Optimisation Project Summary: Electives Selection by Preferences

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This report will go over the proposal made to optimise electives selection for MAM students, accounting for subject interest, number of credits, GIFTs, and preferred experiences.

I. A Problem Faced by Students Every Year

LBS students are faced with an important decision during their master's programme: choosing their electives. From a pool of 60 courses, students have to identify where their interests lie, what they want their schedule to look like in the upcoming months, what type of evaluation they want to be scored on, whether to opt for more technical or managerial courses, what they value from courses at LBS. And all of this must be decided by long and tedious reading and analysing webpages with information regarding each course. It can be difficult to navigate the different topics, ratings, whilst still getting the right number of credits and not having any clashing schedules. As we assume that a typical LBS's student main objective is to pick electives relevant to her topic of interest whilst maximising the course's ratings, we offer the opportunity to those students to have their selection built for them.

II. Model Development

To make this process a little simpler, adaptable and less hour intensive, we have decided to build an optimisation tool that includes MAM student's preferences and inclinations in the elective selection process. To build it, the tool considers:

- The total amount of extra credits allowed for each student (whether they take a GIFT or want to max out credits or not)
- The subject area of each course
- The term and type of scheduling for each elective
- The weight that students give to each of the 7 evaluation scores of electives captured in previous years

From those data points, the model will optimise to choose electives with the highest average evaluation scores given the weight and give a suggestion to students about which electives to choose. But first, we created a comprehensive data set that allowed us to carry out the optimisation.

a. Dataset

We firstly compiled a dataset regrouping the 60 electives available to the MAM cohort, including subject, schedule information, credits and ratings. This data was gathered from the Enrolment Management System (https://ems.london.edu/CourseDirectory).

b. Model Formulation

The *Elective Selection Problem* is an optimisation problem aims to build a tool to simplify the selection process for MAM students simple and less hour intensive that includes student's preferences and inclinations. The algorithm must consider all the factors to optimise the chosen electives with the **highest evaluation score**.

b.1. Decisions Variables

The decision variable, $\boldsymbol{x_{course}}$, for this model is whether to take an elective or not. This binary model would be a binary variable for each course. In addition, a student can manually set the preference for their electives. Since there are a total of 73 unique electives and streams, we have a total of 73 decision variables to make.

b.2. Constraints

b.2.1 Stream Constraint

The student can shortlist electives for the selection process. Our algorithm will make sure that the two different streams of the same elective cannot be selected. Our approach of setting this constraint is to first identify the electives that has multiple streams and set constraints saying the decision variables of the same elective must sum up to be less than or equals to 1. Since there are a total of 12 electives that has multiple streams, we set 12 stream constraints at this stage.

b.2.2 Timetable Constraint

Students need to ensure that there are no clashes in classes and there are not more than 3 electives in the same term to prevent too much overload. This is modelled with 3 types of constraints in our algorithm which are:

- Block Week: We cannot have a clash in block weeks, i.e. take two electives that are on the same block week. We use similar approach as our stream constraint, there are a total of 5 block weeks that has multiple electives, hence we have 5 constraints.
- Scheduling: We cannot have a clash in scheduled time of classes. It is important to note that we can have classes with the same schedule in the case that they are in different terms. There are a total of 3 unique terms and 24 schedules, hence the number of constraints is the multiple of them, 72 constraints.
- Term: We cannot have more than 3 electives in the same term. We need to set a constraint for each term, therefore, we have 3 constraints.

In total, we handle the complexity of non-clashing schedules for our selected electives, we used 80 constraints.

b.2.3 Credits Constraint

While selecting electives, students will have to keep in mind the total available credits. The default case is set as not taking GIFTs nor the extra credit, therefore, it will be limited to 44 total credits. These constraints will be removed when a preference is given, hence we do not actually set any constraints here.

b.2.4 Preferences Constraint

This constraint will allow for additional constraints based on the student preferences. There could be 4 types of such constraints:

- Whether to take GIFTs
- Whether to 6 Extra Credit electives
- Subject Preferences
- Experience Preferences (Adding weights on particular questions)

The combinations of the first two preference gives a credit constraint and a constraint of whether taking 6 credit electives are allowed. One constraint is also added with subject preference and lastly experience preference only changes our objective function and hence does not introduce any constraints. We have a total of 3 constraints here.

b.3. Objective function

As mentioned above, the objective function of our model can change based on the student's desired experience. This is done by using a weight vector that changes based on student's preference, and this is multiplied by our vectors of evaluation scores for all our electives. We choose to use subtract for the evaluation score of Question 7 because it is more desirable for electives to require less prior knowledge. Therefore, the aim of the model is to maximize our objective function.

c. Outputs

The output of our model comes in two aspect. First, the output of our binary decision variables informs the student the electives to choose that will maximum the evaluation score (have the best elective experience). Secondly, the value of the objective function can be divided by the total number of electives chosen and the sum of the weight vector, to obtain the average evaluation score of the desired questions of our selection of electives. This is implemented in the *printSolution()* function in our prototype and hence the output from our prototype is directly interpretable.

III. User guide and room for Next Steps

a. Model Instructions

To use the prototype we have built, we can set our elective preferences in the first cell by changing the input of the corresponding variables. Possible selections include:

* **gifts:** Yes, No
* **extra:** Yes. No
* **subject:** All, Strategy & Entrepreneurship, Marketing, Finance, Management Science & Operations, Organisational Behaviour, Accounting, Economics
* **experience:** Overall, Learning Experience, Coursework, Class Participation, Prior Knowledge

The inputs are case-sensitive. After changing the preference variables, we can run the whole prototype. The electives recommended will be shown in the outputs of cell 28 and the average evaluation score of our preferred questions will be shown in the ouputs of cell 27.

b. Dashboard Access

For better user experience, we offer access to an online dashboard, allowing the student to input its preferences and parameters and get its personalized electives selection, without needing to access a back-office and manipulate an optimization model (see Appendix B).

c. Model limitations and further improvements

There are limitations of our current modelling method can be discussed in two different sections.

Data Collection:

1. There are missing values in our evaluation score for electives that are new and wouldn't taught last year. We filled the missing evaluation scores with the average score of other electives that the same faculty teaches. For those that are taught by new faculty, we took the departmental average. This method of filling could lead to bias in that the model recommend several electives that are taught by the same elective just because they have one good performing elective.
2. We took the evaluation score of previous electives of the same stream. However, we did not consider possible change in faculty. This could lead to different experience for the students that we did not account for.
3. The data are manually collected from EMS, there could be human error in our dataset.

Modelling:

1. There is scaling issue in our objective function that makes our final output less interpretable when experience preference is "Overall". Currently, our objective function is the sum of the evaluation score of first six questions minus the evaluation score of the last question. However, we know that both the mean and the median of the first six questions are a lot higher than that of the last question. This leads to a scaling issue with the output of total evaluation score. However, since all electives' evaluation score are scaled in the same way, this issue will not lead to non-optimal decisions made but merely make outputs less interpretable.

Appendix

Appendix A: Constraints

Stream Constraint:

$$\sum_{stream} x_{stream} \leq 1$$

where x_{stream} are decision variables of the electives that are the same electives but are just of different streams. The courses above have multiple streams for the same elective name. We can then set constraints on those by locating their index and setting the sum of these indices to less than or equal to 1, i.e. only one of them can be selected.

Timetable Constraint:

- **Block Week**

$$\sum_{block} x_{block} \leq 1$$

where x_{block} are decision variables of the electives that have same block week number.

- **Scheduling**

$$\sum_{n \in allCourses} x_n * s_{tc} \leq 1$$

where s_{tc} is a vector in the one-hot matrix representing the schedules of our classes, column names are all possible schedule times (separated by time of day, weekday and term).

- **Term**

$$\sum_{term} x_{term} \leq 3$$

where x_{term} are decision variables of the electives that are in the same term.

Credit Constrain:t

$$\sum_{n \in allCourses} x_n * credit_n \leq 44$$

where $credit_n$ is the credit of elective n.

Preference Constraint:

If we are **taking GIFTs** and **the extra 6 credit elective**, we will be setting the following constraints:

$$\sum_{n \in allCourses} x_n * credit_n = 39$$

$$\sum_{extra} x_{extra} = 1$$

where x_{extra} are decision variables of the 6 credit electives.

If we are **taking GIFTs** and **not taking the extra 6 credit elective**, we will be setting the following constraints:

$$\sum_{n \in allCourses} x_n * credit_n = 33$$

$$\sum_{extra} x_{extra} = 0$$

If we are **not taking GIFTs** but **taking the extra 6 credit elective**, we will be setting the following constraints:

$$\sum_{n \in allCourses} x_n \ * \ credit_n = 50$$

$$\sum_{extra} x_{extra} = 1$$

If we are **not taking GIFTs** and **not taking the extra 6 credit elective**, we will be setting the following constraints:

$$\sum_{n \in allCourses} x_n \ * \ credit_n = 44$$

$$\sum_{extra} x_{extra} = 0$$

For our subject constraint:

$$\sum_{subject} x_{subject} * credit_n \ \geq \frac{TotalCredit}{2}$$

Objective Function

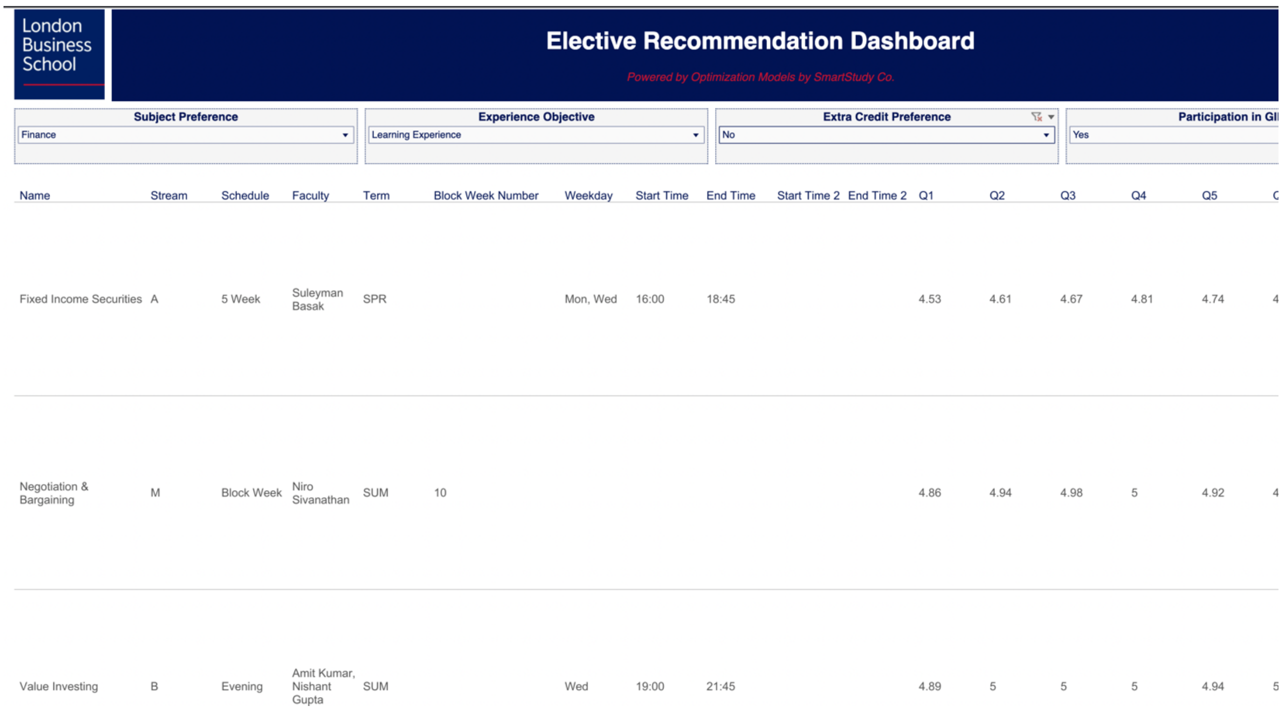
Our objective function is:

$$\sum_{n \ \in courses} x_n \left[\left(\sum_{Q1-Q6} weightVector \ * evaluationScore \right) - weightVector_{Q7} * evaluationScore_{Q7} \right]$$

where $weightVector$ is a vector of length 7, indicating the weights to each evaluation question and is obtained based on our experience preference.

Appendix B: Tableau Dashboard

We created an interactive dashboard to allow users to conveniently choose their preferences and quickly view the corresponding elective recommendation with the related course information. We used a joined dataset of the resulted elective recommendation dataset containing potential student preferences and recommendations and the course information dataset that contains more details for each elective.


London Business School

Elective Recommendation Dashboard

Powered by Optimization Models by SmartStudy Co.

Subject Preference: Finance

Experience Objective: Learning Experience

Extra Credit Preference: No

Participation in Gl: Yes

Name	Stream	Schedule	Faculty	Term	Block Week Number	Weekday	Start Time	End Time	Start Time 2	End Time 2	Q1	Q2	Q3	Q4	Q5	C
Fixed Income Securities	A	5 Week	Suleyman Basak	SPR		Mon, Wed	16:00	18:45			4.53	4.61	4.67	4.81	4.74	4
Negotiation & Bargaining	M	Block Week	Niro Sivanathan	SUM	10						4.86	4.94	4.98	5	4.92	4
Value Investing	B	Evening	Amit Kumar, Nishant Gupta	SUM		Wed	19:00	21:45			4.89	5	5	5	4.94	5

The tableau dashboard can be accessed through this link : https://public.tableau.com/app/profile/sarah.wu2185/viz/ElectiveRecommendationDashboard/Dashboard1?publish=yes