PathRec: Visual Analysis of Travel Route Recommendations

Dawei Chen[*†], Dongwoo Kim[*], Lexing Xie[*†], Minjeong Shin[*], Aditya Krishna Menon[†*], Cheng Soon Ong[†*], Iman Avazpour[‡], John Grundy[‡]
[*]The Australian National University, †Data61/CSIRO, ‡Deakin University
{u5708856,dongwoo.kim,lexing.xie,minjeong.shin,aditya.menon,chengsoon.ong}@anu.edu.au
{iman.avazpour,j.grundy}@deakin.edu.au

ABSTRACT

We present an interactive visualisation tool for recommending travel trajectories. This system is based on new machine learning formulations and algorithms for the sequence recommendation problem. The system starts from a map-based overview, taking an interactive query as starting point. It then breaks down contributions from different geographical and user behavior features, and those from individual points-of-interest versus pairs of consecutive points on a route. The system also supports detailed quantitative interrogation by comparing a large number of features for multiple points. Effective trajectory visualisations can potentially benefit a large cohort of online map users and assist their decision-making. More broadly, the design of this system can inform visualisations of other structured prediction tasks, such as for sequences or trees.

CCS CONCEPTS

• Information systems → Learning to rank; **• Human-centered computing → Visualization**;

KEYWORDS

Route Visualisation, Travel Recommendation, Learning to rank

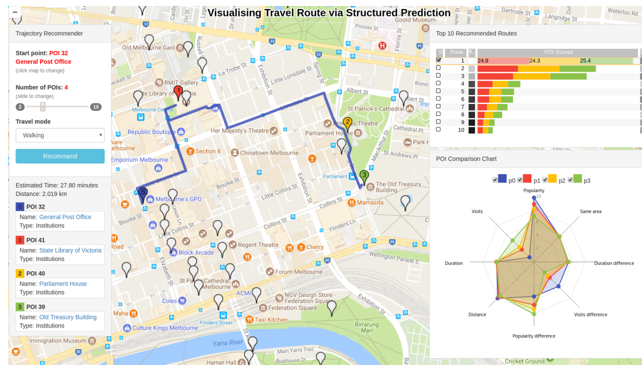

Figure 1: Travel route visualisation system[1]. Given a starting POI and the number of POIs to be visited, the system recommends multiple routes from travel history of tourists. Shown above: recommendation in central Melbourne.

1 INTRODUCTION

Sequence recommendation has emerged as an important framework for modelling diverse problems such as travel route and music playlist recommendation [2]. Unlike classical ranking algorithms where items are considered independently [6], a sequence recommendation algorithm requires modelling a structure between items and suggests a set of items as a whole. For example, consider recommending a trajectory of *points-of-interest* (POIs) in a city to a visitor. While a classical ranking algorithm can learn a user's preference for each individual location, it may ignore the distances between them and could suggest a longer trajectory than is optimal. Several sequence recommendation algorithms have been proposed to solve this problem and demonstrated superior performance compared to classical ranking algorithms [2, 7]. Nonetheless, recommendation algorithms for sequences and trajectories [1, 2] have many components and can be difficult for a user to understand. This is part of the general challenge of introducing transparency and accountability for machine learning algorithms [3].

In this paper, we tackle the problem of sequence visualisation, specifically focussing on travel routes recommendation. A travel route is a sequence of POIs, and the sequence recommendation problem can be formulated as a structured prediction problem [2]. Based on a diverse set of features for individual and pairs of POIs, we train the prediction model with trajectory data extracted from geotagged photos taken in Melbourne [1]. To visualise the suggested routes, we develop a novel tool that efficiently displays multiple suggested routes, which helps users understand the process behind the recommendations. Specifically, our system decomposes a total score of each route into a set of features and their corresponding scores, and shows the total score as a stacked bar plot of the features. The system also visualises the differences between POIs in a single route to show how POIs in that route can exhibit vast diversity.

This visualisation helps tourists who want diverse experiences by choosing the best route among multiple recommendations. Generalising to a broader class of routes, such a visualisation could also help users of online mapping apps to make decisions on suggested travel routes, such as by trading off distance, traffic, and scenery.

2 TRAVEL ROUTE RECOMMENDATION

The travel route recommendation problem involves a set of POIs in a city. Given a trajectory query $\mathbf{x} = (s, l)$, comprising a start POI s and trip length l, the goal is to suggest one or more sequences of POIs that maximise some notion of utility.

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[1] http://www.pathrec.ml

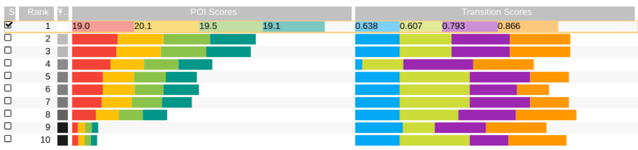

Figure 2: Visualisation of POI and transition scores for top 10 recommended routes. Each bar from left to right represents a relative score of each POI or transition along the route. The length of stacked bars represents the total score of the suggested route.

Following [2], we first cast travel recommendation as a structured prediction problem, which allows us to leverage the well-studied literature of structured SVMs (SSVM) [5]. From a visualisation perspective, an advantage of the SSVM is the explicit representation of feature scores in its final decision process. Specifically, we can disassemble the final score of a route into feature scores of each POI and the transition between two adjacent POIs. We use hand-crafted POI features such as the category, popularity, and average visit duration of previous tourists. We also crafted transition features such as the distance and neighbourhood of two POIs to maximise the interpretability of the outcome.

3 VISUALISATION

Our goal is to design an interactive visualisation system on top of the structured prediction framework. Figure 1 shows the overview of a live demo system, which consists of five major components: a map to display the suggested routes, an input box for user query (upper left), a stacked score of routes (upper right), a POI list box (lower left), and a radar chart to compare features of multiple POIs (lower right). The role and the construction of the four major components, besides the main map, are as follows:

Query input: A query consists of a starting POI and a trip length. Users can choose the starting POI by clicking icons on the map and can adjust the slide to set the trip length. In addition, three different travelling modes (e.g. bicycling, driving and walking) are supported, and we optimise the suggested routes for each mode.

Route score visualisation: The SSVM evaluates relevance scores of POIs and transitions in a candidate route to the given query and uses the sum of the relevance scores to determine the ranks of the routes. To visualise the POI and transition scores, we adopt a stacked bar representation [4], designed to support the visualisation of multi-attribute ranking. In Figure 2, the system decompose the scores of top 10 recommended routes into POI and transition scores via the stacked bar representation, where the size of each bar is proportional to the relevance score of the corresponding POI and transition in the route. Note that the POI and transition scores are scaled differently to support better visual discrimination[2]. For a seamless match between a route on the map and the corresponding POI scores in the bar plot, we use the same colour for both POI score and POI icon on the map. We also allow users to select multiple rows to visualise the corresponding routes on the map.

POI list: The POI list box provides the list of POI names and categories along the recommended route. The list is sorted according to the suggested visiting order, and again, the same POI colour is

[2]See Appendix for details at http://arxiv.org/abs/1707.01627

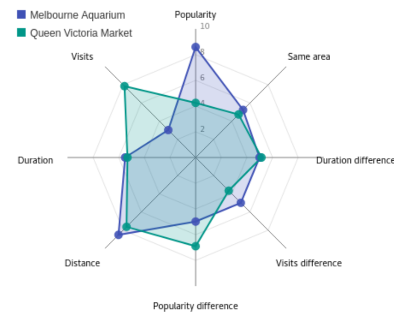

Figure 3: POI feature comparison between *Melbourne Aquarium* and *Queen Victoria Market*: the former scores higher on *Popularity* and *Visits difference* features whereas the latter scores higher on *Visits* and *Popularity difference* features.

used to match the corresponding POI on the map. On top of the list, the system also provides an estimated travel time and total distance of the route. The POI list box is updated whenever a user selects a different route or the system makes a new recommendation. If more than one route is selected, the system displays the information of the most recent chosen route.

POI feature visualisation: We further provide a radar chart to analyse the variation between POIs in a single route. For example, in Figure 3, we compare two POIs (*Melbourne Aquarium* and *Queen Victoria Market*) in terms of POI features and their importance in the suggested route. The radar chart shows the corresponding POI feature scores when a user selects a route. In particular, the user can check/uncheck any POI in the selected route, and the feature scores of all checked POIs will be shown in the chart.

4 CONCLUSION

In this demonstration, we detail an interactive route analyser which helps the interaction between users and a route recommendation system. The system benefits from the explicit feature construction of the structured prediction model, and visualises recommended routes in terms of information on both the routes and the POIs.

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