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# Multi Objective Genetic Algorithm for Optimal Route Selection from a Set of Recommended Touristic Activities

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**Abstract.** It is a known fact that the order in which touristic activities are experienced plays a role in how enjoyable they are. This is the reason why tourists prefer to book carefully prepared day tours on arrival to a new destination, as they allow them to see the essence of the destination while traversing scenic routes. Tours are great, but they are expensive, do not allow room for personal exploration, and are built as a one-size-fits-all which does not consider the individual preferences of the tourist. In contrast, it is possible to make an optimal selection and ordering of touristic activities from a larger set of possibilities that match a tourist's personal preferences, balancing important aspects like diversity, spatial proximity, or degree of interest on popular places. We propose a multi-objective genetic algorithm that uses a weighted averaging operator to balance four diverse objective functions crafted to maintain diversity, proximity, interest on popularity, and cultural preference. The system has been evaluated against four baseline algorithms and found to perform significantly better for the specified purpose.

**Keywords.** Multi-Objective Genetic Algorithm, Travel Route Optimization, Weighted Average Objective Balancing

## 1. Introduction

Tourists are aptly named for their interest in touring new destinations to experience new cultures, cuisines, etc. Effectively touring a new destination requires prior information on attractions to visit, routes to take, or local cuisines to sample, which can only be gotten from destination marketers, who design purchasable guided tours which allow tourists to experience the destination without further planning. This is beneficial to both the destination marketer and the tourist, as the latter can relax and enjoy a leisure trip while the former can use the opportunity to increase the visibility of certain attractions while profiting from sales. However, these tours lack personalisation and don't allow for much exploration.

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Quite a bit of research has gone into developing algorithms for building and recommending personalised tours [1]. One of them is the *Genetic Algorithm* (GA), which is a heuristic search algorithm that is relatively fast at finding a good solution for a combinatorial optimization problem. A variant called *Multi-Objective Genetic Algorithm* (MOGA) is perfect for building personalised tours because solutions are optimized to meet multiple objectives. Notable works that use MOGA for tour recommendation start by defining constraints relevant to tourists (e.g. time, distance, budget), and then they evaluate possible solutions from a list of Points of Interest (POIs) based on these constraints while ensuring solutions match tourist preferences [2,3,4]. Our proposed method extends our previous work [5], which recommends a set of POIs that match the user's preference considering their relatedness. It addresses the problem of selecting and ordering a subset of the recommendable POIs to minimize the distance between them and maximize their diversity while maintaining the ratio of popular POIs and types of POIs preferred by the user. These four criteria are formulated into objective functions which are balanced using a weighting vector.

## 2. Methodology

Our previous recommender system utilises trace data provided on Twitter to build user profiles that capture the interests and travel habits of tourists for recommending a set of related POIs considering their popularity and category. A full description of data collection, preprocessing and the recommendation process can be found at [5]. The output POIs from the recommender system are used in the MOGA to find the solution that fits better the requirements.

The problem is formulated as a combinatorial optimization with the objective of finding an optimal combination of objects from a finite set of objects. In this case, we are looking for a combination of five POIs from a set of ten recommended POIs. Let $R = \{r_1,...,r_n\}$ be the set of recommended POIs, and $S = \{s_1,..,s_k\} \equiv \{(r_{n1},..,r_{n5}),...,(r_{m1},..,r_{m5})\}$ be the search space of possible solutions. The goal of the MOGA is to pick a solution $s_i$ from $S$ that best balances the objectives.

Our proposed algorithm comprises four objective functions that are combined using weighted averaging and a predefined weighting vector to form the fitness function. The objectives are defined as follows:

- **Proximity**: This objective ensures that the mean distance between adjacent POIs is minimized.
- **Diversity**: This objective ensures that the solution contains a diverse set of POIs. POIs are categorised in [5] using a hierarchical structure called an *Activity Tree*. As such, POIs are diverse when they share less categories and subcategories in their path.
- **Popularity**: This objective ensures that the ratio of popular POIs in the solution matches the tourist's degree of interest in popular POIs (computed in [5] as the percentage of tweets sent from popular spots).
- **Preference**: This objective ensures that the POIs in the solution are interesting to the tourist. Relevant POIs are categorised under types of activities frequently visited by the tourist (obtained with an analysis of the places from which the user has tweeted, [5]).

The main steps of the MOGA are the following:
**Step 1**. Generate randomly an initial population, which is a subset of *S* of size 150.
**Step 2**. Calculate the objective functions and aggregate them using weighted averaging to get the fitness values of all members of population.
**Step 3**. Select two solutions with a good fitness value (i.e. better objective function score) from the population as *parents*, then *crossover* them to form two *children* according to a crossover rate (60%), and then *mutate* children by swapping the positions of POIs according to a mutation rate (1%). If children are fitter than their parents they are added to the new population, otherwise parents are added to the new population (*weak parent replacement*).
**Step 4**. Repeat step 3 until the new population is up to size 150, signaling the completion of generation 1. Cache the best solution in the new population.
**Step 5**. Repeat steps 2 to 4, to move through generations replacing the cached best solution with any better solution. If there is no better solution for 20 generations or 100 generations are completed, stop and return the best solution.

## 3. Experiments and Results

For the experiments, the dataset consisted of 1140 Twitter users with 10 recommended POIs each suggested by our recommender system, which extracts the user's interest in activities, popular or unpopular attractions, and their touring preferences from their tweets in order to make recommendations [5]. The weighting vector `[proximity:0.4, diversity:0.3, popularity:0.1, preference:0.2]` was used in the fitness function. Each user's POIs were passed through the MOGA and the fitness of the results was compared against the following four baseline algorithms:

1. **First five**: Select the first 5 recommended POIs as the solution (i.e. the ones considered better by the recommender).
2. **Random five**: Select randomly 5 of the 10 recommended POIs as solution.
3. **Minimize distance first start (MDFS)**: Select 5 of the 10 recommended POIs that minimize the distance between adjacent POIs using a greedy algorithm with the following steps:
   (a) Add the *first* POI from the 10 recommended POIs to the initial solution.
   (b) Add a POI in front of the last POI in solution or behind the first POI of the solution with the least distance to travel.
   (c) Repeat step b until the solution contains 5 POIs.
4. **Minimize distance random start (MDRS)**: This algorithm is the same as MDFS but the first POI added to the initial solution is picked randomly.

Table 1 showcases the fitness value of our MOGA against all baseline algorithms, highlighting the minimum, maximum and mean values across all 1140 users. MOGA performs significantly better than all baseline algorithms. This result is further enforced in Figure 1, which shows a box plot of MOGA and all baseline algorithms. The MOGA results outperform the baseline algorithms, as the lower quartile of MOGA sits above the upper quartiles of the rest. A sequential check of all possible solutions is feasible in this case due to a small search space of 30,240 options, but a test showed the MOGA to be 27% faster with a runtime of 7 minutes per case compared to 11 when searched sequentially, while obtaining the same optimal result.

**Table 1.** Minimum, maximum and mean fitness values for all algorithms.

| Fitness value | MOGA | First five | Random five | MDFS | MDRS |
|---|---|---|---|---|---|
| Minimum | 0.479 | 0.297 | 0.319 | 0.258 | 0.273 |
| Maximum | 0.748 | 0.665 | 0.680 | 0.676 | 0.680 |
| Mean | 0.639 | 0.512 | 0.510 | 0.519 | 0.516 |

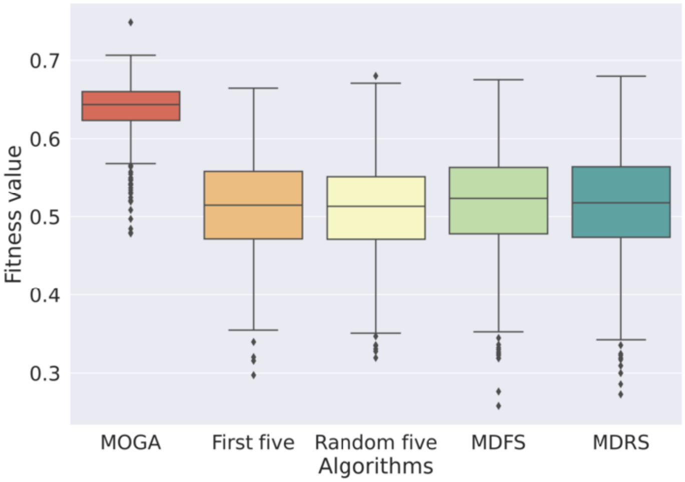

**Figure 1.** Box plots of fitness values for all algorithms.

## 4. Conclusion

In this paper we have proposed a multi-objective genetic algorithm for selecting and ordering a fixed set of POIs from a larger set of recommended POIs. It works by balancing four objective functions, *proximity*, *diversity*, *popularity*, and *preference* using weighted averaging. Experiments show our MOGA to outperform certain baseline algorithms.

## References

[1] Lim KH, Chan J, Karunasekera S, Leckie C. Tour recommendation and trip planning using location-based social media: a survey. Knowl Inf Syst. 2019 Dec; 60:1247–1275, doi:10.1007/s10115-018-1297-4.

[2] Yochum P, Chang L, Gu T, Zhu M. An Adaptive Genetic Algorithm for Personalized Itinerary Planning. IEEE Access. vol. 2020 Apr; 8:88147-88157, doi:10.1109/ACCESS.2020.2990916.

[3] Zheng X, Luo Y, Sun L, Yu Q, Zhang J, Chen S. A Novel Multi-Objective and Multi-Constraint Route Recommendation Method Based on Crowd Sensing. Appl Sci. 2021 Nov; 11(21):10497, doi:10.3390/app112110497.

[4] Yuan C, Uehara, M. Improvement of Multi-Purpose Travel Route Recommendation System Based on Genetic Algorithm. In: 7th International Symposium on Computing and Networking Workshops (CANDARW); 2019 Nov 26-29; Nagasaki, Japan. IEEE; 2019, p. 305-308, doi:10.1109/CANDARW.2019.00060

[5] Orama JA, Borràs J, Moreno A. Combining Cluster-Based Profiling Based on Social Media Features and Association Rule Mining for Personalised Recommendations of Touristic Activities. Appl Sci. 2021 Jul; 11(14):6512, doi:10.3390/app11146512.