International Journal of Computer Applications (0975 – 8887)
Volume 184– No.38, December 2022

Generating an Optimal Tour Plan with Optimization

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ABSTRACT
Tourism is an industry that has widespread acrossthe globe. It was built around the natural desire of humansto travel and to facilitate their needs. With the evolution ofinformation and technology, the tourism industry is expanding,popularizing lots of new travel destinations among tourists. Thesimple tour plans made by tourists earlier are no longer goingto work as the number of travel destination choices availablein any country has gone high with the information availability.The higher the number of choices is the higher it goes withthe complexity of generating tour plans that returns satisfactorytour experiences. This research paper discusses the ability to usethe concepts of optimization in machine learning to generate anoptimal tour plan by evaluating the tourist's interests. The paperexpresses how the 0-1 knapsack algorithm can be improved andused against a data set in a heuristic approach to generate anoptimal tour plan that can minimize the waste of time and moneyof the tourist while maximizing the relevance of the segmentsincluded in the tour plan for the tourist.

Keywords
Machine Learning, Optimization, Genetic Algorithm, Tour Planning.

1. INTRODUCTION
Humans have been traveling among locations since the beginning of existence on earth. In the preliminary stages, traveling mainly happened for the purpose of survival. Ancient man traveled over continents for food, water, and protection. Now that it is the 21st century and the world is way more civilized than how it began, one might wonder why traveling is still happening to make large stats. Human desires such as exploring new territory on their own, experiencing different climates, exploring nature, etc. drive them to travel around.

The tourism industry is built around the so-called natural desire of humans to travel and explore to fulfill their needs during a tour. Like in every day-to-daytasks, having a tour plan is essential for traveling. Tour planning over the past two decades was mainly based on the information published in magazines/newspaper articles, television, and past experiences of humans. If a comparison was made between the popular travel destinations before 20 years and present trending travel destinations, it would show a significant increase in trends of visiting new destinations. One of the main reasons for humans to travel to these new destinations is that as of now, an enormous amount of information has become available through the resources on the internet such as video logs, blog articles, social media, etc. People would get to know attractive places more easily. Even though technology has made information available at the fingertip, a valid argument can be made that it complicates tour planning since it floods a lot of choices into the scope. After all, it is the tourist's brain that needs to analyze all this information and generate the best optimal plan out of it.

It has been scientifically proved that a modern computer could take more than 5 billion years to analyze 77 items and generate a collection of optimal items set for a knapsack in the standard approach [1] [2].Toovercome this problem, mathematicians have introduced a solution and named it the 0-1 knapsack algorithm which is capable of using the concepts of machine learning and generating an optimal output in minimum time.

This research paper will present and explain how the research was carried out using the 0-1 knapsack algorithm with modifications to generate an optimal tour plan that maximizes tour experience by suggesting most related travel destinations to the tourist's interests within the tourist's allocated budget and minimizing the time waste happened due to poor navigational ordering.

The tourists will be the first beneficiaries of the outcomes of the research as it suggests optimal tour plans according to the tourist's needs. Also, since travel planning happens on a manual approach presently, this algorithm can reduce save a lot of time spent on planning. Due to the availability of data and the time frame allocated for the research, the geographical scope of the research was limited to Sri Lanka. Information was collected from Sri Lankan communities and a data set was chosen that includes travel destinations of Sri Lanka.

2. LITERATURE REVIEW
Several materials were followed as literature including about 15 research papers and the most related content from the said research papers is summarized and included below.

A research was conducted on "user-location vector-based approach for personalized tourism and travel recommendation" by Ajantha D, Jobi Vijay, Raji Sridhar of Chennai India [3]. The research paper suggests using the records on e-commerce websites and social media to provide a personalized shopping list. Also, the history of the user's social profiles is used with the information collected from other similar profiles of people who have similar interests. The researchers call their methodology a hybrid recommendation system that uses a combination of content-based and filtering-based recommendation systems. They introduce a collaborative approach to recommend places to users by adopting Aprirorialgorithmbased travel pattern. This pattern is used to understand users' preferences and analyses behavior. Based on that in turn this pattern recommends travel plans to users. Also, the landmarks collected from popular websites and travel blogs are also used for further development.

Another research was done by a group of Chinese researchers in year 2013 was titled as "Personalized E-Tourism Attraction Recommendation based on Context" [4]. According to the paper, it states that modern tourism has become highlycontext sensitive. Therefore, monitoring the situation of the active user and providing real-time personalized recommendations are the two most intense factors in the tourism research industry nowadays. The paper suggests that the context theory can be used in mobile commerce to improve penalization and accuracy of service and production recommendations and efficiency of customer service.

The next research was conducted by a group of Ukrainian researchers to IEEE titling as "Modelling decision-making processes in the field of individual tourism" [5]. They have identified a trend in tourism nowadays where individuals start going on tours themselves rather than travelling in groups. The concerns identified in this method of travelling are lack of awareness, lack of safety etc. They have introduced a modelling decision-making process that can be applied to the field of individual tourism to streamline the planning and implementing of tours. This includes defining goals, problem identification, obtaining necessary information, consideration of possible alternative solutions, decision making and assessments.

Another Research was done by a group of Bangladeshi [6] researchers proposing a mobile application where the tourists will be able to achieve certain requirements like, selecting a tourist destination, buying transport tickets, reserving hotel rooms, finding tour guides and local dine-in, etc. The aim of this research is to make tourists feel comfortable when traveling in Bangladesh

A research that titles "Design of the Tourism-information service-oriented Collaborative Filtering Recommendation Algorithm" [7] has found out that when it comes to tourism user preferences can be changed at any time. So, to handle sudden and quick changes, it suggests that the recommendation systems need further improvements in terms of real-time and recommendation quality.

Research on Japanese tourism industry [8] has identified the importance of integrating information and communication technology and web technology together. Accordingly developing a decision support system to support tour planning to match personal satisfaction under varied constraints such as time and cost has been identified as the best solution to attract tourists around the globe. So, to represent the time-dependent parameters in the one network model in the static network structure, authors have introduced a time-expanded network with satisfaction values based on the evaluation of tourist multi-criteria decision-making approaches such as AHP.

Another research that was carried out by a group of Malaysian researchers [9] states that Location-based mobile applications which are embedded with GPS technology are largely benefited to tourism as it determines travelers' exact location and provides information regarding users' friends nearby and points of interest. These applications make the tour experience better as they can access information anytime anywhere. However, the paper expresses that this depends on the purpose of the application and for improved interactivity and to provide relevant and user-preferred filtered information further enhancements are needed. Authors suggest that semantic web technologies will facilitate the development of intelligent location-based services in the user's context with more accuracy. The framework they proposed highlights technologies that can be considered in developing personalized location based tourist mobile applications that leverage semantic web technologies. For further development in-depth user privacy concerns need to be assessed.

Apart from the above research papers, few more research papers were referred [10], [11], [12], [13] and the approaches and findings mentioned in those papers were also considered when doing this research.

3. METHODOLOGY

3.1 Data Collection

A group of employees divided into different teams was chosen for an interview as they get to plan their team trips each year. According to the inputs provided it was observed that as an average value each team spends 16.3 hours time planning a trip with a full board (lunch, dinner, and breakfast) plan. They further stated that even though they take a long duration in planning, after the tour the level of satisfaction is low. The key reasons for this dissatisfaction are the destinations traveled not returning the value for the cost, time being spent on the roads due to poor traveling order, chosen destinations not matching everyone's area of interest, etc. Obviously, every member of a team cannot be satisfied with a single tour plan as humans are born with different interests biologically, a tour plan can be created including everyone's areas of interest in a manner that will minimize dissatisfaction.

The next stage of this research was carried out to confirm whether these concerns raised are valid in the general cluster of tourists. A questionnaire was created with 10 questions in multilingual form and was made available publicly. That way tourists from different backgrounds can take part and respond. The questionnaire was open for 14 days and was able to collect 104 responses. The coming paragraph will contain the statistical presentation of the responses.

3.2 Statistics

Identified sources of information were divided into 5 categories.

- Internet - Search engine results, blog posts.
- Social Media - Posts, Images, Video logs etc.
- Travel Agencies - Common Travel Plans
- Past experiences of known associates
- Other

1) Travel Experience and Budget: In getting information on the budget required for the tour, out of the responses 85% stated that they refer search engine results and blog articles when they plan a tour. 67.3% of them are using information available over social media while 14% of participants stated that they get in touch with a travel agency in gathering information and assistance. As the response to the next question 56% of the participants stated that they believe they can rely on the information available on the sources that they refer and can plan ahead. And the third question was on their experience after the tour whether they were able to gain the expected outcome with the allocated budget. 82.6% of the participants believed that they could have had the same or better experience for a lower cost at a different travel destination than their choice.

2) Travel Duration: Tour duration is the second most important in a tour. Especially when traveling to an unfamiliar territory where the tourist has to eyeball over the destinations and measure the duration. The question on sources of duration related information got similar responses from the participants. On the 'Internet' it was over 80% and for 'Social

Media' it was closing 70%. The second question on tour duration got a 60.2% of positive responses which said that tourists believe they can rely on the duration-related information available from the chosen information providers. However, once again the response to the third question shows that 66% of the tourists believe after their tour that the planned duration was not enough as they had spent time more than expected on the roads.

3) Relevance: The next question in the questionnaire evaluated the satisfaction of the tourist with regard to the relevance of the destinations that he chose or recommended to him against his areas of interest. The results show that 61.5% of the tourists believe that their recent tours were not totally into their expectations.

4) Food & Accommodation: The next few questions were on the level of satisfaction of the tourists with finding food and accommodation near their travel destinations. 75.9% of the tourists usually find it difficult to find preferred food items close to their travel destinations and 70.19% tourists stated that finding accommodation close to their destinations was also a challenge.

3.3 Analysis of Data

The information gathered from the questionnaire was then analyzed and the observations are as follows. It was observed that a majority of tourists nowadays are using modern tools to find information when planning their tours. During the interviews, the tourists stated that the reason they do not involve a third party like a travel agency in their tours is that they need their tour to be personalized to the maximum level. Only 14% of the tourists considered taking the service of travel agencies according to the questionnaire responses. However, even after planning the tour on their own using all the information available on the modern platforms, their satisfaction after the tours was low. This suggests that there is a gap in tour planning when identifying the optimal set of travel destinations (Tour Plan) from a big collection of choices, in a manner that will minimize expenses and time waste while maximizing the relevance of the suggested destinations to the tourist.

Furthermore, the choices of sources of information by the tourists showed that the majority of the tourists were familiar with digital device usage and using applications on these devices. It suggested that the tourists would be able to absorb and adapt to a solution implemented with modern technology. A solution to bridge this gap could involve big collections of data and analysis. In other terms, it suggests that the solution should be an algorithm based on machine learning. When analyzing the results and interview findings even deeper a travel destination suggesting algorithm would not be able to fulfill the requirements identified as the gap. According to the stats, tourists were looking for a tour plan that is maximum relevance and minimized waste. This specific requirement narrowed down the solution approach to a concept in machine learning. It is optimization.

3.4 Approach & Overview of the Solution

There are multiple optimization algorithms available, and an analysis of their capabilities was conducted after which it was decided to carry this research on as applied research by using one of these algorithms. Tour planning is all about making a set of good combinations. Therefore, the most suitable algorithm in this situation will be a combinatorial optimization algorithm. After evaluating the suitability of different combinatorial algorithms, the 0-1 knapsack algorithm was chosen as the core algorithm. One of the major reasons to choose this algorithm is its execution efficiency and simplicity in implementation.

Among the digital devices that the tourists carry, the smartphone happened to be the most common digital device, therefore it was decided that the ideal solution would be a mobile app that interacts with the tourist and the said optimization algorithm. The architecture of the system involves two cloud servers, a MySQL database, a data set, and a hybrid mobile application. One of the servers will be occupied by the algorithm and the other server will act as the back end for the front end. The database will contain the records of executed tours the tourists. It can be helpful when the tourists select the same categories over and over to avoid suggesting destinations that had been already visited. Displayed below is the high-level architecture of the solution

3.5 Implementation

Tourists prefer a tour with variance. For example, a tour will never give away a good experience if it is only on safari. A tour with good experience would include a mixture of safari, surfing, hiking, etc. Providing an optimal tour plan that is having this variance was the first research objective. To accomplish this, it was decided to provide the user with a list of tourism categories where he can select up to 3 categories that he prefers. Once the 3 categories are selected, the data that falls into these categories will be extracted from the data set and be fed to the algorithm. However, this requirement opened another gap where it became possible that the algorithm to select destinations from a single category when the destinations of that category have higher values than the other two. To overcome this problem an approach of ranking the selected categories was taken. After the categories have been ranked, the tourist is asked to fill in the budget per head and the duration of stay in a form that appears next in the mobile app. The user will also be prompted to select the starting point on the following screen. Once this information has been collected the user input-gathering phase is complete, and the collected information will be sent to the server.

The collected data will first arrive at the back end for the front-endlayer and it will then be directed to the second server via a REST call where the optimization algorithm is contained. During execution, the original knapsack algorithm extracts all the records available in the data set, which in tour planning could be a huge number of records and is not recommended when considering the performance aspect. That is where the categories selected by the tourist come into play as the data selection approach was slightly modified to retrieve and create subsets of data by category. For this research, there will not be a single feed of the entire data set to the algorithm, but it will be three different subsets of data fed to the algorithm in three executions.

Going forward, the next expected question to arouse was allocating the duration selected by the user without compromising the optimality of the tour plan. It is the reason for the solution to include a ranking mechanism of tour categories that the tourist selects. It was decided that the duration should be divided among the categories in a manner that the higher ranked tourism categories get a higher percentage of the total duration. Since it is limited to 3 categories in this research the first category would get 50% of the duration while the second category is getting 30% and the third category get 20% of the duration. These calculations are done before the algorithm, that way the fitness function would be just a model that generates the optimal solutions using the data and parameters that are fed.

However, the original implementation of the knapsack algorithm considers the maximum weight that the knapsack can hold, as the maximum fitness value for the fitness function. This works without a problem with knapsacks because no matter what the inputs are the knapsacks behave the same. Even though in a tour the maximum limit gets changed as the boundaries of the tour knapsack can be changed by the tourist by changing duration and budget values. Therefore, a way to calculate the maximum fitness value for each tour was needed. The data set contained an attribute that contained the star rating of the destination which was pre-processed into a percentage and the decision was made to calculate the max fitness value using the value attribute of the destination. The way of calculating the maximum fitness value is simple. It is obvious that the maximum value that a destination can take is 100 since it is a percentage, and the maximum value can never exceed the value of the destination count multiplied by 100. The formula to generate the maximum fitness value is as follows.

MaximumFitnessValue = NumberofDestinations∗100

During the execution, this maximum fitness value will be calculated for each selected category, and rather than generating a plan with a single execution, multiple executions with a categorized data set ensured that the top-valued destinations from each category get included in the tour plan. After these calculations, the condition within the fitness function of the original algorithm was modified to consider two arguments instead of one. The two arguments which will be evaluated are the duration and the budget. The fitness function will evaluate each destination and will only include the destination if the destination's duration is to cover and the price is below the tourist's preferred duration and budget. If either one of these two conditions fails, that destination will not be considered.

Once the algorithm is executed up to this stage it will now be capable of giving away a tour plan with an optimal set of destinations. However, according to the findings of the user interviews, tourists do not consider a tour plan optimal if it is not navigation friendly no matter how much the destinations match the given parameters. Therefore, as the next research objective, a search for an optimal sorting approach was also done. The data set contained the latitude and the longitudes of the destinations so they could be plotted on a graph easily. the in finding a way to generate an optimal navigation approach several related optimization algorithms were considered. After multiple analyses, the algorithmic solution for the 'Travelling Salesman Problem' was considered the most suitable optimization algorithm for the scenario. Algorithms like A Star & Dijkstra's were also considered for the solution, but they were turned down as they are about finding the shortest path to a destination out of a set of coordinates while this research objective is about visiting all the available coordinates in an optimal manner. However, during the implementation of including the Travelling Salesman Algorithm into the developed solution, it was observed that it takes a huge amount of time to produce results. Figuratively the knapsack algorithm is capable of generating its solution within 1 - 2 seconds while the Travelling Salesman Algorithm takes more than 5 minutes to generate an optimal navigation plan out of those generated results. This delay is unacceptable, and it was the motivation to find another approach to solve this.

Also, during the analysis stage and the development stage it became clear that a tour plan practically does not include more than 500 destinations. Based on that finding, lead the research to consider the basic array sorting approaches to find a solution for this matter. Without much effort, it was decided to use the selection sort to accomplish this requirement and a custom mathematical formula was used to calculate the air distance by the coordinates when the array elements are compared. This way it was observed that a result can be generated in less than 1 second. Altogether it could take around 3 to 5 seconds to generate an optimal tour plan and communicate over the network to the user on his mobile device.

4. TESTING AND EVALUATION

It was decided to conduct the testing using the full data set. Since the research was conducted as applied research using an existing algorithm with modifications, the best way of testing was by comparing the results generated by the original algorithm and the improved algorithm. Testing was done in two streams evaluating the two aspects' performance and the accuracy of the results. In evaluating the above aspects, 5 different test approaches were followed. The coming sections will explain how each test was conducted and its results.

Planned Test Approaches

1. Generate plans with no filtering by categories.
2. Generate plans with filtering by categories and in singleiteration.
3. Generate plans withfiltering by categories in multipleiterations.
4. Generate plans having destination max value as
5. Generate plans having destination max value as 100.

For all the parameters to be equal in each test approach the number of executions is limited to 100 cycles. During these 100 cycles, 5 different pairs of budgets and durations will be used. Also, the generation count of the algorithm was modified with 3 values 100, 1000, and 10000 for every 20 executions.

Combinations of the Budget and the Duration

1. 3000$ & 5 days (20 executions) – Plan 1
2. 5000$ & 10 days (20 executions) – Plan 2
3. 7500$ & 14 days (20 executions) – Plan 3
4. 10000$ & 20 days (20 executions) – Plan 4
5. 15000$ & 28 days (20 executions) – Plan 5

The expectation of conducting tests using the first 3 approaches is measuring the performance of the modified algorithms against the original algorithm. Each plan was executed with the above-mentioned generation limits. The graphs below show how the time taken in generating results varied against different plans of the original algorithm against the single-executed category filtering algorithm and multiple-executed category filtering algorithms.

As the graphs (Fig. 2, Fig. 3, Fig. 4) show, the algorithm that accepts tour categories as user inputs has made a significant improvement in performance with the reduction of time taken to generate the optimal tour plan. Even though the performance of the algorithm which was executed multiple times with categories is not visible to the naked eye, the figures show that it even has a slight improvement in performance in generating optimal tour plans when compared with the single-stepped algorithm. After the calculations were done in measuring the overall gain from the multiple-stepped algorithm over the original algorithm, it returned a result of

54.6%. This says that the multi-stepped algorithm that accepts tour categories from the user can reduce the time taken to generate results by above half.

The next two tests were conducted to measure the accuracy of the generated results by the algorithm. Both primitive and modified algorithms were considered for this evaluation and the test cycles were performed with the destinations having a value range of 0 to 100. The accuracy was measured by getting the average of tour plans having destinations that fall into the selected tour categories in the 5:3:2 ratio. The 5 should be the destinations that fall into the most interesting category. After the evaluation, the accuracy percentages were plotted into a graph that compares all the 3 algorithms. The graphs in Fig. 5, Fig. 6 & Fig. 7 display the results received under different generation limits.

As the graphs display when comparing the accuracy of the results generated by the 0-1 Knapsack Algorithm and the modified algorithm that uses the 0-5 value scale, it shows that under each generation limit, the accuracy of the generated tour plan has improved from around 50% to above 80%. This is an indication that with the modified algorithm, the tourists will be able to retrieve a tour plan that contains destinations in the 5:3:1 ratio which they will feel highly relevant andpersonalized when comparing the tour plan generated with the primitive approach. The results generated by the modified algorithm that uses the 0-100 value scale are almost identical to the 0-5 approach. After the calculations, it showed that the modified algorithm can produce 53.4% more accurate and personalized tour plans than the 0-1 Knapsack Algorithm.

After the algorithm was tested, the full solution was evaluated with a 10% cluster of the respondents who participated in the survey. They were given a star rating to express how they feel, and a rating including 3 stars and above was considered positive. After the evaluation 80% of the respondents found the solution as interesting as they had rated it above 3 stars.

5. CONCLUSION AND FUTURE IMPROVEMENTS

Humans often find it difficult to finalize a selection from a group of choices and it applies in tour planning as well. Therefore, the possibility of applying an existing optimization algorithm of machine learning to generate an optimal tour plan, out of various travel destinations was researched within this research project.

After evaluating many optimization algorithms, it was decided to use the 0-1 knapsack algorithm as the core algorithm. The solution considers the budget, duration of stay, and three preferred categories of interest as inputs and generates a tour plan using a data set that contains travel destinations in Sri Lanka.

To improve the performance, accuracy, and relevance of the generated tour plan, two main modifications were made to the original algorithm. The first modification is related to the performance where only the destinations that fall into the selected tour categories by the user will be used as the entries when running the algorithm. The second improvement was made to the maximum fitness limit value where the value will be calculated in a dynamic manner allowing tourists to generate tour plans with different durations and limits of expenses.

The results after 5 different approaches of testing show that these modifications are effective in generating results with a 54.6% increase in performance and a 53.4% increase in generating a relevant and accurate tour plan. During the evaluation stage 80% of the users stated this algorithm as useful in their tour planning.

One of the main limitations identified during this research is lack of previous studies related to using optimization for tourism. It made applying concepts of optimization and genetic algorithms in a real-world scenario a challenge. Another limitation that was faced during the research is the sampling size. The ideal size of a sample for research on tourism should be in the thousands. Due to time limitations, the sample size had to be limited to hundreds.

In future work, the possibility of using machine learning and optimization for finding accommodation and restaurants can be done as accommodation and food are essential in any tour where these segments make an impact on the final tour experience.

6. FIGURES/CAPTIONS

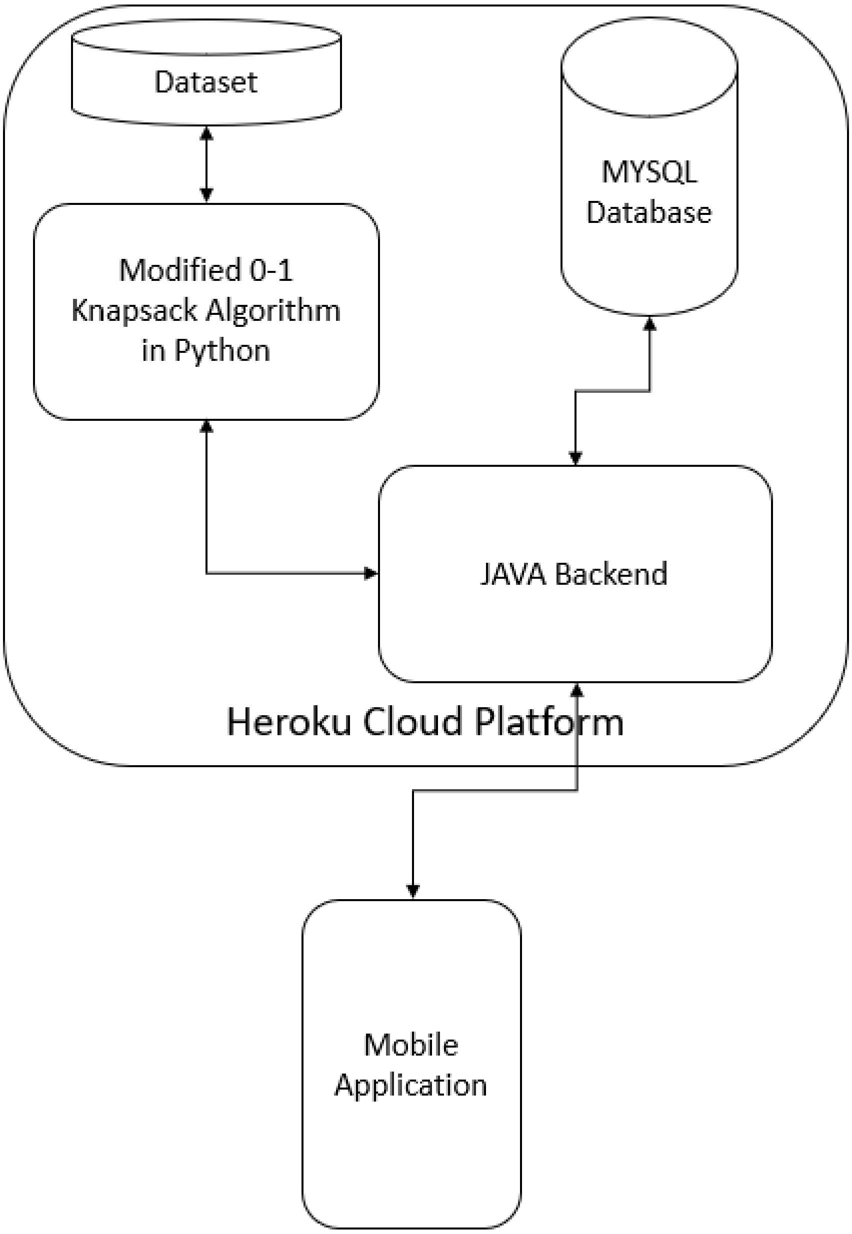

Figure 1 High-level Architecture

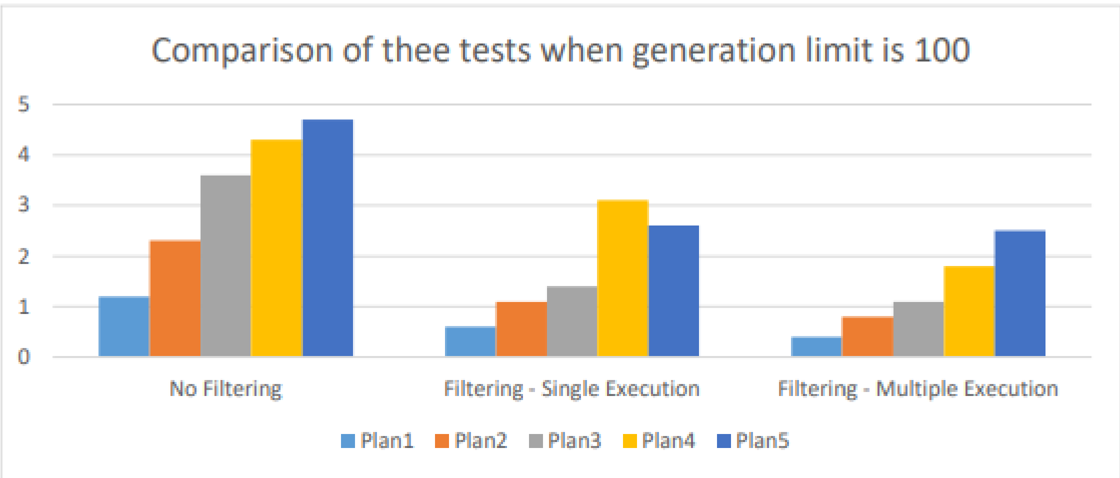

Figure 2 Time taken to generate results by the 3 algorithms when generation

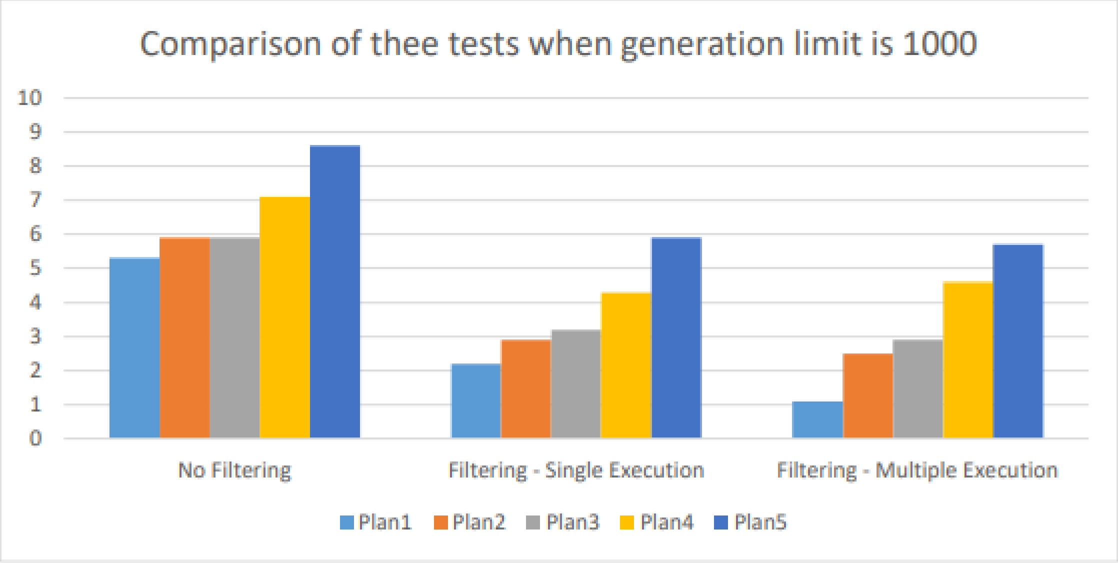

Figure 3 Time taken to generate results by the 3 algorithms when generation

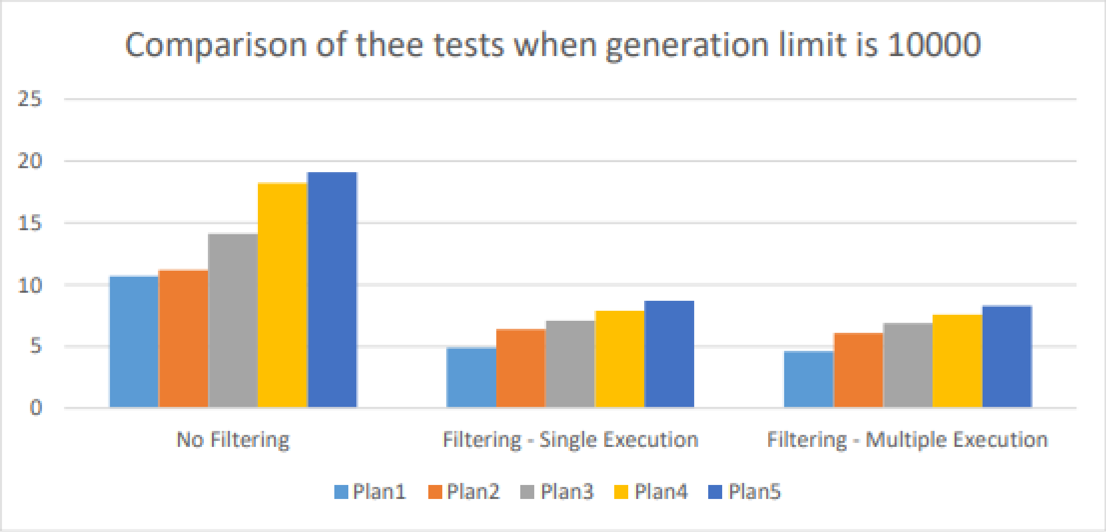

Figure 4 Time taken to generate results by the 3 algorithms when generation

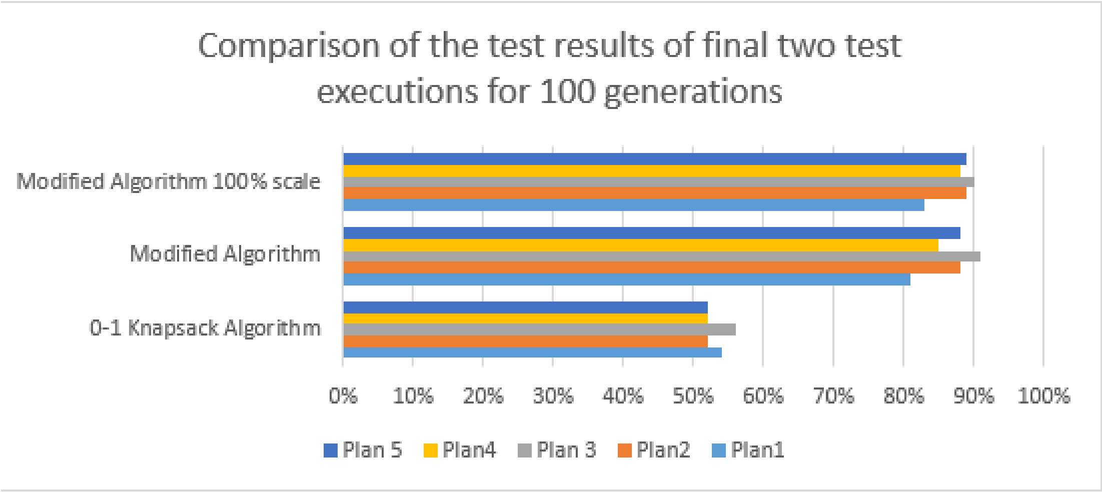

Figure 5 Accuracy with generation limit at 100

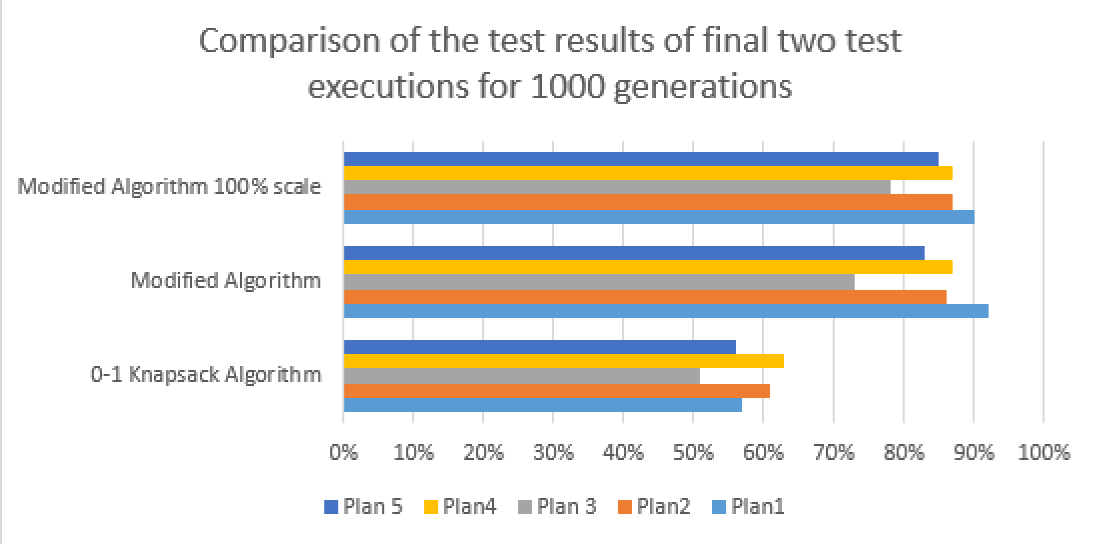

Figure 6 Accuracy with generation limit at 1000

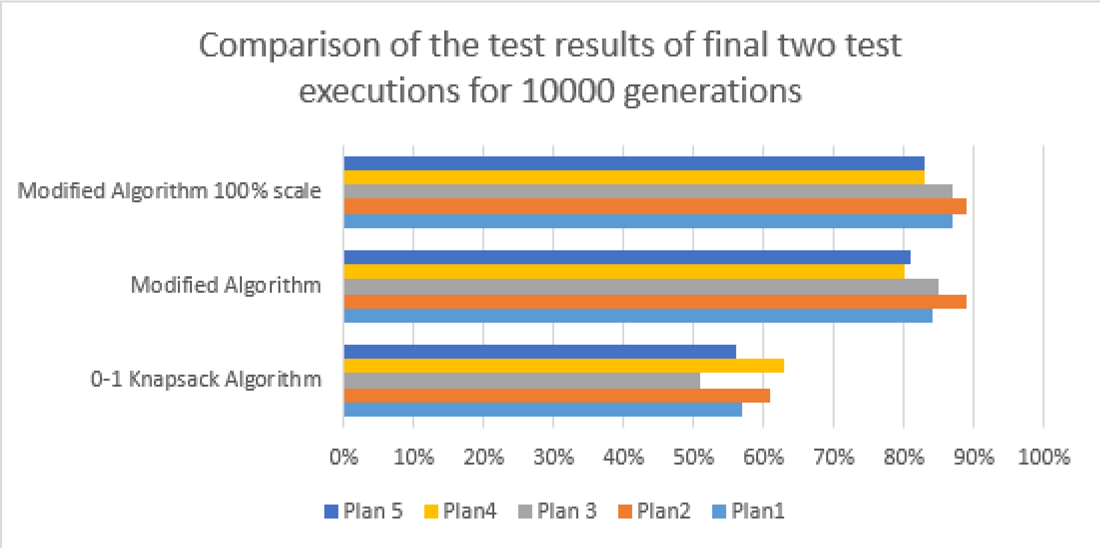

Figure 7 Accuracy with generation limit at 10000

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