OptiDule

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I. Introduction

Achieving academic success is a top priority for both students and institutions in the dynamic world of higher education. It is an intricate puzzle of selecting the right courses at the right time, considering prerequisites, course difficulty, and course professors. Making these decisions can be overwhelming, and students often seek answers to questions like, ”Which combination and order of Georgia Tech (GT) classes will yield the best and worst GPAs for my chosen courses?”. Our project ”OptiDule”, aims to address these concerns by providing students with a powerful tool that enables them to discover the ideal sequence of classes that will maximize their GPAs, while also offering a tailored, optimal course schedule.

With our dashboard, students can input their chosen courses and prerequisites and instantly receive recommendations for the ideal schedules to optimize their GPA. Our rough scheduling tool allows students to estimate when they should take each class, factoring in the predicted GPA trends for different semesters. Courses that exhibit increasing difficulty over time are scheduled at the outset to ensure students engage with them when they are most manageable during their study period. Conversely, courses displaying a decline in complexity are positioned towards the end, providing students the opportunity to take them when they are at their easiest. This strategic approach optimizes the progression of their academic journey.

Our project’s applications are far-reaching. It enables students to approach their college education with a well-informed plan, fostering improved academic performance and satisfaction. Academic advisors can also use this tool to better assist their students in making course selections that align with their goals.

Our work is inspired by a growing body of data-driven innovations in education. Past projects, such as predictive analytics models in various universities, have demonstrated the transformative potential of harnessing data to enhance student success. By building on this foundation and leveraging Georgia Tech’s extensive data set, we are committed to providing a practical tool that promises to make a real difference in the lives of students. In doing so, we strive to redefine how students engage with their education and embark on a journey towards academic excellence.

II. Literature Survey

A. Current State of Predicting GPA

Current literature on predicting GPAs mainly focuses on using past performance as an indicator of future GPAs. Gershenfeld et al. show that the first semester GPA is a strong indicator of graduation rates and career success, especially for underrepresented students [1]. This highlights how GPA is important for students to look at before even picking classes, but we would add to this benefit by optimizing GPA every semester. Studies have used various machine learning models to predict students’ final GPA, including decision trees and a Bayesian Belief Network as examples [2] [3]. We will test these different models and aim to improve upon their approach by using information about previous GPA trends in courses for our predictions.

Other studies have focused more on different factors. Plant et al. suggest that previous performance should be considered along with previous knowledge, quality, and quantity of studying [4]. McAbee and Oswald look at GPA prediction from a psychological viewpoint, finding that conscientiousness is the best predictor of GPA out of the big 5 personality traits [5]. Another study also confirmed that conscientiousness is related to higher GPAs while digging deeper into how students’ social lives could be used for GPA prediction [6]. We obviously do not have access to that sort of data, as it required students to be tracked using their smartphones for 10 weeks. However, all of these studies remind us that past performance is not the only predictor of GPA, which is a limitation of our work. Another study suggests using student data and time series analysis to predict individual academic outcomes [7]. While it primarily focuses on online courses, its predictive framework can help us forecast GPAs and optimize schedules. Jha et al.’s 2015 paper explains how sparse data can be used in forecasting using clustering, which would be crucial for relatively new courses with few data points at Georgia Tech [8]. Hence, we can leverage the paper’s insights into many classes in our dataset for better accuracy. Another study highlights the importance of optimizing course schedules by considering teacher and student preferences. However, it lacks a detailed exploration of the challenges and potential limitations associated with using only mathematical models for course scheduling [9].

B. Importance of GPA

A study from China highlights how GPA influences students’ mental health, especially low-income students, suggesting that our dashboard could have impacts beyond GPA due to relieving stress. However, this study is from China, so their findings might not apply in a US context [10]. Another study from Australia also shows that planning ahead helps reduce students' stress but suffers a similar shortcoming as the previous study [11]. A study by Kern investigates the relationship between college retention and GPA [12]. Although the study may not account for all potential confounding variables, the study reinforces the need for our model, emphasizing that increased GPAs contribute to better student retention.

C. Interesting Aspects Effecting GPA

Research on GPA variation across academic quarters and external factors at Ohio State offers insights into temporal effects on grades, useful for predicting Georgia Tech class outcomes, even though it is limited to Ohio State's context and lacks some detailed data [13]. Another paper highlights how professor ratings take more than the course grades into account, suggesting that we should not use professor ratings as a direct proxy for predicted grades [14].

D. Online Courses

A paper on optimizing online course delivery through student interaction analysis suggests some data-driven methods that can guide our GPA forecasting and dynamic course scheduling [15]. Even though it is centered on online courses, it mentions factors that we should consider like courses' length, complexity, and frequency/difficulty of assignments and quizzes it. Another study from 2014 tracks online education and provides useful insights into predicting the GPA of online courses, as some in Georgia Tech are. However, it is limited to a pre-COVID-19 context [16].

E. Importance of Scheduling

A 2009 study explores how class timing impacts college algebra achievement at Old Dominion University. Though limited to one subject at one university, it offers insights into class timing's influence on performance that can aid in our schedule optimization [17]. Another study from 2012 investigates the impact of grading scales from 2005 to 2010. This will be useful to us when predicting future grades, though the paper only focuses on letter to plus minus grades and does not provide a view of the overall change in grade scales [18].

III. Proposed Method

A. Data Cleaning and Formatting

Before starting any modeling, data must be encoded, split, and cleaned correctly. The original data received from the Georgia Tech Institutional Research and Planning team was formatted as shown in Figure 6 with some columns not shown that displayed the other grades, pass/fail rate, as well as withdrawal rate. Using groupby methods along with pandas dataframes, the original data (fig 6) was manipulated into the format shown below in Figure 2. This includes columns ranging from 2014 Spring to 2023 Summer and including 3 semesters per year to account for Spring, Summer, and Fall for each year. The rows include every course offered at any point

	Trm Code	Year	Academic Year	Month Start	Term	Course Subject	College (imperfect mapping)	Course Subject and Number	Primary Instructor Name	Section	...	B	C	D
0	202208	2022	2022-23	8	Fall	ACCT	Scheller College of Business	ACCT 2101	Blunck, Ryan	E	...	0.231884	0.144928	NaN
1	202105	2021	2021-22	5	Summer	ACCT	Scheller College of Business	ACCT 2101	Blunck, Ryan	ES	...	0.060606	0.030303	NaN
2	201902	2019	2018-19	2	Spring	ACCT	Scheller College of Business	ACCT 2101	Blunck, Ryan	A	...	0.235294	0.058824	0.044118
3	201408	2014	2014-15	8	Fall	ACCT	Scheller College of Business	ACCT 2101	Carlisle, Melissa	TSB	...	0.413793	0.137931	0.068966
4	201408	2014	2014-15	8	Fall	ACCT	Scheller College of Business	ACCT 2101	Carlisle, Melissa	TSC	...	0.371429	0.200000	0.085714

Fig. 1. Original Dataset

between the year and semester range along with the average GPA for that semester across all professors and sections.

	2014_Spring	2014_Summer	2014_fall	2015_Spring	2015_Summer	2015_fall	2016_Spring
ACCT 2101	3.136000	3.29	3.038000	3.210000	3.21	2.998000	3.086000
ACCT 2102	2.770000	3.27	3.120000	3.150000	3.55	3.290000	3.156667
AE 1350	3.336667	NaN	NaN	NaN	NaN	NaN	NaN
AE 1355	4.000000	NaN	3.956667	3.900000	NaN	4.000000	4.000000
AE 1601	NaN	NaN	3.596667	3.746667	NaN	3.626667	3.783333

Fig. 2. Formatted Data

As can be seen above, many classes have missing values for certain semesters as they were not offered. This issue could lead to less accurate modeling or predictions later, so the values need to be imputed. Linear interpolation was utilized in order to fill in the NaN values. Spring, Summer, and Fall were imputed separately as the seasonality of GPAs was important to be considered and created far better models than imputing all together. The dataset that was obtained only contained GPA, Professor, course, and semester as shown in fig 6, but ideally a prerequisite column would also be received with all prerequisite courses for each course. The time span of this project did not allow for this data to be obtained and this is a limitation that can be seen later in the model. First a random assignment of prerequisites was utilized to make sure the model could accommodate them, and then the dashboard was transformed to receive user input on these courses instead.

B. Forecasting

Once such a dataset is created, it can be utilized within our forecasting model. First a train-test split is done by utilizing the last 10 percent of the model as the testing values as the model is supposed to forecast the future average GPA. an ARIMA (autoregressive moving average) model was utilized, and a Grid Search was implemented to determine the best parameters to train the model, by testing a total of 256 parameter combinations, with p,d and q all varying between 1 and 4 inclusive. For ARIMA p= number of lag observations in the model, d: number of times the raw observations are differenced, q: the size of the moving average window. Finally p,d and q were found to be best at (p=2,d=1,q=1).These values were then plugged into individual ARIMA models for each course to predict the next 18 semesters of grades. ARIMA was utilized because it is very applicable to predicting future values from time series data, as the parameters help smooth the lagged moving average. The instructors of courses in future semesters was predicted by seeing which professor last taught the course for a specific semester (ie. Spring, Summer, Fall). Thus the predictions for each course for the next 4 years were made, and this was stored in a pandas dataframe in csv format to be utilized by the optimization model.

C. Optimization

The optimization process utilized the PULP package in python to develop and implement a model. The primary function known as "run" takes inputs of a list of courses that the user wants to take, the minimum and maximum hours for each semester, whether summer courses are feasible (default is no), a set of prerequisites for each class as a list of lists(no input is assumed to mean no prereqs), and the procured forecasting dataset from the previous section. The main decision variable is a binary variable that determines whether a class is taken (1) or not taken (0) in a certain semester. A secondary integer decision variable is also created to maintain that the number of hours per semester fits within bounds by its in model constraints. Alongside this constraint, the model contained constraints to have prerequisite courses precede their respective course, and every course must only be taken once. All of this creates a model where the "run" function can pass through all possible semester values, determined by dividing sum of all course hours possible by min and max hour inputs, and find and return a model that minimizes the number of semesters needed to graduate as well as maximizing the average GPA of all courses needed by utilizing the forecasted GPA values.

D. User Interface

1) Decision and Description: The selected interface must be visually appealing, user-friendly, and be able to leverage the optimization and forecasting back end. The decided method to display the dashboard was via a Flask python app that launches a web-based dashboard. The dashboard utilizes a Bootstrap framework including the containers: Course Selection, Scheduling Constraints, Schedule, and Interactive Graphs, with descriptive text informing the user how to navigate the page. This layout, and the process for how it was decided, is described in detail in section IV.

2) Interface Flow: The student selects and adds all their courses from dropdown menus, then have the option to select prerequisite courses to add to the adjacent menus corresponding to the courses they have selected. Next, they can choose to alter the default scheduling constraints in the window to select a preferred minimum or maximum credit hour limit for each semester, and if they will take summer courses. Then, after pressing a "Get Schedule" button, an optimizing python function generates a schedule, and another script generates an interactive visualization.

3) Schedule: The 'Schedule' section of the dashboard, an integral part of the user interface, is meticulously designed to display the optimized course schedule in a clear and user-friendly tabular format. It showcases each academic year in separate rows, with columns representing the semesters (Fall, Spring, and optionally Summer), allowing for an intuitive and chronological view of the course plan. This section not only lists the courses for each semester but also prominently features the average GPA for each academic year in the "End of Year GPA" column, providing students with a snapshot of their academic performance. A significant highlight of this section is the display of the "Predicted Cumulative GPA" at the end of the table, boldly emphasizing the forecasted overall GPA based on the scheduled courses. The table dynamically populates in response to user inputs such as course selections, prerequisites, and scheduling constraints, all of which are factored in by the back-end Python script upon clicking the "Get Schedule" button. The design of the schedule table, enhanced by the Bootstrap framework, strikes a balance between visual appeal and clarity, ensuring ease of reading and comprehension. Furthermore, the responsive nature of the dashboard guarantees a seamless user experience across various devices, from desktops to smartphones, making it an effective tool for students to visualize and understand their academic trajectory and its impact on their GPA.

4) Visualization: Given the core insight of forecasting grade point average data, it was paramount to include a temporal aspect in the visualization. It was also important to give insight to the user how courses' grade point averages were expected to change. Thus, the visualization plots a line chart GPA against semester. The graph is unique in that it shows each class's forecasted GPA for every semester, even in semesters where it is not chosen. It highlights semesters the course was chosen with a large 'plus' sign, and marks the semesters with the highest forecasted projected GPA with a triangle. If a semester has both a triangle and a plus, i.e. the course is being taken when it's predicted GPA is a maximum, then only the plus is visible. An example output can be found below, which shows an example output for scheduling 8 courses, subject to minimum 3 and maximum 6 credit hours per semester, allowing for summer courses, and with prerequisite courses. The exact inputs are provided in Figure 3 below, and Figure 4 shows the outputted graph.

Each course's GPA line is assigned a different color. Hovering over a datapoint marked with a cross or triangle displays information about that course, while hovering over a line highlight's that course's line and puts everything else in the background. Thus the user can glean more information about a course by interacting with the graph. In Figure 5 below the tooltip is shown when hovering over the ACCT 2101 course's optimal semester. In the tooltip the user can see the minimum and maximum GPA achievable for that course, the model's chosen semester's GPA, a list of prerequisites, and the Professor teaching the class. For instance seeing that MGT 2250 is a prerequisite of ACCT 2101 here helps explain why MGT 2250 (grey color) is being taken in Semester 1, even

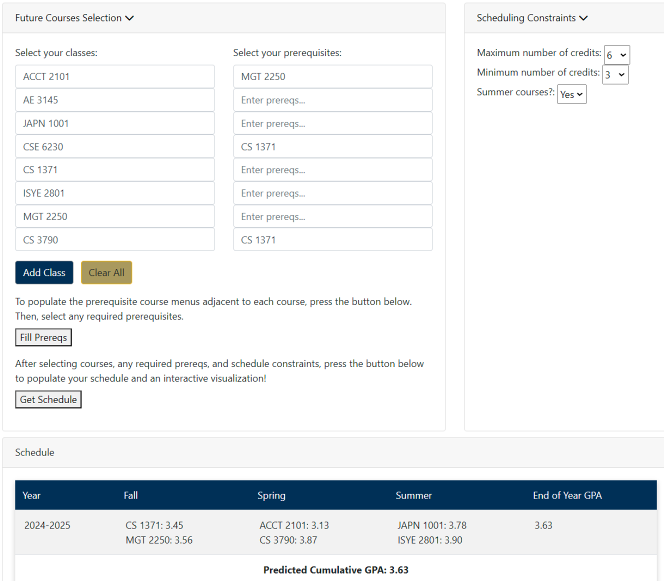

Fig. 3. Inputs to Generate Example Interactive GPA Graph

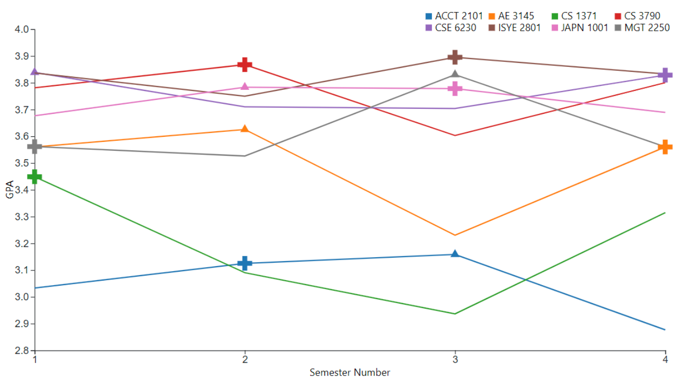

Fig. 4. Interactive GPA Graph

though it has the maximum predicted GPA at semester 3.

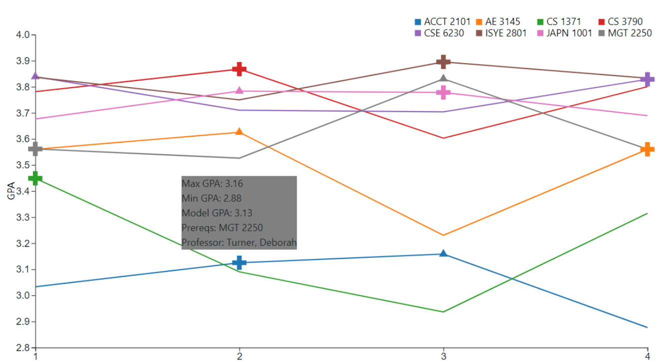

Fig. 5. Interactive GPA Graph with Tooltip

Figure 6 below shows how the interactive graph brings a course in focus when the user hovers over the relevant line.

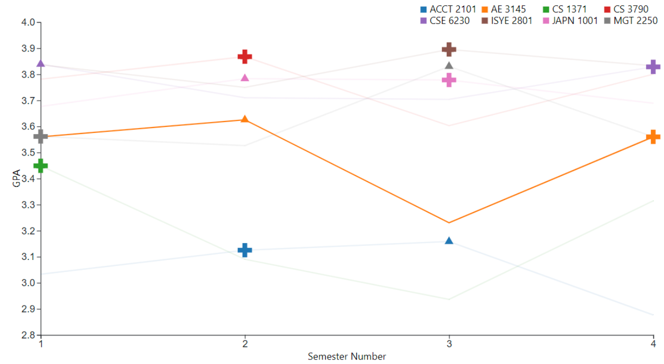

Fig. 6. Interactive GPA Graph with Tooltip

E. *List of Innovations*

The first clear innovation is using past trends to predict future course GPA. Current software only displays some information for students but does not aid with prediction of whether the course is getting harder or easier than the last semester data. The second innovation is on creation of the schedule that maximizes GPA. This could fit into the current advising from counselors and create schedules based on more than just prerequisites alone. The last innovation is a concise dashboard that students and advisors can use to full benefit. Currently any and all information of this sort is time consuming to obtain and difficult to easily understand; our dashboard aims to solve both these issues. This is done with a easy to use interface that has been user tested along with creative and descriptive visuals that thoroughly show the benefits of optimizing your schedule. Current websites that aim to provide a similar benefit do not have any of these innovations that make the product of OptiDule much better suited to tackle the issue.

IV. Experiments and Evaluation

A. *Accuracy*

For every course, we trained separate ARIMA models for each of the three semesters as the original data had significant seasonality. Our optimal parameters ($p = 2$, $d = 1$, $q = 1$) gave an average error of 0.082 when predicting GPA. Thus our model tends to slightly overestimate GPA. However, further analysis showed that the overprediction error was a mostly consistent bias across all courses. This suggests that the optimization process would still give accurate optimal schedules, since a small systematic bias would not significantly affect the relative weighing between different GPAs.

B. *Usability*

First, we tested usability internally with the members of our team who were working mostly on the back end. One early problem was that if there was a problem that caused the optimization to be infeasible, the user did not get any feedback on whether it was an input problem or something else. We thus implemented an error message in the case where the optimization constraints are violated. Future work should include creating a custom error message explaining which constraint specifically was violated.

After working internally, we had peers look at our site for the first time and give their feedback. This was very helpful, since it led to us adding more descriptive text in our final dashboard.

Feedback from 37 respondents sheds light on the dashboard's usability, revealing a positive experience with 83.8% finding it easy to navigate while 16.2% encountered challenges. The majority (91.9%) acknowledged that the provided schedule and information are helpful for academic decisions. Impressively, 89.2% also deemed the optimized schedule practical for their academic goals. These insights, gathered from a diverse group of users, not only highlight the tool's positive impact on decision-making and scheduling but also underscore the need for interface refinements to improve overall usability.

V. Conclusion

In conclusion, our application is unique since it optimizes students' schedules based on GPA forecasting, while intelligently taking various constraints into consideration. A student may input all the courses they wish to take in the next several years while specifying whether they want to take summer courses and the maximum and minimum credit hours they are willing to take. These are especially relevant for international students with credit hour constraints or students facing financial constraints. Through the interactive graph the student can understand why the optimizer made the choices it did. The student may tailor the results to suit their liking more, for example if they would be happier increasing CS courses' GPAs to the detriment of all other courses. The graph in this case helps them see how they can shuffle around courses as they can see the difference between Optidule's choice and the course specific GPA maximizing choice. They can also tell whether prerequisites force their hand into certain choices.

There are some limitations to our approach, however, that provide room for future work. This dashboard is specifically tailored to Georgia Tech's grade distribution dataset, so might not be easily scaled to other universities. We also only had the correct credit hour information for courses currently in the course catalog. For those courses that were not listed, we assumed that they were most likely 3 credit hours. The largest limitation, as mentioned in the data cleaning section, comes from the lack of prerequisite course data. A future model would have this data from the college pre-loaded and lead to less required input from the user leading to a more holistically smooth experience.

Future iterations of OptiDule should have an option for students to select their preferred professors. The forecasting back end would then need to predict which professor will teach which class based on seasonal trends.

One other key feature for future work is to integrate the application with more accessible features, such as an audio option to explain what is on the screen for those who are visually impaired, etc.

All team members have contributed a similar amount of effort.

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