Project Final Report

Project Title: College Audit
Team Name: Full-timers (Team Number 003)
Team Members: Hayung Suh, Nicolas Swanson, Satish Uppathil, Jacob Minson, Taeyeon Kim

INTRODUCTION

Admissions into US colleges are now holistic, considering students' backgrounds and academic performance, leading to a lack of transparency. Exceptional test scores and high GPAs don't guarantee admission, creating anxiety for students. Rising tuition costs and student debt worsen the issue. Student loan debt negatively affects health, life transitions, and wealth accumulation, forcing students to make tough choices during their college years [3]. Our project, College Audit, recommends colleges based on a holistic view of a student's background, addressing the need for such tools. Existing approaches focus on limited parameters like rankings and test scores. College Audit uses the complete feature set from the US Department of Education's college scorecard data to help students make informed decisions. It considers academic strengths, financial situation, location preferences, and field of study, though it has limitations as it relies on data from students who received federal financial aid, not representing all students. This project tackles the rising dropout rate and student debt crisis in US higher education [11].

PROBLEM STATEMENT

Stellar academic achievements do not ensure admission, contributing to stress and dropout rates, heightened by rising tuition costs and student debt. The College Audit project addresses these challenges by providing user-tailored results and transparent information about each school.

LITERATURE SURVEY

The mounting dropout rate and student debt in the U.S. higher education system have been further exacerbated by the pandemic [11]. Farcnik's research underscores the pandemic's impact on students' decision making regarding educational pursuits, resulting in a significant increase in dropout rates [10]. Due to the changing academic environment, many students' primary focus shifted toward work which increases the probability of dropping out. The project is in line with recent research advocating for improved student completion rates and a redefinition of academic success and retention to better suit the needs of today's millennial students [13]. Non-traditional students, who often grapple with the complexities of balancing work and higher education, can also benefit from this tool. This is evidenced by findings in research by Maher and Macallister [14]. The issue with this paper is the sustainability of the strategies mentioned, but we can correct for this by closely observing how our tool holds up in the long run and if it makes a significant difference for students. Furthermore, the structure of the college scorecard data is not conducive to interactive visualization, partly explaining its underutilization [4]. To improve such papers, our tool will assist students in choosing their majors, reducing the likelihood of dropout due to mismatches between occupational preferences and major selections [7].

In terms of dropout, Bayona-Ore's paper, which reviewed recent scientific papers related to student dropout and compared the motivations proposed in each paper, confirmed that the primary motives for dropout encompass institutional, academic, individual, economic, and vocational factors [8]. Our project meticulously ensures that we considered all these variables when recommending the best college for users to address the challenge of reducing dropout rates [12]. Studies have shown that not all degrees offer the same earning potential at entry-level, and wage differences among majors tend to grow over the course of one's career [6]. Finally, making the tool widely accessible could have a substantial impact on retention rates, promoting "quality assurance and accountability," which are crucial in higher education worldwide as addressed in our research [15][16]. However, the project acknowledges the challenge of the non-transparent college pricing system in the U.S. Past attempts to address this issue have found partial success, due to a lack of comprehensive data [4]. Nevertheless, these approaches demonstrate that data may not fully capture the entire student population, potentially affecting reliability [8].

Levine [4] discusses the opacity in the college pricing system and how such information deficits reduce the likelihood of attending college. The sticker price seen on the college websites is markedly different from the actual cost. The importance of factoring in a better estimate of the cost at the time of application is mentioned. The financial burdens of student loan holders, the rising cost of higher education, and the student loan debt in the U.S. limit opportunities for some Americans – as the student loan debt negatively affects life transitions and wealth for university students while studying [3][5]. Rothstein and Rouse [3] also discuss the issues on student loan debt negatively affecting life transitions and wealth for university students while studying. To overcome rising student debt, our goal is to ultimately help future college students decide which school to apply to with the right tuition range on their budget.

There is a university ranking and recommendation system built to give personalized ranking listed based on user's preferences [1]. They use collaborate filtering, which filters based on other user's preferences as well, to generate the personalized ranking list and k-nearest neighbors (KNN) to predict university scores for each user. While this technique considers correlation of various user behaviors, the time and memory efficiency decrease as the number of users increases due to the large amount of calculation with large data [17]. Another recommender system by Manley and Krishnakumar [2] was built using support vector machine, KNN and random forest, to simultaneously generate a personalized ranked list and recommend schools for each graduate student to apply. From this, we can see that using an ensemble method like Random Forest to predict would be beneficial in terms of efficiency for large datasets [18]. However, this paper only uses 45 universities which is quite a small number of schools as it only handles graduate schools. To overcome these limitations, we will rank various universities by predicting universal university scores in the U.S. with the datasets from College Scorecard.

METHODOLOGY

Data: Before beginning our work on data processing and modeling, we decided to set up our own data dictionary of the college score data to better understand our data. In our data dictionary, we categorized files, defined variables and column names, and identified which parts of the data were integral for our project. Once we identified which files were important, we began to process our data by merging data files of the same type but with different years, converting "Privacy Suppressed" entries into blank, and dropping columns that had over 90 percent null values. From this condensed dataset, which was a little over one gigabyte of data, we identified important variables that will be used for the model and the UI such as school name, school longitude and latitude, graduation rate, test scores, admission rate, family income, net price of school, median earnings of students who graduated, debt, and more. Out of these variables, some required modification such as merging NPT4_PUB and NPT4_PRIV, which represent average net price for public and private institutions respectively.

Model: We chose gradient boosting for our main model to rank the universities as it is an ensemble method that is powerful in improving the accuracy and robustness of regression models, while handling large datasets. Ensemble methods often outperform individual models, providing better predictive accuracy. They work by training multiple weak learners sequentially and combining their predictions and can capture complex non-linear relationships. As gradient boosting can manage outliers and can handle noisy data effectively, we can easily fine-tune hyperparameters to optimize the model's performance and control overfitting – which allows it to overperform random forest. We will use *LightGBM*, which is an algorithm for gradient boosting in *Python* that uses a leaf-wise tree growth strategy. While another algorithm *XGBoost* is also effective, we chose *LightGBM* as it is designed to be memory-efficient during training, which is beneficial when dealing with our large dataset with millions of rows. Below is the list of the main processes including evaluation.

- **Data:** We load the dataset containing the following features [9], used to score and rank schools: School Name, Graduation Rate, Tuition, Acceptance Rate, Salary after Graduation, Student Debt Loan, Student Population – as well as other variables needed for filtering and generating the UI.

- **Ranking Universities:** Next, we assign weights to each feature above which allows us to rank the universities according to their individual predicted rated scores.
  - **Scoring:** Weights* for each university scoring feature are declared by measuring how much factors affect dropout rate according to the study by Behr [9]. Salary and size of school were two of the main factors in dropping out (see Appendix A). Then, we add a new *university_score* column by calculating the total score for each university – summing the products of feature weight and its corresponding feature values. Finally, we split the final data into training and testing sets to start optimization and modeling.

(* Graduation Rate = 0.16, Net Price = 0.12, Acceptance Rate = 0.14, Salary = 0.24, Debt = 0.12, Size of School = 0.22)

- **Optimization:** We tune the parameters to improve performance using grid search and cross validation.
  - To ensure that our model generalizes well to new data, we perform 10-fold cross-validation for hyperparameter tuning as our dataset is large. It divides the dataset into 10 subsets, trains and tests the model 10 times, and computes the average performance metrics. This equips us to provide a stable and interpretable evaluation of the model. Along with using grid search for hyperparameter tuning, we also evaluate the results retrieved from random search in case it may have better performance.
- **Modeling:** Model is trained on the features and makes predictions on the testing data (score).

An outline of our process for College Audit (Fig. 1) includes data-preprocessing, modeling, and UI. College Audit seeks to offer users an interactive experience, enabling them to explore numerous factors while also providing information about different majors and suitable school options that fit within their budgets. As mentioned above, College Audit's intuition and novelty is focused on generating a universal *ranked_list* (Fig. 2) of all universities from our dataset and then apply customized filters (*filtered_list,* Fig. 3) upon specific user's information, rather than ranking universities again for every new user – for finer time and memory efficiency than other existing university recommendation systems. Our model gives scores on universities with tuned parameters and ranks them by the predicted scores, which allows the UI to filter them afterwards. As a result, this model aims to mitigate the ongoing, rising student debt and dropout rates in US higher education.

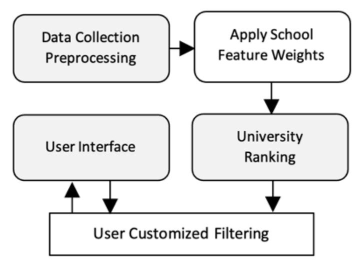


Fig.1 Overall Process for College Audit

Name	Actual Score	Predicted Score
University of Phoenix-Arizona	37086.05172	36778.086919
Southern New Hampshire University	22813.61233	22695.852054
Liberty University	20854.53932	20659.504255
Grand Canyon University	19595.48730	19592.110361
New York University	19255.62852	19207.029242

Name	Major	Actual Score	Predicted Score
University of Illinois Urbana-Champaign	Mathematics	14511.35225	14538.669640
Arizona State University Campus Immersion	Mathematics	13801.38140	13748.511615
High Point University	Mathematics	12814.89834	12912.691739
Rensselaer Polytechnic Institute	Mathematics	12740.81753	12700.261455
University of San Diego	Mathematics	12263.53873	12215.950624

Fig. 2, 3 Example of *ranked_list* of universities and *filtered_list* of top 10 by major for instance

User Interface: The UI was designed to offer an intuitive and user-friendly interface for easy start-up. An example screenshot is shown in Fig. 4 (See Appendix B for detail). The user inputs are taken in the Filtering Options sidebar on the left. The model uses these inputs to sift through the *ranked_list* to identify the universities that best match the user's profile, and the top ten universities are displayed on the right with the list in the top right sub-window. The variables used to rank them and how each fare based on these metrics is shown in the sub-window below. The historical trend for any university in the top ten can be viewed by selecting one. Finally, their locations are shown on a map in the bottom sub-window. The inputs expected from the user are major, location, test scores, income, net price and debt, acceptance rate, type of school, size, and men/women only. The UI was developed using *Dash* and *Plotly* libraries in Python.

One of the innovative features of our UI is the consolidated single-page view of results. This design allows users to simultaneously examine detailed information while grasping the broader picture, effectively highlighting the strengths and weaknesses of each college for easy comparison. In contrast, existing tools (e.g., college scorecard website hosted by the US Department of Education), limit users to viewing details for one university at a time, creating challenges for meaningful comparisons.

The second distinctive feature involves presenting historical trends of pertinent variables. Unlike most existing college search tools that offer static information, our approach recognizes the rapidly changing environment and economics surrounding colleges. Merely providing the latest information may not suffice for setting accurate expectations. Given that the target audience for this product is prospective students planning for future college attendance, analyzing historical trends in relevant information enhance their ability to predict admission rates, expenses, and tuition fees more accurately.

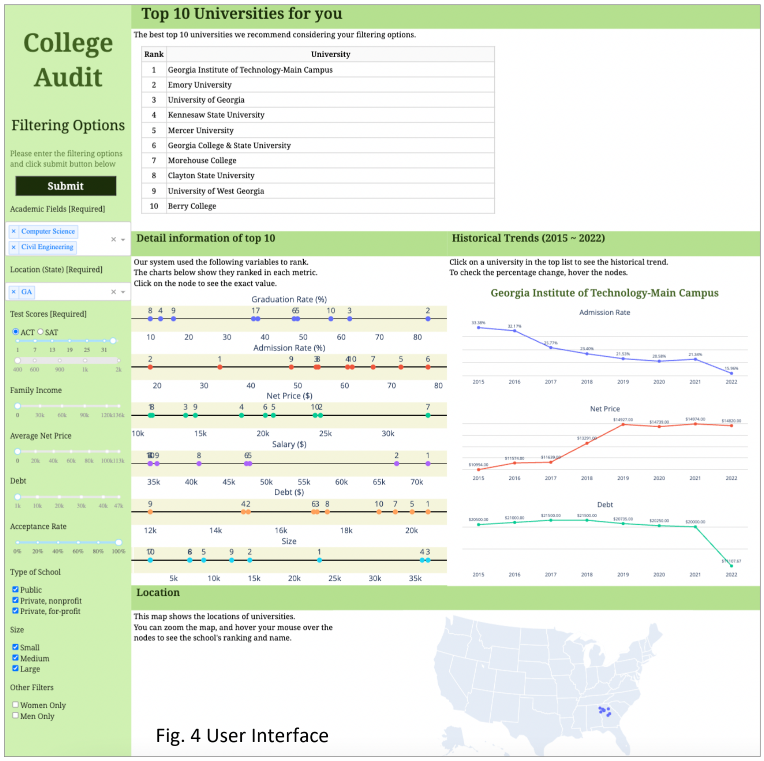


Fig. 4 User Interface

EXPERIMENTS/EVALUATION

Our testbed serves as a comprehensive platform for evaluating College Audit, encompassing three key experiments: Scalability, User Study, and Runtime & Accuracy Evaluation. The key questions addressed include: What is the impact on prediction model performance when dealing with a larger dataset and what aspects of the dashboard contribute most significantly to user satisfaction? Are there specific features or design elements that users find particularly beneficial or challenging? How does the runtime and accuracy of the College Audit system compare to a benchmark under varying scenarios?

Scalability Evaluation: After building the model, we evaluated its performance using the testing dataset. The performance metrics include MAE, MSE, RMSE, and R-squared to measure the differences between the predicted and actual scores and the proportion of variance in the scores. We conducted hyperparameter tuning by using grid search and random search. Then, we evaluated each method's performance to finalize which tuning method to use for the final gradient boosting model. According to Fig. 5, the model using grid search has lower MAE and R-squared while random search has lower MSE and RMSE. Along with this, grid search was chosen over random search because the results of a random search vary even when it is run with the same dataset and under the same conditions due to sampling a set of hyperparameter combinations randomly from a predefined search space. As the randomness in the selection of hyperparameter values can lead to different results each time the random search is executed, we decided to use grid search instead so that we can have a fixed ranked list every time we run the model. Moreover, a scatterplot that compares predicted and actual scores was used to identify a few outliers or areas where the model is performing imperfectly. In Fig. 6, there are a couple outliers present on the scatterplot but performance shows that our model executed decently with an R-squared value of 0.9822.

	Grid Search	Random Search
Mean Absolute Error (MAE)	82.05	88.21
Mean Squared Error (MSE)	169805.87	165638.12
Root Mean Squared Error (RMSE)	412.08	406.99
R-squared	0.9822	0.9826

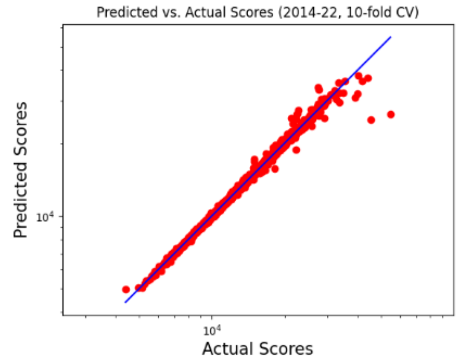


Fig. 5, 6 Performance metrics of tuned model and Scatterplot comparing predicted and actual score

User Study: The assessment of College Audit's usability involved a trial wherein 21 participants, comprising high school juniors or seniors, undergraduates, and recent college graduates, actively engaged in the study. The primary objective of the trial was to evaluate the usability, effectiveness, and marketability of College Audit. Each participant received a link to download and run College Audit on their computer, accompanied by a questionnaire designed to gather their insights. The questionnaire featured prompts for free-form feedback in addition to rating questions on a scale from worst (1) to best (5) as in Fig. 7.

There is a strong consensus among participants regarding the overall usefulness and user-friendliness of College Audit. More than three-quarters (~76.2%) of participants indicated that College Audit is intuitively easy to use, offering a positive validation of our UI design. Additionally, two-thirds of participants expressed a likelihood to recommend College Audit to others. Figure 7 presents a tabulated summary of feedback derived from ratings. Free-form feedback emphasized the desire for customization options for international students, increased flexibility in inputting filtering choices (including GPA), clearer explanations for charts depicting detailed information and historical trends. Most participants appreciated the simplicity and ease of use of the UI.

Questions	1 (Extremely Dissatisfied)	2 (Dissatisfied)	3 (Neutral)	4 (Satisfied)	5 (Extremely Satisfied)
1. How likely are you to recommend College Audit to others based on its usability and functionality?	0	0	7	9	5
2. How satisfied (with the accuracy) are you with the results from College Audit?	0	1	5	11	4
3. How would you rate the intuitive ease of using College Audit?	1	2	2	8	8
4. How appealing did you find College Audit's User Interface design?	0	4	9	5	3
5. How satisfied are you with the runtime of College Audit?	0	0	4	6	11

Fig. 7 User study results (See Appendix C for detailed survey results)

Runtime & Accuracy Evaluation: Our experiments involved a quantitative analysis of our platform's runtime vs the college scorecard's runtime, and a qualitative analysis of user experience feedback between the two. Findings show that overall, there was not a significant difference between the control (College Scorecard) and our test (College Audit). One user observed that being able to see all the data in one place in college audit was preferable to scrolling through many results (often entirely blank) to see a few useful data points. College Audit was also consistently slightly faster, with almost no delay for runtime, while college scorecard had a momentary delay (usually less than two seconds) while loading. While it is difficult to objectively determine the accuracy of a model such as ours (given that recommending the ideal school for an individual is not guaranteed due to variation in individual preferences and needs), we did work to compare our findings with those of the competition and our simple findings are as follows (Fig 8.):

Input	Results
1. Major: Computer Science 2. ACT: 33 3. Location: GA 4. Type: Public and Private 5. Size: Small to Large	- College Audit returns Georgia Tech in top 10. - College Scorecard does not show Georgia Tech on the list.
1. Major: Civil Engineering 2. ACT: 33 3. Location: GA 4. Type: Public to Private 5. Size: Small to Large	- College Audit shows Georgia Tech, University of Georgia, Kennesaw State, and Mercer in the top 10. - College Scorecard gives Georgia Tech, University of Georgia, Mercer, Kennesaw State, and Georgia Southern University.
...	...

Fig. 8 Example inputs and results of College Audit and College Scorecard

Our results differ for a few reasons, primary among them being that our approach in weighting and ranking the data was more focused on optimizing the experience for low-income and non-traditional students. Overall, given the positive feedback from users, we can see that our accuracy is not necessarily problematic, but the only truly reliable way to prove our accuracy would be to survey users who chose a school based on our recommendation and evaluate their satisfaction because of the decision.

DISCUSSION

A notable constraint within our project stems from the inherent limitation in our dataset. The current dataset is confined to students who have received federal financial aid, which introduces an inherent bias of the comprehensive student demographic. Another pertinent limitation is the exclusive focus on data gathered from admitted college students, precluding the integration of refined filters like high school GPA, AP classes undertaken, and other intricacies specific to the high school milieu. Consequently, a potential project extension involves the incorporation of high school data. This augmentation would serve to enrich our array of filters, thus facilitating a more nuanced and personalized approach in curating the top 10 list.

CONCLUSION

College Audit was initiated in response to the growing concerns over increasing student debt burdens and the rising dropout rates among college students. Our aim was to address these issues by developing a multifaceted informational tool to assist students in making informed decisions about college admissions. We successfully designed and implemented a dashboard that not only suggests optimal college choices tailored to individual user profiles but also surpasses the limitations of existing search dashboards. The dashboard's uniqueness lies in its comprehensive approach, offering varied information simultaneously and prioritizing key factors contributing to dropout rates. Upon user trials, the dashboard received positive feedback for its performance and user-friendliness. This response underscores our success in creating a tool that resonates with the needs and expectations of our target audience.

Furthermore, College Audit would be particularly beneficial for first-generation and non-traditional students who often lack access to comprehensive college-related information. The significance of this extends beyond immediate user satisfaction. We anticipate that College Audit will play a crucial role in alleviating the student debt crisis. By guiding students towards educational paths aligned with their financial capabilities and academic goals, we aim to reduce the incidence of students dropping out due to unsustainable debt. This aspect is critical considering the detrimental effects of student loan debt on borrowers' mental health, life choices, and long-term financial stability.

In conclusion, the College Audit stands as a testament to our team’s dedication to enhancing the college selection process, with each of the five team members significantly making contributions, reflecting our collective commitment to improving students’ financial well-being and education experiences. Also, all team members have contributed a similar amount of effort on the project and report.

References

[1] Mehdi Elahi, et al. 2020. Exploring Personalized University Ranking and Recommendation. In Adjunct Publication of the 28th ACM Conference on User Modeling, Adaptation and Personalization (UMAP '20 Adjunct). Association for Computing Machinery, New York, NY, USA, 6–10. https://doi.org/10.1145/3386392.3397590

[2] Manley, J., & Krishnakumar, S. University Recommender System for Graduate Studies in USA.

[3] Rothstein, J., & Rouse, C. E. (2011). Constrained after college: Student loans and early-career occupational choices. Journal of Public Economics, 95(1–2), 149–163. https://doi.org/10.1016/j.jpubeco.2010.09.015

[4] Levine, P. B. (2014). Transparency in College Costs. Brookings Institution Economic Studies Working Paper. https://www.brookings.edu/articles/transparency-in-college-costs/

[5] Lee, J. M., Kim, K. T., Hong, E. J. (2018). Exploring financial burdens of student loan holders in the United States. Family & Consumer Sciences Research Journal, 46(4), 247-362

[6] Carnevale, A. P., Cheah, B., Hanson, A. R. (2015). The Economic Value of College Majors. Georgetown University Center on Education and the Workforce Report. https://cew.georgetown.edu/cew-reports/valueofcollegemajors/

[7] Fouarge, D., & Heß, P. (2023). Preference-choice mismatch and university dropout. Labour Economics, 83, 102405. https://doi.org/10.1016/j.labeco.2023.102405

[8] Bayona-Oré, S. (2023). Dropout in Higher Education and Determinant Factors. In: Yang, XS., Sherratt, S., Dey, N., Joshi, A. (eds) Proceedings of Seventh International Congress on Information and Communication Technology. Lecture Notes in Networks and Systems, vol 464. Springer, Singapore. https://doi.org/10.1007/978-981-19-2394-4_23

[9] Behr, A, Giese, M, Teguim Kamdjou, HD, Theune, K. Motives for dropping out from higher education—An analysis of bachelor's degree students in Germany. Eur J Educ. 2021; 56: 325–343. https://doi.org/10.1111/ejed.12433

[10] Farcnik, D., Domadenik Muren, P. and Franca, V. (2022), "Drop-out, stop-out or prolong? The effect of COVID-19 on students' choices", International Journal of Manpower, Vol. 43 No. 7, pp. 1700-1718. https://doi.org/10.1108/IJM-06-2021-0353
https://doi.org/10.1108/IJM-06-2021-0353

[11] Dickler, J & Nova, A. (2022, May 6). This is how student loan debt became a $1.7 trillion crisis. *CRS Reports*. https://www.cnbc.com/amp/2022/05/06/this-is-how-student-loan-debt-became-a-1point7-trillion-crisis.html

[12] Velez, E. D. (2014, Jan) America's College Drop-Out Epidemic: Understanding the College Dropout Population. American Institutes for Research. https://www.air.org/sites/default/files/downloads/report/AIR-CALDER-Understanding-the-College-Dropout-Population-Jan14.pdf

[13] Manyanga, F., Sithole, A., & Hanson, S. M. (2017). Comparison of Student Retention Models in Undergraduate Education From the Past Eight Decades. Journal of Applied Learning in Higher Education Vol. 7, Spring 2017 29-41. https://files.eric.ed.gov/fulltext/EJ1188373.pdf

[14] Maher, M. & Macallister, H. (2013, March 25). Retention and Attrition of Students in Higher Education: Challenges in Modern Times to What Works. Higher Education Studies; Vol. 3, No. 2; 2013 ISSN 1925-4741 E-ISSN 1925-475X. https://files.eric.ed.gov/fulltext/EJ1080196.pdf

[15] Strategies for Improving Student Retention (2014, Sept). Hanover Research. https://www.hanoverresearch.com/media/Strategies-for-Improving-Student-Retention.pdf

[16] Crosling, G., Heagney, M., Thomas, L. (2009). Improving student retention in higher education: Improving Teaching and Learning. Australian Universities' Review; vol. 51, no. 2, 2009. https://files.eric.ed.gov/fulltext/EJ864028.pdf

[17] F.O. Isinkaye, Y.O. Folajimi, B.A. Ojokoh, Recommendation systems: Principles, methods and evaluation, Egyptian Informatics Journal, Volume 16, Issue 3, 2015, Pages 261-273, ISSN 1110-8665, https://doi.org/10.1016/j.eij.2015.06.005.

[18] R. V. Karthik, S. Ganapathy and A. Kannan, "A Recommendation System for Online Purchase Using Feature and Product Ranking," 2018 Eleventh International Conference on Contemporary Computing (IC3), Noida, India, 2018, pp. 1-6, doi: 10.1109/IC3.2018.8530573.

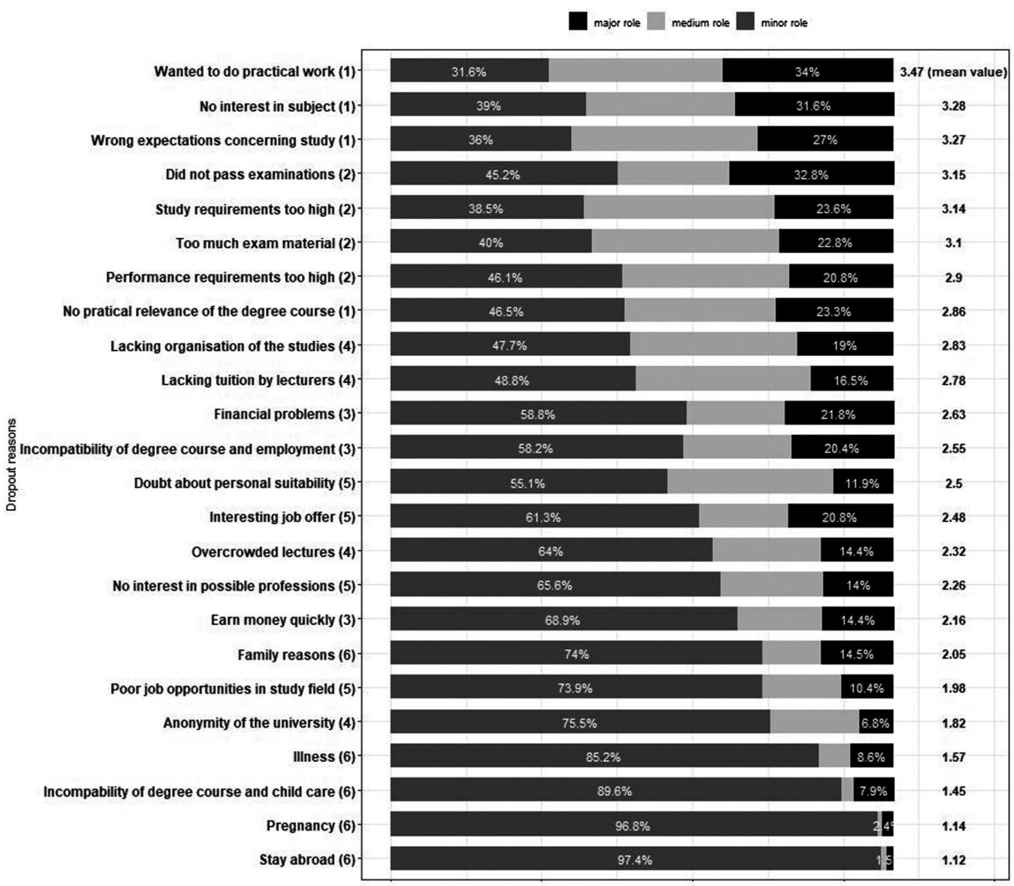
Appendix

A. The computation of getting feature weights was based on how much various motive factors affect dropout rate according to the study by Behr [9]. Figure 2 in Behr's paper (provided as below) depicts various dropout motives according to their importance. First, we categorized the dropout reasons into five: interest or expectation from school, performance from school, financial aspect, study conditions, and employment. We excluded family or personal reasons suggested in the paper because it is not directly related to measuring the university score. Then, we matched each category to our corresponding features that we use for our ranking model: acceptance rate, graduation rate, average annual cost and debt, size, and salary. The metrics (%) for major roles were added by category and averaged to make the final feature weights as in Table 1 below.

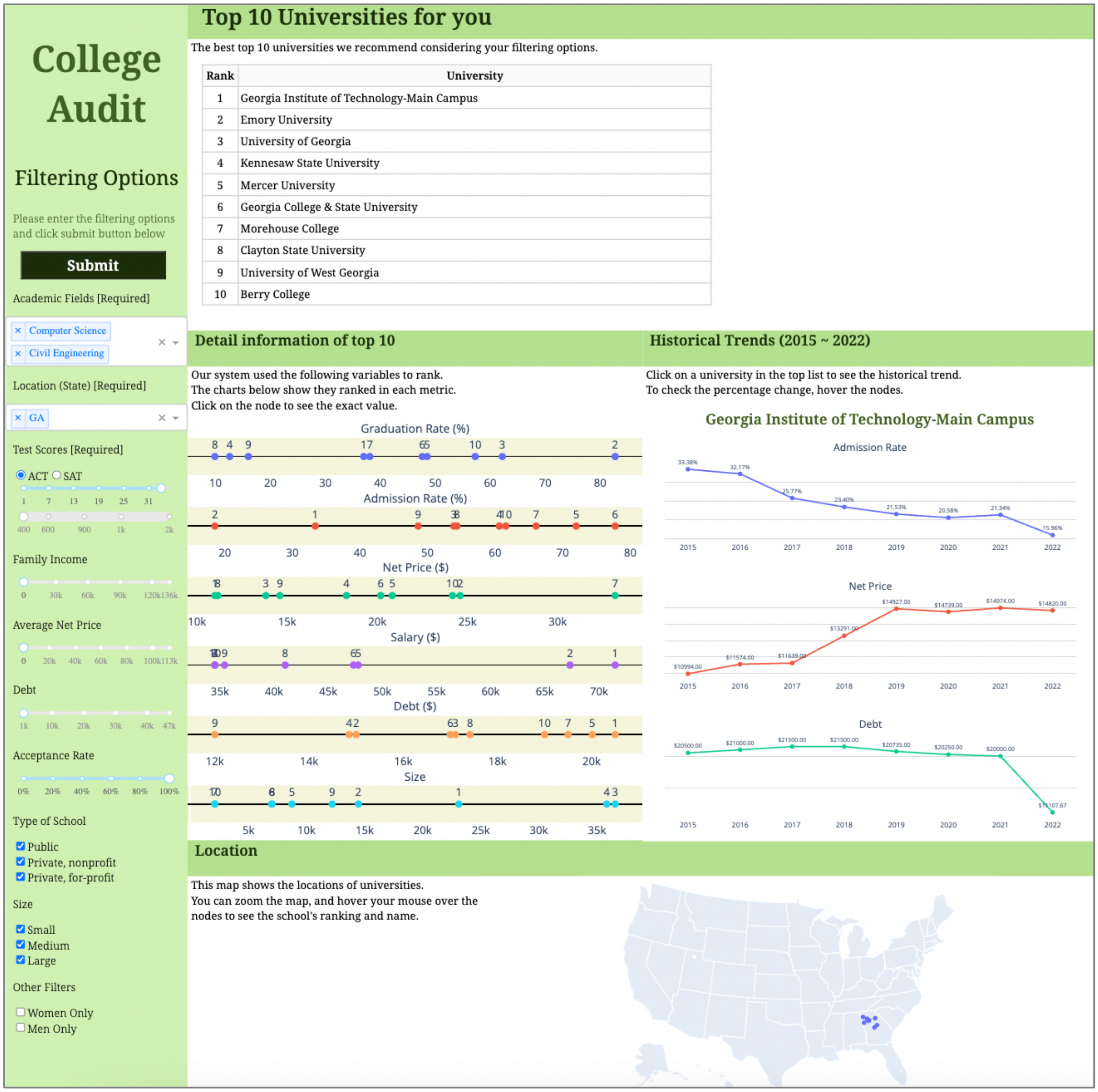
Table 1.

Final Weight		(Rounded)
Performance	Graduation Rate	0.16
Financial Aspect	Net Price	0.12
Interest/Expectation	Acceptance Rate	0.14
Employment	Salary	0.24
Financial Aspect	Debt	0.12
Study Conditions	Size	0.22
SUM		1

Figure 2 in Behr's Paper [9]



B. Outline of the User Interface in more detail (only Academic Fields, Location, Test Scores, Acceptance Rate, Type of School, and Size filters are applied)



C. The table displaying the analysis of user study on College Audit, with the actual survey questions and open feedbacks included.

Questions	1 (Extremely Dissatisfied)	2 (Dissatisfied)	3 (Neutral)	4 (Satisfied)	5 (Extremely Satisfied)
1. How likely are you to recommend College Audit to others based on its usability and functionality?	0	0	7	9	5
2. How satisfied (with the accuracy) are you with the results from College Audit?	0	1	5	11	4
3. How would you rate the intuitive ease of using College Audit?	1	2	2	8	8
4. How appealing did you find College Audit's User Interface design?	0	4	9	5	3
5. How satisfied are you with the runtime of College Audit?	0	0	4	6	11

6. Any open comments/feedback for College Audit.	More information for international students.
	Easier input of filtering option (drag scale slightly difficult to use); quick explanation of each category; range indication for size (ex: small=less than 10000), include financial aid data for each school
	Providing reasons for drastic changes to different stats (reasons for major drop/increase) Additional information of living expenses in each cities
	I think including an option to select all states in the audit would be nice
	It is a little difficult to understand the UI of detailed information of top 10, as I have to look at the university table and the graph at the same time.
	In the top 10 universities for you table, I want to see each school's actual values of the parameters I selected (ACT score, etc). I think it will tell more about the rankings.
	UI design is not fancy but easy to use.
	I wish there was GPA as one of the filters.
	I like the simplicity of the website.
	Easy to use, and actually saw undergraduate schools I have been accepted into.
	Somewhat useful, would have been nice to set the parameters myself.
	UI is simple and easy to get started.