Visual Analysis of Travel Route Recommendation

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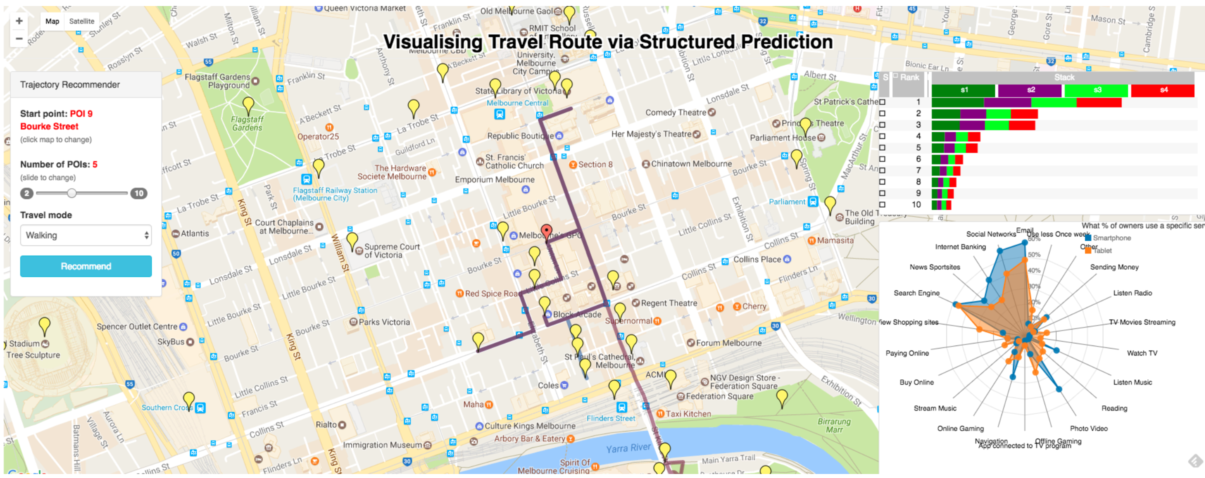

Figure 1: Travel route visualisation system. Given a starting POI and a number of POI to be visited, the system recommends a set of routes from a history of previous tourists.

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**;

KEYWORDS

Visualisation, Recommendation

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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 each item considers independently, the sequence ranking algorithm requires modelling a structure between items and suggests a set of items as a whole. For example, let us consider recommending a trajectory of points of interest (POI) in a city to a visitor. If the classical ranking algorithm learns a user's preference for each individual location while ignores the distances between them, the algorithm may create a long trajectory, which should be shorter in optimal routeing. Several sequence ranking algorithms are proposed to solve the problem and achieve relative success to compare with the classical algorithms. An important challenge remaining is to construct a visualisation of the recommendation system so that a user can analyse the suggested sequences and plan a better trip based on the interaction with the system.

In this paper, we tackle the problem of sequence visualisation, especially, in the travel route recommendation. We first define a travel route as a sequence of POIs and then formulate the sequence

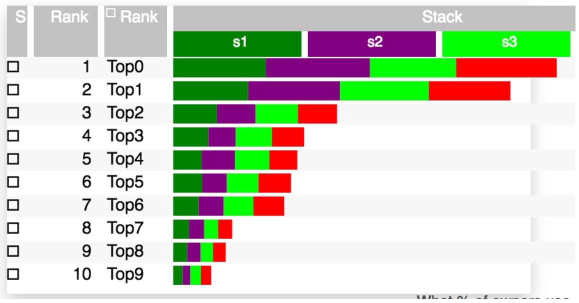

Figure 2: Visualisation of feature scores for top ten recommended routes. ?What are the features here?

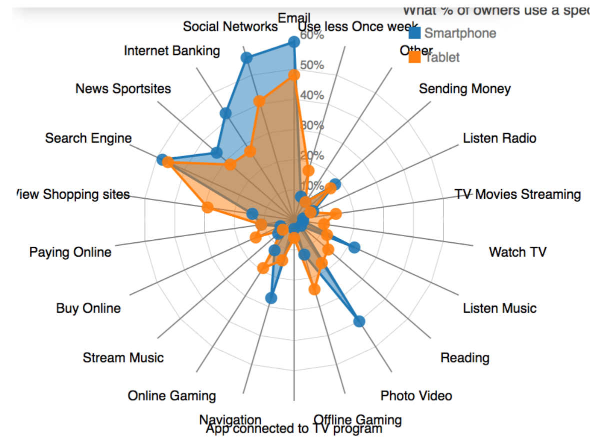

Figure 3: Comparison between two POIs with respect to multiple features.

ranking algorithm as a structured prediction problem. Based on hand-crafted features for each POI 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 and helps users understand the rational behind the recommendations. Specifically, we 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 features. We also visualise differences between POIs in a single route to show how POIs in the single route can diverse to each other. This feature helps a tourist who wants to have diverse experience to choose the best route among the set of recommended routes.

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 the travel recommendation as a structured prediction problem, which allows us to leverage the well-studied literature of structured SVMs (SSVM) [3, 6]. There are two obstacles to prevent us applying the SSVM directly to the sequence recommendation problem; first, there would be multiple possible routes among a set of POIs, second, a naive application of SSVM would generate repeating sequence in the prediction time. To eliminate possible loop in a prediction time, we adopt serial list Viterbi [4, 5] algorithm. We finally trained our model on the trajectory data extracted from Flickr photos [1].

From a visualisation perspective, an important advantage of the SSVM is the explicit representation of feature score 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 hand-crafted POI features such as the category, popularity, average visit duration of previous tourists, etc, and also crafted transition features such as the distance and neighbourhood of two POIs.

3 VISUALISATION

Our goal is to design an interactive system on top of the structured prediction framework. The Figure 1 show the overview of live demo system, which consists of four major component: 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, a radar chart to compare multiple features of POIs on lower right side. The role and construction of three major component are as follow:

- **User query** A query consists of a starting POI and a trip length. Users can choose the starting POI on the map and adjust slide to set the trip length. In addition, we support three different traveling modes: bicycling, walking, and driving. Based on the different mode, we optimise suggested routes between POIs in a sequence.
- **Route score visualisation** A score of each route consists of different contributions of multiple attributes. While the visualisation of a proposed route is straightforward, its interpretation is not, because the rank of the route consists of multiple attributes. We adopt the LineUp framework [2] devised to support the visualisation of multi-attribute ranking via stacked representation. Figure 2 shows the stacked scores of top ten recommended routes.
- **POI feature visualisation** We further provide a tool to analyse a variation between multiple POIs in a single route. For example, Figure 3 shows the feature scores of two POIs.

4 CONCLUSION

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

[6] 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.