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University Recommender System based on Student Profile using Feature Weighted Algorithm and KNN

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***Abstract*—**

This article removes the recommender structure for undergrad and graduate understudies which can help with picking the best schools matching their profile. The proposed model has used different extracting techniques for scrapping the data based on student profiles who have secured the seat successfully earlier. Then, machine learning technology is used to calculate the weighted scores based upon the training and testing data. This research study has introduced the KNN and Feature weighted algorithms to display the top N comparable clients for the test clients and recommend the Top M colleges to clients from the N comparative clients. As there is a colossal course of action of data and User profile, this research work is highly intended to use Knowledge-based techniques for two unmistakable models. Case-based information recommendation is used to calculate Graduate recommendations and constant-based recommendation is used for Undergraduate proposals.

Keywords: Undergraduate, Graduate, Knowledge-based, Case-based

I. INTRODUCTION

Understudies who need to want their higher examinations to apply for various colleges with their scholarly profile past state-sanctioned [13] test scores like GRE, TOEFL, IELTS, and SAT. However, all through the interaction, college Choice is the main advance in applying for a degree Entrance. Information acquired from the data set Successful candidates will be to the point of observing their responses Questions, for example, what elements decide financing open doors.[14] For candidates to explicit doctoral level colleges? What class of understudies is normally completely subsidized by MSc software engineers? Or on the other hand, seek after a Ph.D. School? For a confident student for an understudy who prerequisites to apply for higher appraisals in different nations, the school assurance process is troublesome [8]. A part of various rules that need to consider during the application process depending on the person's necessity. This issue can be tended to by demonstrating a recommender framework dependent on different grouping calculations [9]. In this task depending on the Graduate and Undergraduate student dataset and client profile, an overview of the best universities will be prescribed so much that it extends the chances of a student getting entry into those schools [10]. Finally, our recommender system recommends a list University to users who propose to apply for higher studies Facilitates the admission of knowledgeable students who are eager and trying to further their studies based upon financial support [11, 12].

II. LITERATURE SURVEY

Garcia-Mart al. [1] Investigate the stream, types, and uses of proposal frameworks in training. The examination study's principal objective is to foster a proposed framework for graduate affirmation searchers that targets investigating past information of currently enlisted understudies in graduate projects. They proposed an alumni college suggestion framework that will apply SVM.

Ricci et al. [2] Proposed a suggestion framework that will help the forthcoming understudies of Bangladesh in picking the most appropriate private colleges for getting confirmation, they showed that applying KNN, content-based proposal separating strategy thinking about the college data and client inclinations

Santos et al. [3] address the problem has been tended to by demonstrating a recommender framework in light of different arrangement calculations Random Forest, K-Nearest Neighbour, and future-weighted models have been successfully used for building the university recommendation system

Schafer et al. [4] proposed a structure Intelligent Recommender System (IRS) for understudies in advanced education foundations the proposed IRS structure is created by the strategies of information mining and AI in

foreseeing and suggestion Algorithms utilized SVM, naive Bayes, k-means

Janet et al. [5] Suggestion Engine gathers User information from social media and fabricates User profiles in light of different boundaries w.r.t. schools like Faculty, Campus life, Placements, and so on in like manner, it thinks about Alumni or current understudy information thought for building College Profile. In light of User and College Profiling suggestions are created for data searchers utilizing a mixture approach.

Vilardi-Sacín al. [6] proposed the same recommendation system for the college, due to this recommendation system students get clearer about which branch or college is proper for admission.

Herlocker al. [7] utilized Collaborative sifting and content-based separating to shape a mixture model on different secret credits. Half breed Filtering which is the blend of cooperative sifting and content-based separating will be used. The user sees the top-3 universities on-screen as output after the working of the recommendation engine.

The general recommendation system includes content based, collaborative based and hybrid-based system [17-22] and it having the features which includes difference data science applications including machine learning [23-30], deep learning [31-38] and data analytics & IOT [39-46]. Based on the previous recommendations in this work, we have proposed collaborative based recommendation system for analyzing the various student's profile.

III. LIMITATIONS IN THE EXISTING SYSTEM

By the past survey, we observe that they recommended a set of colleges to the user by applying various machine learning algorithms. By that user will faze whether he will get university admission or not.

IV. DATASET

A. Dataset Description

The first step in building a recommender system is to identify records. Inside To build a classification model for a recommender system,[15]it is necessary to organize this data with appropriate labels. The core data of the application process is in Internet direct consumption. However, this whole method is based on maximum usage available information. The data for graduate students come from the following websites www.thegradcafe.com, undergraduate student data scraped https://collegescorecard.ed.gov/data/. Graduate Records: For graduate dates, we crawl the website www.thegradcafe.com. In fig [1] About 271807 rows of raw data Student data is obtained through web scraping.

To use the obtained data for our analysis, we must perform preprocessing and cleaned it up because there are many anomalies in the dataset. For this, we use pandas and NumPy packages in python. Data is cleaned. Use the Delete Columns feature to delete irrelevant columns. Fill empty values with appropriate values or delete rows with empty values. Remove spaces in the data and reduce the size of the data set.

X normalization = (x – x min) / (x max – x min)

In our graduate data set, GRE scores are also adjusted because they include scores from both old and new versions of the exam. Again, available GPA scores are based on different scoring frameworks so that all GPA results are consistently scaled to a 4-point scale Normalize function. Where x is the value of the GPA

Column	Non-null Columns	Data Type
Univ Name	485250	Object
Degree	485243	Object
Program	485250	Object
Season	453842	Object
Decision	429029	Object
Method	484213	Object
Decdate	484449	Float64
Decdate_ts	484449	Float64
Cgpa	114197	Float64
grev	123272	Float64
greQ	123272	Float64
greA	119051	Object
Is_new_greA	123272	Float64
Is_new_gre	123272	Object
Gre subject	16881	Float64
Status	440499	Object
Post data	485250	Object
Post timestamp	485250	Int64
comments	309700	Object

Fig. 1: Table

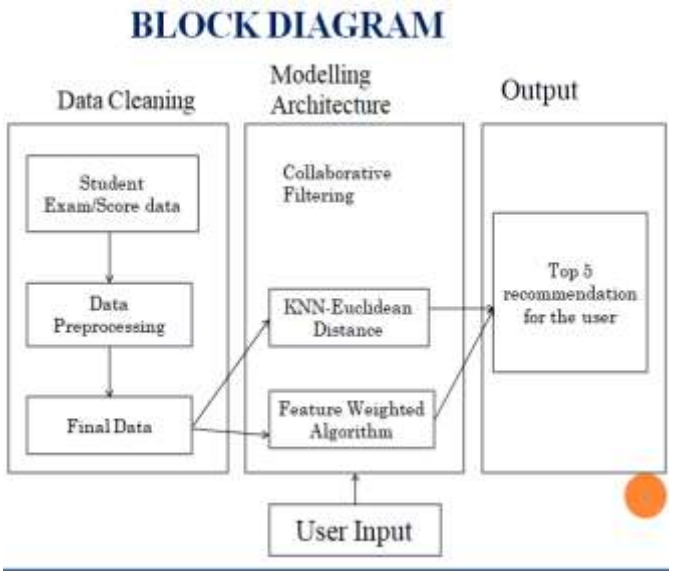

Fig. 2: Modeling Architecture

In Fig [2] the Modelling Architecture, we took Final data and applied machine learning algorithms KNN and Feature weighted Algorithm. From that, we have calculated the top 5 universities for Graduate and the acceptance rate for the Undergraduate students

V METHODOLOGY

From undergraduate, we have considered only a few rows of data like Institution Name, City, Tuition fees, Sat Score, Admission rate, Debt, and Men ratio. For test data such as

SAT score and Maximum tuition fees and training the model has been done with the help of this data. In this model, we have collected information on GPA from different universities. To make a normalized CGPA we have to divide each CGPA by four so we get a new normalized GPA of the individual. Finally, this system helps the students to get accurate recommendations without any further issues of their CGPA.

VI TRAINING AND TESTING

On the Applicability of Data Mining and Machine Application. We made a preparation dataset for the gaining calculation in light of data from effective candidates, for example, Undergraduate CGPA, GRE, TOEFL_IELTS scores. We determined a weighted score for this exercise. Once more, we determined different weighted scores from a test dataset framed from the given information about current candidates, such as Undergraduate CGPA, GRE, TOEFL scores. The test dataset is to work out the comparability between weighted scores recently utilized the mean squared likeness measure Apply the k-nearest neighbor calculation

VII K-NEAREST NEIGHBOR

At first, we have gathered the dataset, and afterward, we have pre-handled the information for preparing and testing. Under the preparation dataset, we had assessed the weighted score from earlier data from the fruitful candidates, for example, undergrad CGPA, GRE, TOEFL scores, and under the testing informational collection we had worked out on weighted scores from the earlier data of current candidates, for example, undergrad CGPA, GRE, TOEFL scores. Further, we had figured the comparability between the weighted scores utilizing the mean square deviation closeness metric. From that, we had assessed the top n comparable clients for test clients in light of the KNN calculation from the acquired result we will favour the best 5 colleges to the test clients from n comparable clients. At last, the Top 5 colleges will be shown on the UI's which assists with getting an affirmation and seat for the client.

K Nearest Neighbour algorithm is used for graduate students. In Fig [3] KNN, the prepared information is contrasted and test information and distances are improved because of Euclidean distance Then it classifies to find the nearest neighbors and recommend the top 5 nearest neighbors.

1. Initialize the worth of k
2. Forgetting proposal, repeat from 1 to number of prepared information
3. Work out the distance between test information and each column in the prepared information.
4. Sort the distances in rising request
5. Get top k lines and prescribe to the client

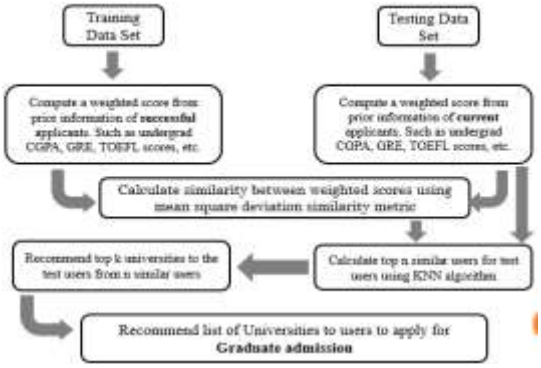

Fig 3: Implementation of graduate system

VIII IMPLEMENTATION

Fig. 4 shown the training data for KNN algorithm.

	univName	cgpa	greV	greQ	greA
14	Ohio State University	4.00	150.0	166.0	3.0
17	Texas A&M University	3.57	157.0	151.0	5.5
46	University Of California, Irvine	3.66	155.0	167.0	4.0
64	Boston University	3.10	161.0	157.0	4.0
203	Oregon State University	3.38	154.0	170.0	4.0

Fig 4: Training data

IX FEATURE WEIGHTED ALGORITHM:

The weightage of the multitude of elements is taken and observe the closeness score. Because of the similitude score, the colleges with the most noteworthy likenesses will be prescribed to understudies. Assume w1, w2 are loads and f1 and f2 are included the similitude is determined by the equation

Similarity score = w1* f1+w2*(1-f2)

1. Initialize the value of k
2. Forgetting recommendation, iterate from 1 to the number of trained data
3. Calculate the distance between test data and each row in the trained data.
4. Sort the distances in ascending order
5. Get top k rows and recommend to the user

X IMPLEMENTATION OF GRADUATE SYSTEM

As we discuss In Fig [5] we created the webpage in that we included the two fields graduate and undergraduate page in that we set up the fields by giving the inputs by the user it will check the past successful applicants it will display the output

a) home page

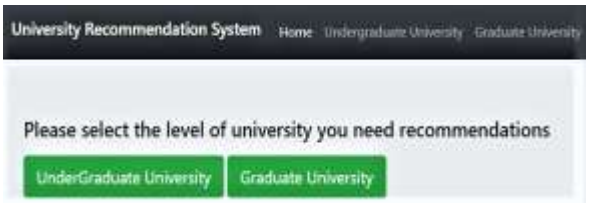

Fig5: Dashboard

b) undergraduate webpage:
In Fig [6] we created the two fields sat score and maximum tuition fees by giving inputs by the user it will check the past applicants between a range of 400-1600 it will check the past applicants and will display the university name and acceptance rate. The acceptance rate is nothing but how many students will eligible for that university

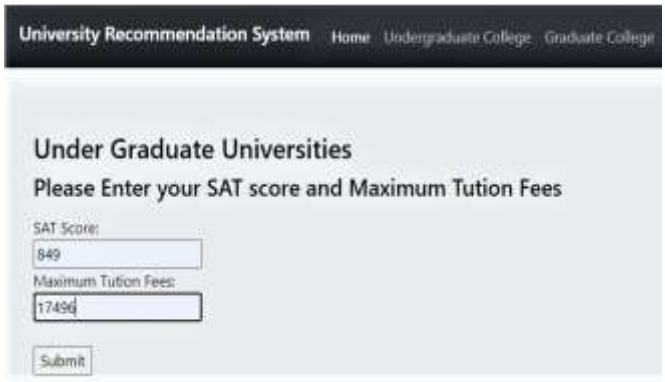

Fig 6: Undergraduate page

c) graduate webpage
In Fig [7] we have created another page described as a graduate page. For the user requirement undergraduate page, we had created four fields i.e., verbal score, quantitative score, GRE writing score, GPA in undergraduate. By the KNN, the trained data is compared with test data, and distances are calculated based upon the Euclidean distance. It then classifies an instance by finding its nearest neighbour by recommending the top n nearest universities

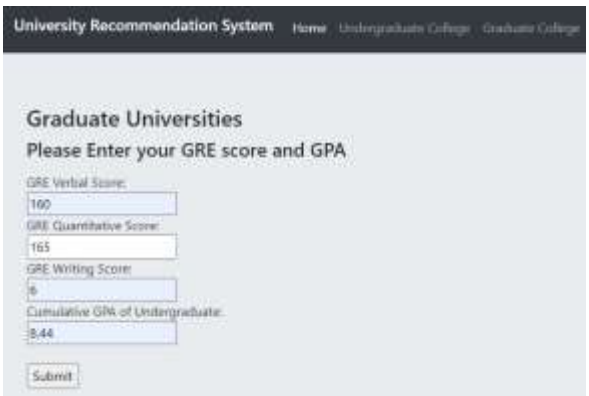

Fig. 7: graduate page

X RESULT AND DISCUSSION

Most of the authors have designed their model by recommending the top 5 schools. But our framework helps the users by providing an acceptance rate of getting a seat in a college in addition with recommend the top 5 schools. We have included an attribute "tuition fee" such that the user can select the school-based upon their financial status.

XI CONCLUSION

This project helps understudies in the decision-making of the colleges in which they apply. The information of the past fruitful candidates can be considered. The information from the scholarly records of candidates is vital for the confirmation searchers in unfamiliar. In this research, I have fostered a procedure of involving those scholarly records of effective candidates for making a school recommender framework, which can help the current confirmation searchers. From the outset, I work out comparability among preparing and testing informational index given weighted scores. The weighted scores are determined from earlier data of effective candidates like undergrad CGPA, GRE, TOEFL Scores, and any remaining significant records found in the general data set. I have involved K-nearest Neighbor calculation for graduate colleges and component weighted calculation for Undergrad Universities to compute top N comparative clients and afterward suggest top K colleges to the clients. Our proposed recommender framework will prescribe a rundown of colleges to candidates attempting to seek after higher concentration abroad and help them to apply for graduate affirmation in proper colleges.

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