Visual Analysis of Travel Route Recommendation

Dawei Chen*‡, Dongwoo Kim*, Lexing Xie*‡, Minjeong Shin*, Aditya Menon*‡, Cheng Soon Ong*‡, Iman Avazpour†, John Grundy†
*The Australian National University, ‡Data61, †Deakin University
{u5708856,dongwoo.kim,lexing.xie,u1033719}@anu.edu.au,{aditya.menon,chengsoon.ong}@data61.csiro.au,{iman.avazpour,j.grundy}@deakin.edu.au

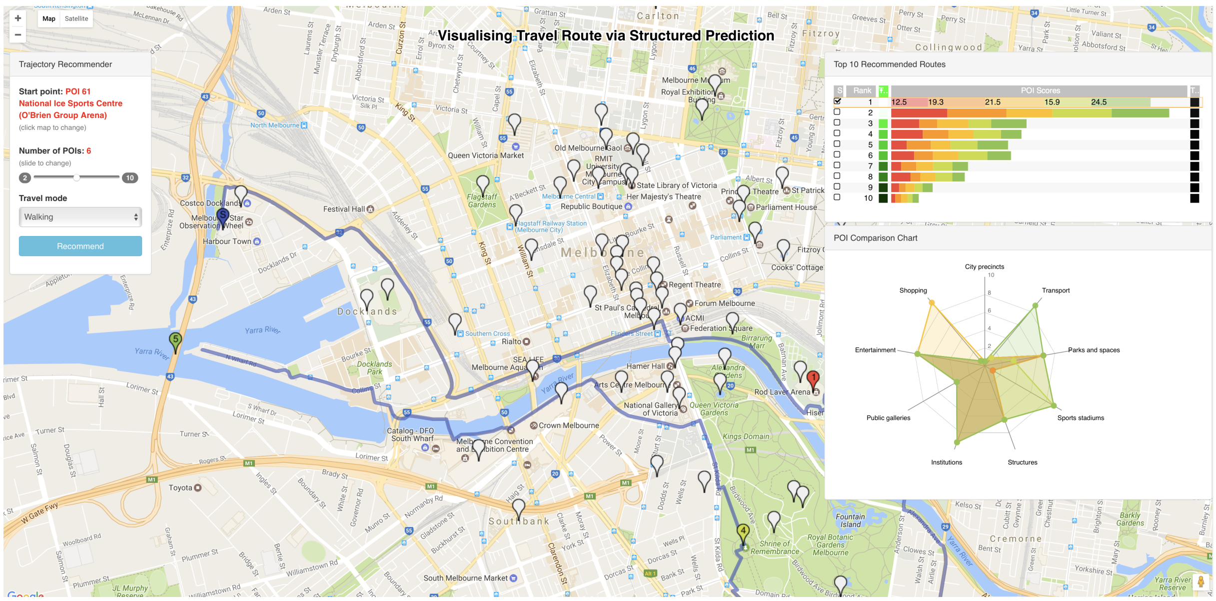

Figure 1: Travel route visualisation system. Given a starting POI and a number of POI to be visited, the system recommends a set of routes from a history of previous tourists.

ABSTRACT

We propose a novel travel route visualisation tool to help an interaction between tourists and route recommendation system. While the route recommendation algorithm shows promising results in a laboratory setup on benchmark dataset, the process of recommendation is still invisible to end-users who would benefit the information used to recommend the routes. Based on a structured prediction algorithm tailored for the route recommendation, we propose a route visualisation which aims to reduce the gap between the end-users and recommendation system by visualising recommendation scores on various attributes of the suggested routes.

CCS CONCEPTS

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

ACMMM2017, October 2017, Mountain View, CA USA

ACM ISBN 123-4567-24-567/08/06...$15.00
https://doi.org/10.475/123_4

KEYWORDS

Visualisation, Recommendation

1 INTRODUCTION

Sequence ranking has emerged as an important tool for solving diverse problems such as travel route and music playlist recommendations. Unlike the classical ranking algorithm where items are considered independently, the sequence ranking 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 (POI) in a city to a visitor. While the classical ranking algorithm can learn a user's preference for each individual location, however, it may ignore the distances between them and could suggest a long trajectory, which should be shorter in optimal routing. Several sequence ranking algorithms are proposed to solve this problem and achieve relative success when compared with the classical ranking algorithms. Nonetheless, a remaining challenge is to construct an interactive recommendation system so that a user can analyse the suggested sequences and plan a better trip.

In this paper, we tackle the problem of sequence visualisation, in particular, for travel routes recommendation. We define a travel route as a sequence of POIs and formulate the sequence ranking problem as a structured prediction problem. Based on hand-crafted features for individual and pairs of POIs, we train the prediction model with trajectory data extracted from geo-tagged photos. 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 decompose a total score of each route into a set of features and their corresponding scores and show the total score as a stacked bar plot of the features. The system also visualise the difference between POIs in a single route to show how POIs in that route can diverse to each other. This visualisation helps tourists who want to have diverse experiences by choosing the best route among the set of recommendations.

2 STRUCTURED PREDICTION

Travel route recommendation problems involve a set of POIs in a city. Given a trajectory query $\mathbf{x} = (s, l)$, comprising a start POI s and trip length l, i.e. the number of POIs to be visited during the trip including s. The goal is to suggest one or more sequences of POIs that maximise some notion of utility.

We first cast travel recommendation as a structured prediction problem, which allows us to leverage the well-studied literature of structured SVMs (SSVM) [3, 8]. There are two obstacles that prevent us from applying SSVM directly to the sequence recommendation problem; first, there would be multiple ground-truth routes among a set of POIs, second, a naive application of SSVM would generate a loop during prediction time. To incorporate multiple ground-truth routes in the learning phase, we take an idea from the ranking objective which prevents the ground-truth routes from competing with each others [6]. To eliminate possible loops in prediction, we adopt the serial list Viterbi algorithm [4, 5, 7]. We finally trained our model on trajectory data extracted from Flickr photos taken in Melbourne [1].

From a visualisation perspective, an important advantage of the SSVM is the explicit representation of feature scores in its final decision process. Especially, in our case, we can disassemble the final score of a route into feature scores of each POI and each transition between two adjacency POIs. We use hand-crafted POI features such as the category, popularity, and average visit duration of previous tourists and 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 four major components: a map to display suggested routes, an input box for user query on the left side, a stacked score of routes on the upper right side, and a radar chart to compare multiple POIs on the lower right side. The role and the construction of three major components, except the main map, are as follow:

- **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, we support three different travelling modes: bicycling, walking, and driving. Based on the different mode, we optimise suggested routes between POIs in a sequence.
- **Route score visualisation** Ranks of candidate routes are determined by the total scores from the SSVM. The score of each route can be decomposed into each POI and edge scores along the route. We adopt the LineUp framework [2] designed to support the visualisation of multi-attribute ranking via stacked representation. Figure 2 shows the stacked representation of the top ten scored routes, where the proportion of each bar indicates the importance of each POI in the route.
- **POI feature visualisation** We further provide a tool to analyse the variation between POIs in a single route. For example, in Figure 3, we compare two POIs, the Queen Victoria Market and Melbourne Aquarium, in terms of POI features and their importance in the suggested route.

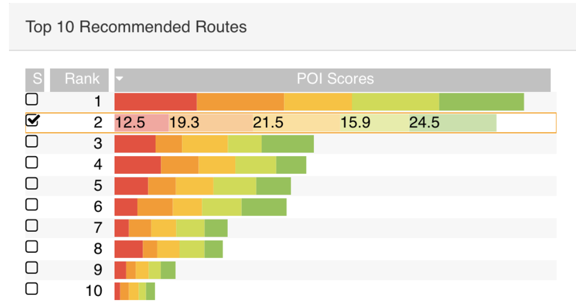

Figure 2: Visualisation of POI scores for top ten recommended routes. Each bar from left to right represent a relative score of each POI along the route, and the total length of stacked bars represents the total score of the suggested route.

4 CONCLUSION

In this demonstration, we showcase an interactive route analyser which helps the interaction between users and route recommendation systems. The system benefits the explicit feature construction of the structured prediction model and visualises recommended routes along with relevant information on both route level and POI level.

REFERENCES

[1] Dawei Chen, Cheng Soon Ong, and Lexing Xie. 2016. Learning Points and Routes to Recommend Trajectories. In *Proceedings of the 25th ACM International on Conference on Information and Knowledge Management*. ACM, 2227–2232.
[2] Samuel Gratzl, Alexander Lex, Nils Gehlenborg, Hanspeter Pfister, and Marc Streit. 2013. Lineup: Visual analysis of multi-attribute rankings. *IEEE transactions on visualization and computer graphics* 19, 12 (2013), 2277–2286.
[3] Thorsten Joachims, Thomas Hofmann, Yisong Yue, and Chun-Nam Yu. 2009. Predicting structured objects with support vector machines. *Commun. ACM* 52, 11 (2009), 97–104.
[4] Christiane Nill and C-EW Sundberg. 1995. List and soft symbol output Viterbi algorithms: Extensions and comparisons. *IEEE Transactions on Communications* 43, 234 (1995), 277–287.
[5] Dennis Nilsson and Jacob Goldberger. 2001. Sequentially finding the N-best list in hidden Markov models. In *Proceedings of the 17th international joint conference on Artificial intelligence*. Morgan Kaufmann Publishers Inc., 1280–1285.

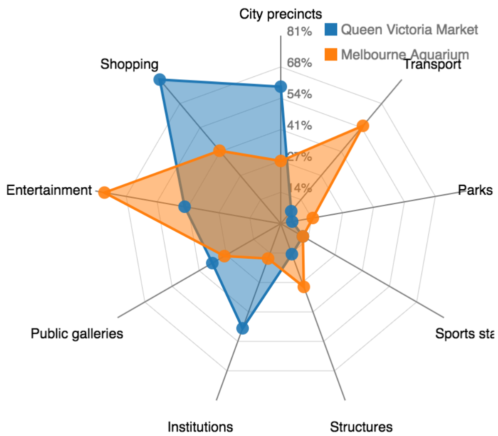

Figure 3: Comparison between two POIs with respect to multiple features. We compare the Queen Victoria Market and Melbourne Aquarium. The Queen Victoria Market has a high score on *shopping* and *city precincts* features whereas the Melbourne aquarium has a high score on *Entertainment* feature.

[6] Steffen Rendle, Christoph Freudenthaler, Zeno Gantner, and Lars Schmidt-Thieme. 2009. BPR: Bayesian personalized ranking from implicit feedback. In *Proceedings of the twenty-fifth conference on uncertainty in artificial intelligence*. AUAI Press, 452–461.

[7] Nambirajan Seshadri and C-EW Sundberg. 1994. List Viterbi decoding algorithms with applications. *IEEE transactions on communications* 42, 234 (1994), 313–323.

[8] Ioannis Tsochantaridis, Thorsten Joachims, Thomas Hofmann, and Yasemin Altun. 2005. Large margin methods for structured and interdependent output variables. *Journal of machine learning research* 6, Sep (2005), 1453–1484.