 2016          | 60   |
| 2     | 2017          | 62   |
| 3     | 2018          | 59   |

Figure 4. Time series plot of data set

ARIMA Model

ARIMA is a well-liked and ductile category of a forecasting model that employs ancient information to construct forecasting. This type of erection is a basic forecasting proficiency that can be used as a footing for many complex constructions.

ARIMA is described by the three parameters order: (p- order of the AR term, d- order of the MA term, and q- To make the time series stationary the no. of differencing needed). The auto regressive (AR (p)) parameter is mentioned to the use of ancient values in the regression equation for the series Y. Auto-regressive part p defines the number of lags utilized in the model and y_t depends


only on its lags i.e. \( y_t \) - function of the lags of \( y_t \). As an example, AR (2) or ARIMA (2, 0, 0), is represented by

\[
y_t = a_1 y_{t-1} + a_2 y_{t-2} + \epsilon_t
\]

where \( y_{t-1} \) is the lag 1 of the series, \( a_1 \) is the coefficient of lag 1, \( y_{t-2} \) is the lag 2 of the series, \( a_2 \) is the coefficient of lag 2 and \( \epsilon_t \) is the error term that the model estimates.

The \( d \) is the degree of differencing in the integrated component \((I(d))\). Differencing a series includes simply the \( d \) times of subtracting its current and previous values. When the stationary thought is not encountered, differencing is used to stabilize the series.

The moving average (MA (q)) part contains the error of the mock-up as a coalition of previous error phrase (\( \epsilon_t \)). The number of terms to be included in the model is determined by the order q., Autoregressive, differencing and moving average constituents are incorporated in a non-seasonal ARIMA model.

Here the model is narrated by two sets of order parameters: (p, d, and q) and parameters relating the seasonal constituents of m periods. These models straightforwardly based on ancient values, and therefore work best on series that are long and stable. ARIMA normally approximates ancient patterns and hence does not focus to explain the structure of the elementary mechanism of data.

If someone wants to choose the model of his/her choice, he/she can apply the arima () function in R. There is another function arima () in R which does not permit for the constant \( c \) unless \( d=0 \) and it does not return everything required for other functions in the forecast package to function properly. At last, this does not allow the estimated model to be applied to the new data that is useful for checking forecast accuracy. The exceptional cases of ARIMA model are listed in Table 3.

### Table 3. Exceptional cases of ARIMA

| Model               | ARIMA (p, d, q) |
|---------------------|-----------------|
| White noise         | (0, 0, 0)       |
| Random walk         | with no constant : (0, 1, 0) |
| Random walk with drift | with a constant : (0, 1, 0) |
| Auto regression     | (p, 0, 0)       |
| Moving average      | (0, 0, q)       |

**Modelling Procedure of ARIMA**

The procedure for putting an ARIMA model to a set of non-seasonal time series data is listed below.

**Step1:** First is to intrigue the data and recognize any unusual inspections/observations.

**Step2:** Alter the data using the Box-Cox transformation if required to stabilize the variance.

**Step3:** In case if the data are immotile, take the differences of the data until the data are stationary first.

**Step4:** Inspect the ACF/PACF that is an ARIMA (p, d, 0) or ARIMA (0, d, q) model relevant?

**Step5:** Apply the model

**Step6:** Examine the residuals from the model by plotting the ACF of the residuals. If they do not match with white noise, try another model.

**Step7:** Once the residuals match with white noise calculate the forecasts.

The Hyndman-Khandakar procedure only takes care of steps 3 to 5. Hence even if we use this procedure, we will need to look after the supplementary steps our self.

![Figure 5. Modelling Procedure for ARIMA](image)

**4.5 Rank Prediction using Time Series Forecasting**

The approach for predicting rank was chosen to be the “Time Series Forecasting” using ARIMA model.

**Proposed Algorithm**

**Input:** Optimized data set for each branch of each IIT having year and rank

**Output:** Predicted rank
Procedure:

Step 1: The optimized data set was prepared for each IIT separately as shown above (Table 2. Input Data Set) was employed as the input to the algorithm.

Step 2: Reading the data set in CSV format.

Step 3: Applying time series to the data with frequency 1 starting with the year 2016.

Step 4: Plotting the data set as per time series.

Step 5: Applying ARIMA model on the time series data obtained in step 3 and storing the result in another variable.

Step 6: Call forecast method with the result obtained in step 5 as an argument. It will return the forecasted data for the subsequent years.

Input Data Set

Table 4. Input Data Set for CSE branch of IIT Bombay

| CSE-IIT Bombay | Rank |
|---------------|------|
| 60            | 2016 |
| 62            | 2017 |
| 59            | 2018 |

Output of Time Series Forecasting using ARIMA

| Points | Forecasts | Lo 80 | Hi 80 | Lo 95 | Hi 95 |
|--------|-----------|-------|-------|-------|-------|
| 2019   | 62.32921  | 61.2342763.42415 | 60.65465 | 64.00377 |
| 2020   | 59.24058  | 57.7470060.73415 | 56.95635 | 61.52480 |

Table 5 shows the predicted rank for 2019 for CSE branch of IIT Bombay.

Table 5. Predicted rank for CSE branch of IIT Bombay (Output Data)

| CSE-IIT Bombay | Rank |
|---------------|------|
| 2016          | 60   |
| 2017          | 62   |
| 2018          | 59   |
| 2019          | 62   |

The above procedure was repeated individually for each branch of each IIT and the predicted ranks were calculated for 2019 using ARIMA forecasting. Finally, outputs obtained from each dataset are put in a table called “predicted rank table for 2019” which is shown below. Table 6 below is the “predicted rank table for 2019”.

Table 6. Predicted rank

| Name of the | CSE   | Electrical | Mechanical | Civil |
|-------------|-------|------------|------------|-------|
| IIT Bombay  | 62    | 281        | 827        | 2566  |
| IIT Delhi   | 104   | 625        | 1077       | 3178  |
| IIT Madras  | 202   | 651        | 1270       | 3984  |
| IIT Kanpur  | 213   | 818        | 1672       | 3845  |
| IIT Kharagpur| 278   | 1341       | 1802       | 4164  |
| IIT Roorkee | 474   | 1933       | 2564       | 4985  |
| IIT Guwahati| 630   | 2146       | 2972       | 5934  |
| IIT Hyderabad| 913  | 2377       | 3086       | 6138  |
| IIT Indore  | 1613  | 3983       | 5085       | 7432  |
| IIT         | 3262  | 5268       | 5446       | 8355  |
| IIT Patna   | 3672  | 5836       | 7636       | 9031  |

Figure 6 shows the graphical representation of Table 6 predicted rank for the year 2019 for each branch of each IIT.

Looking at the plot, a student can get an idea of the college and branch he may get admitted to as per his current rank. This prediction may help the student to get an idea at a high level.

4.6 Random Forest Classification

A forest can be made from constructing numerous decision trees. A random forest works in the following path: First, random samples are created by using the Bagging (Bootstrap Aggregating) algorithm. A new data set D2 is created from the given D1 data set having n rows and p columns by random sampling of n cases with replacement from the original data. The one-third of the rows from D1 is left out which is known as Out of Bag sample. Then, the model train on D2. Out of bag sample is used to determine the unbiased estimate of the error.
The $P \ll p$ columns are picked at each node in the data set out of $p$ columns. Randomly the $P$ columns are chosen. For the regression tree, the by default choice of $P$ is $p/3$ and $P$ is $\sqrt{p}$ for classification tree. Unlike a tree, in a random forest, no pruning takes place. In decision trees, to circumvent over fitting one method is there known as pruning. Selecting a sub tree that leads to the low test error rate is termed as Pruning. To obtain the test error rate of a sub tree the cross-validation is used. Various trees are grown and the final estimation is procured by voting or averaging. On a different sample of actual data each tree is grown. The random forest has the quality to internally enumerate OOB error; cross validation doesn't build many perceptions in a random forest. It gives a more definitive average output. For this, the random forest is robust to correlated predictors.

4.7 K- Nearest Neighbour Classification

KNN can be used in predictive problems such as regression and classification. This method is mainly used in the industry for classification problems. For the evaluation of any technique, we must focus on 3 features:
1. Interpret output easily
2. Time of calculation
3. Predictive Power

KNN algorithm fairs across all parameters of considerations. It is generally used for its ease of interpretation and minimum calculation time.

4.8 Accuracy, Recall and Precision

Accuracy is the ratio of the correctly ranked Indian institute of technology where a student can get admission from the whole pool of Indian institute of technologies. It predicts how many IITs we correctly ranked out of all the IITs. Precision is a measure of exactness that determines the fraction of the relevant rank of IITs retrieved out of all IITs ranked, for example, the proportion of recommended IITs that are good. The recall is a measure of completeness, determines the fraction of rank of IITs retrieved out of all relevant IITs.

5. Implementation of the proposed algorithm and result

5.1 Proposed Model

To implement the proposed system, at first, the design has been made. The following diagram represents the architectural diagram of the high-level end-user view of the proposed system. Based on the student's rank and branch of his/her choice, it recommends the college.

5.2 Tools/Technology

To implement the proposed system, the tool/technology used was ‘R’. R studio was used. Coding has been done in R to develop the model and the model has been applied for predicting the rank and recommending the college. For developing the code in R, the required package and library were installed.

5.3 Implementation

The implementation of the entire work has been done in four parts.
A) Prediction of rank using Time Series Forecasting (ARIMA)
B) Recommendation by classification using Random Forest Classification
C) Recommendation by classification using KNN classification
D) Comparison of the Random Forest Classification and KNN for choosing the best model.

Rank Prediction

Installing the packages and adding a library

For predicting the rank, time series forecasting implemented with ARIMA model. As a pre-requisite to developing R code to run for implementing this forecast method, the "forecast" package was installed and the corresponding library was added.

Reading the input file

Once the package and library were added, the R studio was ready to implement the time series forecasting. Then the input data set was kept in an excel sheet.CSV extension. The file was then read and the time series method was applied to the input file. The dataset was then stored in another variable and then they were plotted.

The below plot shows the data set for CSE, IIT Bombay for the year 2016, 2017 and 2018. The lines of code were executed 44 times to read all the data sets and R plots were obtained for all.
Predicting the rank using time series forecasting

Once the data set was read, the next job was to apply ARIMA model to predict the future rank.

The codes were executed in R to get the predicted rank for each data set. This was also run 44 times to run 44 data sets.

The output of ARIMA forecast is obtained as shown below.

The above result when plotted in R by taking the years and ranks, gives the following graph as viewed in Figure 10.

Recommendation using Random Forest Classification

For random forest classification, the input data are the predicted ranks obtained for 2019 in the above step. At first, to implement a random forest, the library (random Forest) was added. Then input data file was read. Then factorization of data was done. Also, data were normalized. There were 173 observations with 3 variables. Partitioning of data was done. Then training set and testing set of data were segregated. The model was built and trained at first. Then the model was validated with the testing set of data. Out of all the observations, the code demonstrated 47 observations with 3 variables. The model was trained and tested multiple times and results were obtained. This classification technique gave 80% accuracy. The confusion matrix was obtained with a 20% error rate.

Table 7. Result from random forest

| Rank | College | Branch |
|------|---------|--------|
| 1    | IITB    | CSE    |
| 2    | IITB    | CSE    |
| 3    | IITB    | CSE    |
| 4    | IITB    | CSE    |
| 5    | IITB    | CSE    |
| 6    | IITB    | CSE    |
| 7    | IITB    | CSE    |
| 8    | IITB    | CSE    |
| 9    | IITB    | CSE    |
| 10   | IITB    | CSE    |
| 11   | IITB    | CSE    |
| 12   | IITB    | CSE    |
| 13   | IITB    | CSE    |
| 14   | IITB    | CSE    |
| 15   | IITB    | CSE    |
| 16   | IITB    | CSE    |
| 17   | IITB    | CSE    |
| 18   | IITB    | CSE    |
| 19   | IITB    | CSE    |
| 20   | IITB    | CSE    |
| 21   | IITB    | CSE    |
| 22   | IITB    | CSE    |
| 23   | IITB    | CSE    |
| 24   | IITB    | CSE    |

Here 47 obs. of 3 variables are taken as follows:

| Rank  | College | Branch |
|-------|---------|--------|
| 1     | IITB    | CSE    |
| 2     | IITB    | CSE    |
| 3     | IITB    | CSE    |
| 4     | IITB    | CSE    |
| 5     | IITB    | CSE    |
| 6     | IITB    | CSE    |
| 7     | IITB    | CSE    |
| 8     | IITB    | CSE    |
| 9     | IITB    | CSE    |
| 10    | IITB    | CSE    |
| 11    | IITB    | CSE    |
| 12    | IITB    | CSE    |
| 13    | IITB    | CSE    |
| 14    | IITB    | CSE    |
| 15    | IITB    | CSE    |
| 16    | IITB    | CSE    |
| 17    | IITB    | CSE    |
| 18    | IITB    | CSE    |
| 19    | IITB    | CSE    |
| 20    | IITB    | CSE    |
| 21    | IITB    | CSE    |
| 22    | IITB    | CSE    |
| 23    | IITB    | CSE    |
| 24    | IITB    | CSE    |

Table 8. Data Set of 47 obs. of 3 variables

The confusion matrix, train data set and predicted college obtained are shown in Table 9, 10 and 11 respectively.

Table 9. Confusion Matrix

| Rank | College | Branch |
|------|---------|--------|
| 1    | IITM    | MECH   |
| 2    | IITM    | MECH   |
| 3    | IITM    | MECH   |
| 4    | IITM    | MECH   |
| 5    | IITM    | MECH   |
| 6    | IITM    | MECH   |
| 7    | IITM    | MECH   |
| 8    | IITM    | MECH   |
| 9    | IITM    | MECH   |
| 10   | IITM    | MECH   |
| 11   | IITM    | MECH   |
| 12   | IITM    | MECH   |
| 13   | IITM    | MECH   |
| 14   | IITM    | MECH   |
| 15   | IITM    | MECH   |
| 16   | IITM    | MECH   |
| 17   | IITM    | MECH   |
| 18   | IITM    | MECH   |
| 19   | IITM    | MECH   |
| 20   | IITM    | MECH   |
| 21   | IITM    | MECH   |
| 22   | IITM    | MECH   |
| 23   | IITM    | MECH   |
| 24   | IITM    | MECH   |
| 25   | IITM    | MECH   |
| 26   | IITM    | MECH   |
| 27   | IITM    | MECH   |
| 28   | IITM    | MECH   |
| 29   | IITM    | MECH   |
| 30   | IITM    | MECH   |
| 31   | IITM    | MECH   |
| 32   | IITM    | MECH   |
| 33   | IITM    | MECH   |
| 34   | IITM    | MECH   |
| 35   | IITM    | MECH   |
| 36   | IITM    | MECH   |
| 37   | IITM    | MECH   |
| 38   | IITM    | MECH   |
| 39   | IITM    | MECH   |
| 40   | IITM    | MECH   |
| 41   | IITM    | MECH   |
| 42   | IITM    | MECH   |
| 43   | IITM    | MECH   |
| 44   | IITM    | MECH   |
| 45   | IITM    | MECH   |
| 46   | IITM    | MECH   |
| 47   | IITM    | MECH   |

Table 10. Data Set of 47 obs. of 3 variables

Here type of random forest: classification, Number of trees: 100, Number of variables tried at each split : 1 OOB estimate of error rate: 20%
Table 10. Train Data Set

| College | ITB | ITD | ITM |
|---------|----|----|----|
| IITB    | 13 | 3  | 2  |
| IITD    | 1  | 1  | 8  |
| IITM    | 0  | 7  | 1  |

Table 11. Predicted College

| College | Pred | ITB | ITD | ITM |
|---------|------|----|----|----|
| IITB    | 4    | 0  | 3  | 0  |
| IITD    | 0    | 3  | 0  | 1  |
| IITM    | 0    | 1  | 1  | 0  |

Predicted Final Data

| Levels | IITB | ITD | ITM |
|--------|------|----|----|
| IITM   | 1    | 2  | 3  |
| IITD   | 0    | 3  | 0  |

Recommendation using KNN classification

The predicted ranks obtained from section 5.3.1 were given as input to the KNN model. The “Branch” column was encoded with integer value for ease of implementation.

Data were arranged in an unordered way so the “Branch” and the “Rank” columns were normalized using the technique of max-min normalization (Appendix II).

Result obtained from KNN classification

5.4 Discussion

Once ranks were predicted, a recommendation was done by adopting both the classification techniques such as "Random Forest Classification" and "KNN" classification. Random Forest uses most of the voting while KNN searches the nearest neighbor class to arrange the given data. Out of the above-described techniques, the accuracy level of Random Forest Classification is 80% (From the result of the random forest: OOB estimate of error rate: 20%) whereas the accuracy level of KNN is found to be 94.11% (Figure 11). Hence the proposed model which is foremost suited for recommending the college is KNN with 94.11% accuracy.

6 Performance Analysis

This work presents with two classification techniques, the performance measure in terms of Accuracy of classification, in terms of Recall and Precision. See (Table 12).

Table 12. Comparative analysis between KNN and Random Forest Classification

| Classification Technique | Accuracy (%) | Recall  | Precision |
|--------------------------|--------------|---------|-----------|
| Random Forest Classification | 80.00        | 72.10   | 57.06     |
| K-Nearest Neighbor        | 94.11        | 53.97   | 23.24     |

7 Conclusion and Future work

As the accuracy in KNN is 94.11% which is better than the Random Forest Classification having accuracy 80%, so the proposed model is KNN. In this paper, currently, only the top ten IITs have been taken into consideration on a pilot basis for recommending the students to get admissions to the above-specified branches only for general candidates excluding all the reservations. As it was completely a new piece of work about the study of recommendation for educational institutes, it has its limitations such as it is limited to only the general
category and four common branches of IITs. This paper can be further enhanced and exercised for other categories and other institutes.

This piece of work can be enhanced further for implementing the functionality for the other category and also, for other graduate curriculums. Due to the limitations of data availability and time constraint, this work was limited to rank only. This study can be further enhanced and exercised for including other factors such as course fees, quality of the study, placement, ambience, and distance from home city.

Appendix A

Table 1. Synthetic Data

| Year | Name of the IITs | CSE | Electrical | Mechanical | Civil |
|------|----------------|-----|------------|------------|-------|
| 2018 | IIT Bhubaneswar | 2092| 4492       | 5102       | 8116  |
| 2018 | IIT Bombay      | 59 | 265        | 848        | 2544  |
| 2018 | IIT Delhi       | 100| 462        | 1025       | 3107  |
| 2018 | IIT Guwahati    | 554| 1923       | 2942       | 5890  |
| 2018 | IIT Hyderabad   | 777| 2090       | 3192       | 5988  |
| 2018 | IIT Indore      | 1264|3417      | 4905       | 7207  |
| 2018 | IIT Kanpur      | 213| 803        | 1611       | 3707  |
| 2018 | IIT Kharagpur   | 272| 1101       | 1745       | 4078  |
| 2018 | IIT Madras      | 200| 568        | 1333       | 3748  |
| 2018 | IIT Patna       | 2731|5841     | 7053       | 8674  |
| 2018 | IIT Roorkee     | 416| 1735       | 2485       | 4756  |
| 2017 | IIT Bhubaneswar | 2695|5029   | 5522       | 7857  |
| 2017 | IIT Bombay      | 62 | 266        | 738        | 2308  |
| 2017 | IIT Delhi       | 104| 416        | 944        | 2869  |
| 2017 | IIT Guwahati    | 670| 1987       | 2923       | 5284  |
| 2017 | IIT Hyderabad   | 975| 2357       | 3280       | 5773  |
| 2017 | IIT Indore      | 1500|3770     | 4771       | 7258  |
| 2017 | IIT Kanpur      | 206| 816        | 1409       | 3533  |
| 2017 | IIT Kharagpur   | 262| 1174       | 1578       | 4071  |
| 2017 | IIT Madras      | 177| 641        | 1222       | 3632  |
| 2017 | IIT Patna       | 3298|6151     | 7237       | 8281  |
| 2017 | IIT Roorkee     | 449| 1905       | 2343       | 4582  |
| 2016 | IIT Bhubaneswar | 3082|4763  | 4971       | 6294  |
| 2016 | IIT Bombay      | 60 | 583        | 901        | 2251  |
| 2016 | IIT Delhi       | 102| 329        | 778        | 2181  |
| 2016 | IIT Guwahati    | 666| 2127       | 3052       | 5371  |
| 2016 | IIT Hyderabad   | 988| 2609       | 3588       | 4940  |
| 2016 | IIT Indore      | 2074|3724    | 4250       | 6561  |
| 2016 | IIT Kanpur      | 207| 674        | 1192       | 2674  |
| 2016 | IIT Kharagpur   | 300| 1114       | 1377       | 3154  |
| 2016 | IIT Madras      | 186| 605        | 1257       | 2905  |
| 2016 | IIT Patna       | 3483|5733     | 5955       | 6661  |
| 2016 | IIT Roorkee     | 559| 1844       | 2084       | 3419  |

Appendix B

Table 7. Normalized Data after Min- Max operation Branch wise

| Name of the IITs | Branch | Rank |
|-----------------|--------|------|
| IITB            | 3      | 370  |
| IIT Kanpur      | 4      | 3402 |
| IITM            | 4      | 3590 |
| IITB            | 1      | 40   |
| IITD            | 4      | 2718 |
| IIT Kanpur      | 1      | 200  |
| IIT Bhubaneswar | 2      | 4306 |
| IITD            | 4      | 3670 |
| IIT Kanpur      | 3      | 2350 |
| IITM            | 1      | 100  |
| IITB            | 2      | 270  |
| IIT Bhubaneswar | 2      | 4201 |
| IITM            | 3      | 195  |
| IIT Kanpur      | 4      | 3530 |
| IIT Bhubaneswar | 2      | 3304 |
| IITM            | 3      | 210  |
| IITB            | 4      | 3520 |
| IITM            | 3      | 220  |
| IIT Kanpur      | 1      | 213  |
| IITD            | 1      | 150  |
| IITB            | 1      | 50   |
| IITM            | 1      | 90   |
| IITD            | 4      | 3107 |
| IIT Bhubaneswar | 3      | 4911 |
| IIT Bhubaneswar | 4      | 8116 |
| IITB            | 3      | 380  |
| IITB            | 1      | 10   |
| IIT Bhubaneswar | 1      | 2180 |
| IITB            | 4      | 2410 |
| IITD            | 3      | 190  |
| IIT Kanpur      | 2      | 762  |
| IITM            | 1      | 70   |
| IITD            | 1      | 130  |
| IITB            | 3      | 360  |
| IITM            | 3      | 250  |
| IITD            | 4      | 2869 |
| IIT Kanpur      | 1      | 195  |
| IIT Bhubaneswar | 2      | 4492 |
| IITM            | 1      | 60   |
| IIT Kanpur      | 2      | 780  |
| IIT Bhubaneswar | 2      | 4525 |
| IITB            | 2      | 300  |
| IITD            | 3      | 160  |
| IIT Bhubaneswar | 4      | 7028 |
| IIT Bhubaneswar | 4      | 8018 |
| IITM            | 3      | 230  |
| IITD            | 1      | 110  |
| IIT Bhubaneswar | 4      | 7857 |
| IITB            | 4      | 2350 |
| IIT Kanpur      | 1      | 154  |
| IIT Kanpur      | 4      | 3410 |
| IITB            | 1      | 1    |
| IITB            | 2      | 290  |
| IITM            | 2      | 320  |
| IITB            | 1      | 20   |
| IITM            | 1      | 80   |
| IIT Bhubaneswar | 2      | 4306 |
| IITM            | 4      | 3670 |
| IITD            | 2      | 440  |
Appendix C

Abbreviations

| Abbreviation | Description |
|--------------|-------------|
| RS           | Recommender System |
| DM           | Data Mining |
| RSD          | Recommender System Design |
| EI           | Educational Institutions |
| IOP          | Information Overburden Problem |
| PR           | Personalized Recommendation |
| NPR          | Non Personalized Recommendation |
| KB           | Knowledge Base |
| HRS          | Hybrid Recommendation system |

| UB            | User Base |
| IB            | Item Base |
| CRS           | Collaborative Recommender System |
| PPC           | People to People Correlation |
| CBRS          | Content-Base Recommender System |
| DBRS          | Demographic Base Recommender System |
| UBRS          | Utility Base Recommender System |
| KBSR          | Knowledge-Based Recommender System |
| PA            | Predictive Analysis |
| MAE           | Mean Absolute Error |
| RMSE          | Root Mean Square Error |
| IIT           | Indian Institute of Technology |
| JEE           | Joint Entrance Examination |
| KNN           | K- Nearest Neighbor |
| CSE           | Computer Science & Engineering |
| ARIAMA        | Auto Regression Integrated Moving |
| ACF           | Auto Correlation Function |
| PACF          | Partial Auto Correlation Function |
| SVM           | Support Vector Machine |

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