Visual Analysis of Travel Route Recommendation

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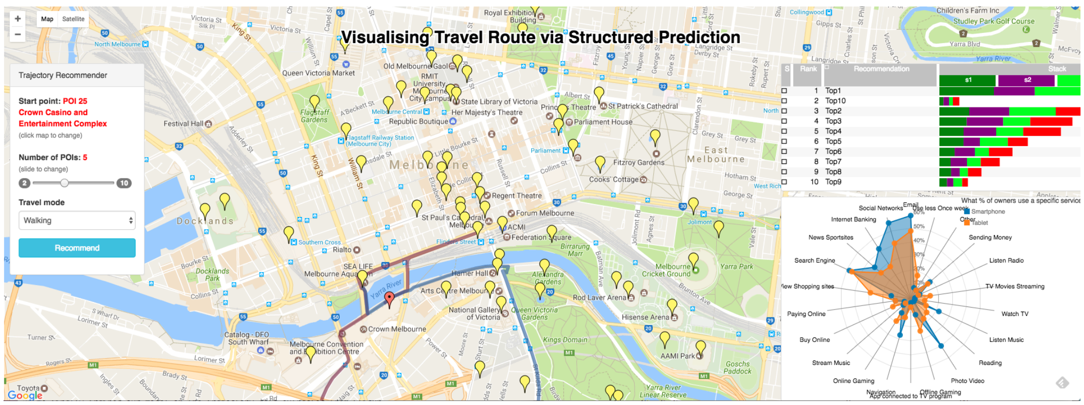

Figure 1: Travel route recommendation visualisation system. Given a starting POI and a number of POI to be visited, the system suggests a set of routes from a history of previous tourists.

ABSTRACT

We propose a novel travel route visualisation tool.

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 context of a travel route recommendation. We first define a travel route as a sequence of points of interest (POIs) and then formulate the sequence 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.

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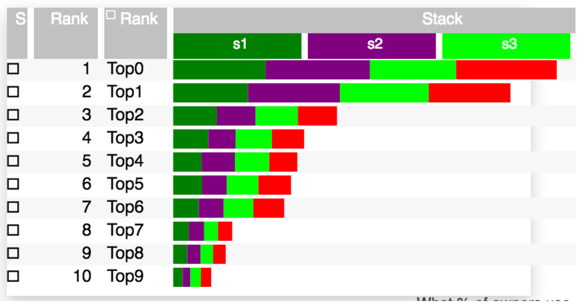

Figure 2: Visualisation of feature scores for each trajectory. From top to bottom, we represent top 10 recommended routes with their scores where each score is further decomposed into multiple features.

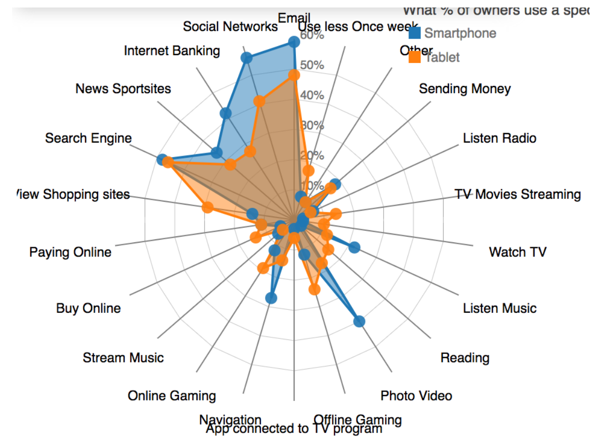

Figure 3: Visualisation of feature score for each POI within a single route.

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 where a user The Figure 1 Break total score into individual feature score, represent using stacked bar graph.

Comparison between two POIs in a single trajectory. Further comparison of POIs within a single trajectory, we use radar chart to show the score of each feature.

We further provide a tool to analyse an internal variation between multiple POIs in a single route. Figure 3 shows the feature scores of two POIs in a single route via a radar plot.

Stacked bar plot [2]

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.