Preference based Filtering and Recommendations for Running Routes

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Abstract: With the current trend of fitness and health tracking and quantified self, hundreds of relevant apps and devices are being released to the consumer market. Remarkably, some platforms were created to collect running-route data from these different sources in order to provide a better value for users. Such data could be employed in finding running routes based on the user's preferences rather than being limited to the proximity to the user's location. In this work, a classification system for running routes is introduced considering performance factors, visual factors and the nature of route. A running-route content-based recommender system is built on top of this classification enabling learning user preferences from their performance history. The system was evaluated using data from active runners and attained a promising recommendation accuracy averaging 84% among all subject users.

1 INTRODUCTION

Personal fitness have been gaining an increasing attention from both hardware manufacturers and software developers in the recent years. Utilizing the built-in smartphone sensors and GPS, many apps have been built to monitor the activity of users and provide useful insights and recommendations based on their performance. New fitness gadgets and trackers with extended capabilities have been also released to the consumer market to further enhance the personal fitness of users. Interestingly, performance data gathered by users through many different apps and devices are aggregated in online fitness platforms such as MapMyFitness[1], which integrates with more than 400 fitness tracking devices, sensors and wearables and contains data of over 160 million of running, cycling and walking routes around the world. The route data is mainly used to retrieve nearby routes based on the user's current location.

Proximity, however, is not the only feature that a person considers in her choice of suitable running routes. In this work, several other aspects of running routes are considered to enable recommending the users routes that best fit their preferences. In this context, the considered features of running routes fall into three categories, namely:

- ***Performance Features:*** such as distance and variation in elevation.
- ***Visual Features:*** describing the route's surrounding environment such as proximity to water or to parks.
- ***Nature of Route:*** such as whether a route is a track or not, an on-road or an off-road route and whether it ends at its starting point.

In this research, a classification of running routes based on different features of the route is proposed in Section 3. Based on this classification, Section 4 presents a route recommender system that is designed to fit the user's needs based on her preferences and performance history. This spares the user the need to set her preferences when looking up a running route by learning her preferences over time. The recommender system is evaluated in Section 5 using data from active runners assuming the use case where users are recommended running routes that match their preferences in new locations in which they had no previous activity.

[1]http://about.mapmyfitness.com/

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2 RELATED WORK

The use of fitness trackers and apps in human activity is a current trend in research. (Shafaee et al., 2014) and (Issa et al., 2015) introduce an approach to assess the reliability of market fitness trackers. (Hirsch et al., 2014) highlights the significance of MapMyFitness data to place physical activity into Neighborhood Context. Several studies such as (Chen et al., 2007) and (Pang et al., 1995) introduced preference-based route navigation for drivers. (Quercia et al., 2014) uses Flickr meta-data to determine pleasant locations and suggests more beautiful walking routes to destinations accordingly. (Knoch et al., 2012) applies artificial neural networks as a data mining methodology for a context-aware running route recommender system. A walking route recommender system considering route safety, amenity and walkability is introduced in (Sasaki and Takama, 2013).

3 FILTERING ROUTES BY FEATURES

A running route is basically a set of ordered location points denoting longitude, latitude and elevation. Through utilizing these data points, several features of the route are inferred enabling the classification and filtering of routes to match the personal preferences of any individual. Sections 3.1 through Section 3.3 describe the significance of the considered features and the approaches used in their computation. It is worth mentioning that in the following computations the original data points are sampled using Ramer-Douglas-Peucker algorithm (Douglas, 1973) to obtain a sufficiently similar route using a much smaller subset of the route data points. This step enhances the performance especially for Section 3.2.2 and Section 3.3 where external API calls are used.

3.1 Performance Features

3.1.1 Distance

The distance of a route is perhaps the most critical feature for people when deciding if a route is suitable for them. Usually the distance is provided among other meta-data in fitness information systems like MapMyFitness.com. However, if not provided, distance between two points in a route are accurately calculated using the Haversine formula (Sinnott, 1984) which computes great-circle distances between two points on a sphere using their longitudes and latitudes.

3.1.2 Variation in Elevation

The loss and gain in elevation along running routes are vital for quantifying their strenuousness with respect to steepness. The variation in elevation is represented by two distinct values, which are the *total descent* and *total ascent*. The *total ascent* value denotes the sum of upward vertical distance covered by the runner in order to complete the route. The total descent value is the value of downward vertical distance that the route entails.

3.2 Nature of Route

According to International Association of Athletics Federation[2] (IAAF), running events are classified upon the nature of their location into track, road and cross-country running. Section 3.2.1 introduces an approach to verify whether a route is a running track or not. Section 3.2.2 distinguishes between road and cross-country running routes.

3.2.1 Running Track

Running tracks are characterized by their standardized shape and length. In order to assess if a route is a track or not, a supervised learning approach is applied. Considering the convex shape of a running track, all the points defining the track must intuitively trace, in close proximity, the smallest convex set containing these points, i.e. their convex hull. Figure 1 and Figure 2 show the convex hull defined by a running track and an arbitrary route respectively. The Quickhull algorithm (Barber et al., 1996) is used to compute the convex hull for each running route. Two features are then computed to enable the classification process, namely:

- ***Average Distance to Convex Hull:*** which is the average of all the distances between the points constituting a route and its convex hull. This feature distinguishes convex and non-convex routes.
- ***Convex Hull Area/Perimeter Ratio:*** which helps distinguish an arbitrary convex-shaped route from a proper running track.

Using a set of 100 labeled routes divided across 20% training data and 80% testing data, the Naive Bayes classifier is used to achieve a 100% accuracy in the classification of routes as tracks or non-tracks.

3.2.2 On-road and Off-road Routes

In order to classify whether a route is on-road or off-road, a mapping API is used to check the proximity

[2] http://www.iaaf.org/disciplines

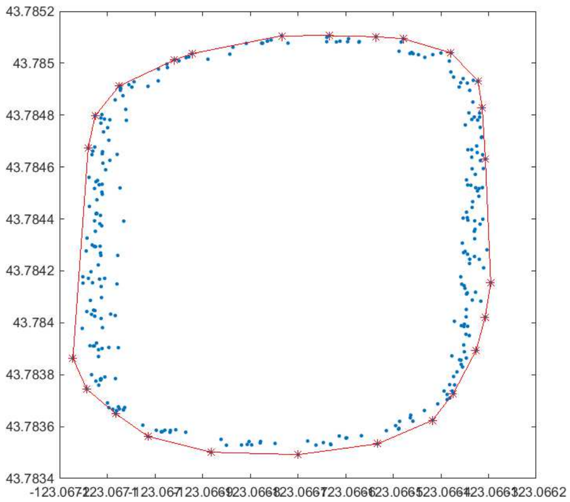

Figure 1: The convex hull defined by the points of a running track.

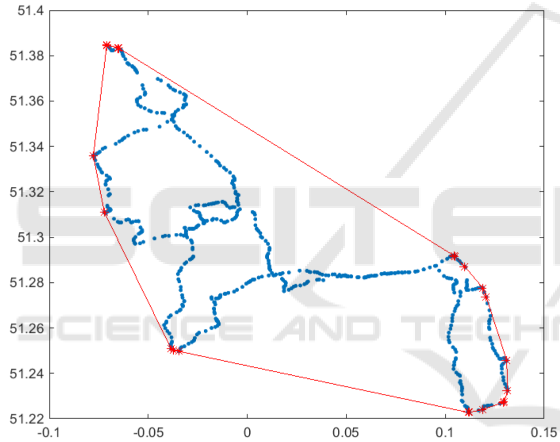

Figure 2: The convex hull defined by the points of an arbitrary route.

of each of the route points to the nearest road. To compensate for GPS inaccuracy, a threshold is experimentally chosen above which a point is considered off-road. Given that running routes can be composed of both on-road and off-road segments, a route is thus described by the percentages of its on-road and off-road segments.

3.2.3 Same Starting and Ending point

People often try to end their runs in the same place of their start to guarantee an equal total ascents and total descents in their runs. This also is useful in situations where the runner starts from a parking spot or near a bus stop for example. This is simply verified by assessing the proximity of the starting and ending points of a route.

3.3 Visual Features

The choice of a perfect running route is also influenced by the route's surrounding environment. In this Section, the proximity to parks and water sources (e.g. lake, sea, etc.) is considered. The same approach, however, could be extended to include other places of interest.

3.3.1 Using Google Places API

Google Places API is used to check the proximity of route's points to a park or water source. In addition to the performance overhead using API calls, several parks and water sources were not recognized by this method.

3.3.2 Using Color Coding for Each Point

Mapping APIs use different colors to annotate different types of terrain in a map. Following the retrieval of an image showing the pixels surrounding each of the route's points as shown in Figure 3, scanning for the color code of water sources and parks enables the verifying the route's proximity to them. This approach is highly precise, however it is computationally expensive as it requires an API call followed by a color scan for each point in the route.

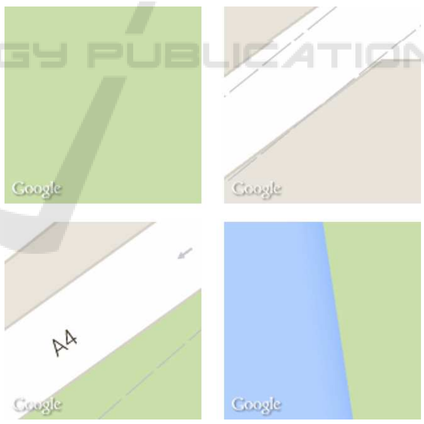

Figure 3: Examples of pixels surrounding route points using Google Maps API.

3.3.3 Using Color Coding for the whole Route

By applying a similar approach to the one presented in Section 3.3.2, however retrieving one pixel map surrounding the whole route as shown in Figure 4 and mapping points of the route to an array of pixels in the retrieved image, highly accurate results are achieved even with reducing the number of API calls to one per route.

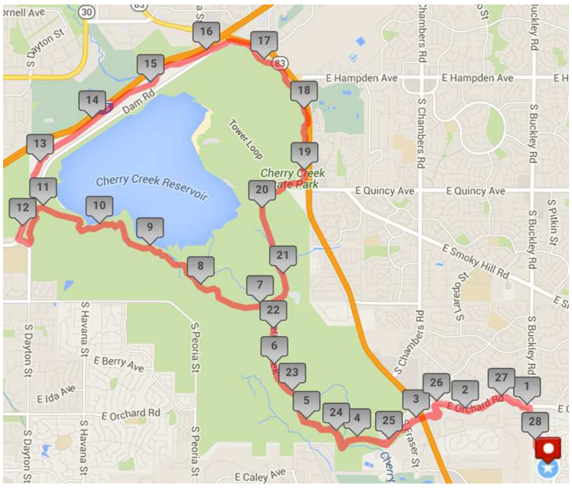

Figure 4: A pixel map surrounding a route as retrieved from Google Maps API.

Evaluated using 150 labeled routes, this method resulted in a precision of 98.3% and a recall 96.77% for park proximity and a precision of 100% and a recall of 91.42% for water source proximity. Table 1 and Table 2 show the evaluation results for park proximity and water source proximity respectively.

Table 1: Results of inferring proximity to a park.

Truth / Inferred	Park	No Park	Total
Park	60	1	61
No Park	2	87	89
Total	62	88	150

Table 2: Results of inferring proximity to a water source.

Truth / Inferred	Water	No Water	Total
Water	32	0	32
No Water	3	115	118
Total	35	115	150

3.4 Route Filtering Application

As discussed in Section 1, MapMyFitness hosts millions of user provided routes all over the world and serves as a reliable data source for physical activity research (Hirsch et al., 2014). Routes from the London-area are retrieved through MapMyFitness API to show the effectiveness of the techniques used above. After processing the route data, a web application is used to enable the user to apply filters to retrieve routes that match her preferences. It is worth mentioning that all the methods introduced can be applied to any route data regardless of its source and MapMyFitness was only chosen for the abundance of its data.

4 ROUTE RECOMMENDER SYSTEM

The goal for building a running route recommender system is to be able to provide a user with running routes recommendations in any location, especially in new locations where the user has a little knowledge of the area and potential routes that might match her preferences. The running route recommender system is chosen to be content-based and uses the features introduced in Section 3 to describe a route. Collaborative Filtering, which relies on the notion that users who have had similar preferences in the past are likely to have similar preferences in the future, could hardly be applied in this context. Arguably, collaborative filtering could be used if the recommendations are limited to locations where a user has a running history, this however does not apply for the intended use case where the recommender system should provide relevant routes in any location of the user's choice.

4.1 Recommender System Overview

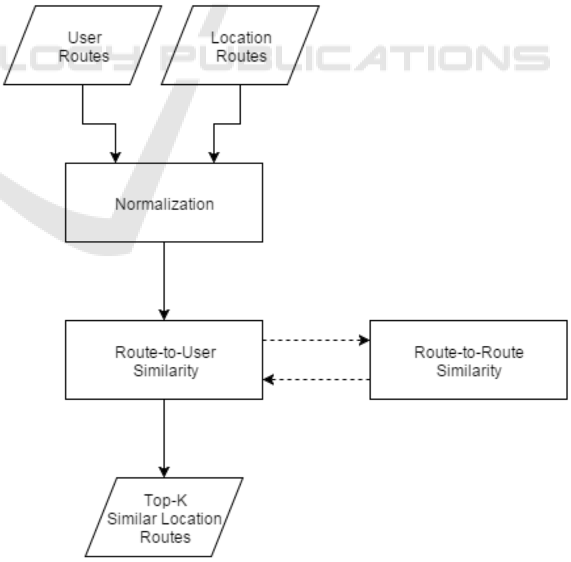

Figure 5: Overview of the Route Recommender System.

Figure 5 shows the main components of the proposed recommender system. The system takes as input two lists representing the user routes and the location routes. Since each route is represented by mixed numerical and categorical features, a statistical approach for normalization of mixed metrics is applied as introduced in (Suarez-Alvarez et al., 2012) where the contribution of each feature to the similarity measure is divided by the contribution mean for this feature. Several approaches are introduced to compute similarity of a route to a user, all of which rely on a consistent route-to-route similarity computation. After a proper aggregation of the route-to-user similarities, the top-k location routes similar to a user are returned as recommendations.

4.2 Similarity Measurement

A normalized route r is defined as an $n-dimensional$ vector representing the n numeric and categorical features of a route namely: distance, elevation, percentage of on-road segment, same start and end point, close to a water source, close to a park, and represents a track.

$$r = (dis, ele, road, closed, water, park, track) \quad (1)$$

Note that elevation is a combined feature of total ascents and total descents in a route as shown in Formula 2. The amount of these contributions, indicated by α, is determined experimentally in Section 5.3. Intuitively, ascents contribute more to the elevation feature as they have a huge impact on the difficulty of a running route.

The similarity of two routes is defined as the Euclidean distance separating the two routes and is defined in Formula 3. This similarity is applied to compute the similarity of a route to a user using multiple approaches as presented in Section 4.2.1 through Section 4.2.3.

$$ele = \alpha.asc + (1-\alpha).des \quad (2)$$

$$ED(r, r') = \sqrt{\sum_{i=1}^{n}(r_i - r'_i)^2} \quad (3)$$

4.2.1 Average Route-to-User Similarity

This approach assigns the average similarity of a location route and all user routes as the similarity score of this location route to the user. Let U and L denote the sets of all user routes and location routes respectively and $card(U)$ denote the number of user routes. The average similarity of a route to a user S_{avg} is presented in Formula 4.

$$S_{avg}(l, U) = \sum_{u_i \in U} \frac{ED(l, u_i)}{card(U)}; \forall l \in L \quad (4)$$

This approach computes all the pairwise similarities of the location routes and the user routes in order to obtain the top-k recommended location routes for a user.

4.2.2 Highest Similarity Pair

Instead of averaging the similarity of a location route to all user routes as proposed in Section 4.2.1, this approach also computes all the pairwise similarities of location routes and user routes, however, for all location routes, it assigns the highest similarity score of a location route to any of the user routes as the route to user similarity. This means that it is enough for a location route to be highly similar to only one user route to be included in the user recommended routes.

$$S_{max}(l, U) = \max_{u_i \in U}(ED(l, u_i)); \forall l \in L \quad (5)$$

4.2.3 User Representative Route

This approach assigns one route u_{rep} to represent all the user routes as a first step (Formula 6). It then computes the similarity of location routes to this user representative route as shown in Formula 7.

$$u_{rep} = \frac{\sum_{u_i \in U} U_i}{card(U)} \quad (6)$$

$$S_{rep}(l, U) = ED(l, u_{rep}); \forall l \in L \quad (7)$$

This approach has a computational advantage over the previous two approaches because it does not require the computation of all pairwise location route to user route similarities.

Following any of the approaches proposed, the recommender system selects the top-k location routes and returns them as an output.

5 EVALUATION OF ROUTE RECOMMENDER SYSTEM

For the evaluation of the proposed system, a testing dataset is built based on user and location routes from MapMyFitness and annotated preferences from participating active runners.

5.1 Dataset and Metric

A group of 14 active users of MapMyFitness with various locations and an average of 177 routes per user are considered for the evaluation. Figure 6 shows the number of logged routes ran by each of these users.

To resemble a real-life situation where users from different locations move to a new location with little or no information about its running routes, a set of 100 routes were selected from the city of London as location routes. The 14 users were required to annotate their ratings on Likert scales for a total of 30

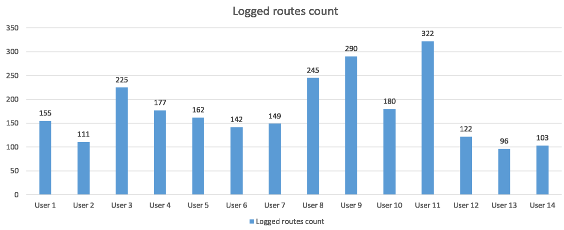

Figure 6: Number of Logged Routes per User.

routes each through a webpage which presents them a map for every running route along with additional data about the route as shown in Figure 7. The user ratings form the ground truth to which the system-produced recommendations are compared. Normalized Discounted Cumulative Gain (nDCG) is then used to measure the performance of the recommendation system based on the graded relevance of the recommended routes (Järvelin and Kekäläinen, 2000).

Figure 7: A snapshot of a Route Rating's Webpage.

5.2 Overall Recommendation Evaluation

After tuning the system to the experimentally determined optimal contribution ratio of ascents to descents and using the best approach to compute route-to-user similarity and as shown in Section 5.3 and Section 5.4 respectively, the nDCG scores of the top 5 recommended routes for each user are presented in Figure 8. The average nDCG score attained in this final configuration is 84.13%. This indicates the quality of the recommendations provided by the system in terms of both the routes selected and the order in which they are recommended.

The performance of the system varies along with the variation of the number of returned recommendations by the system. To study the effect of this variation, nDCG scores of one and up to 30 recommendations per user are computed. The resulting av-

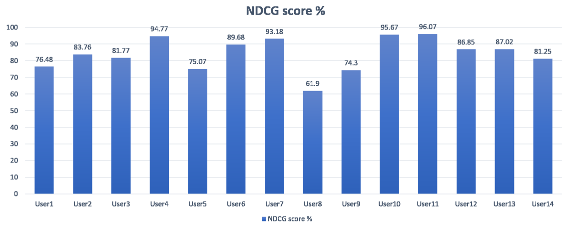

Figure 8: nDCG-5 Scores for System Recommendations per User.

erage nDCG scores per number of recommendations are presented in Figure 9. For a total of 30 rated routes per user, a recommendation of up to five routes seems reasonable as it is not probable to have much more highly similar routes to the user's routes among the 30 rated location routes.

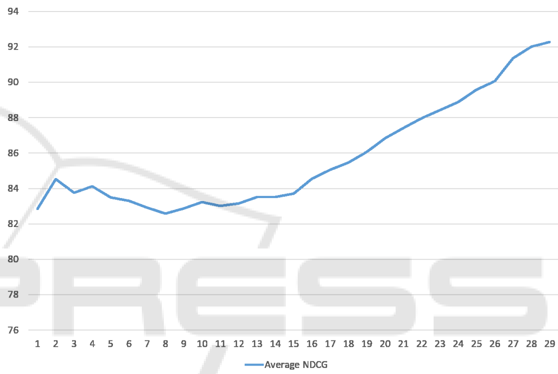

Figure 9: Average nDCG Scores for Different Number of Returned Recommendations.

5.3 Optimal Ascents-to-Descents Ratio

As previously indicated in Section 4.2, the contribution of ascents (resp. descents) to the computation of *elevation* feature is determined by α (resp. $(1-\alpha)$) in Formula 2. Figure 10 exhibits the effect of varying the elevation weight in steps of 0.05 between ascents and descents. The optimal value for α is $0.75 - 0.8$ as shown in the figure where the nDCG hits a maximum of 84.13% indicating that ascents are three to four times as important as descents for determining runners preferences on average.

5.4 Route-to-User Similarity Evaluation

Three approaches for aggregating the similarity of each location route with respect to the user as a whole have been introduced in Section 4.2. The performance of these different approaches is shown in Figure 11. The *Representative Route* approach produces the highest average nDCG score among the 14 partici-

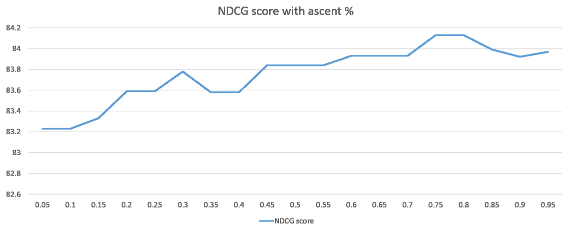

Figure 10: Effect of Varying the Weight of Ascents-to-Descents (α) on the Overall Quality of Recommendations.

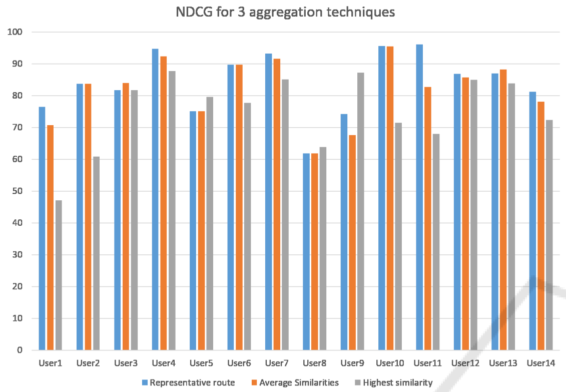

Figure 11: Comparison of the Effect of the different Route-to-User Similarity Methods.

pants, with a score of 84.13%. The *Average Route-to-User Similarity* approach came in second place with a score of 81.93%. Finally, the *Highest Similarity Pair* method produced the lowest result of 75.14%. Notably, and as indicated in Section 4.2.3, the Representative Route approach has the best performance among the three considered approaches as it does not require computing all the pair-wise similarities among all the user routes and location routes.

6 CONCLUSIONS AND FUTURE WORK

In this research, a classification of running routes based on route's nature, performance and visual features is introduced. The classification enables filtering the vast amount of running routes available on the web according to the user's preferences. Using the same features of a route, a recommender system is built to learn the user's preferences from her previous recorded runs and provide recommendations of suitable running routes in the user's location of choice. The recommendations are tested using active runners history data and annotations and attained a recommendation accuracy of 84.13%.

To further extend the capabilities of the system, additional data from sensors included in fitness trackers and smartphones are to be utilized by the system. Such data can provide more information about the surface of the route and the running styles of people. Additionally, providing recommendations for other types of activities such as cycling or skiing forms a potential future use case for this research.

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