

Deriving Tourist Mobility Patterns from Check-in Data

Linus W. Dietz
Technical University of Munich
Garching, Germany
linus.dietz@tum.de

Daniel Herzog
Technical University of Munich
Garching, Germany
herzogd@in.tum.de

Wolfgang Wörndl
Technical University of Munich
Garching, Germany
woerndl@in.tum.de

ABSTRACT

Recommendations in complex scenarios require additional knowledge of the domain. Planning a composite travel spanning several countries is a challenging, but encouraging domain for recommender systems, since users are in dire need for assistance: Information in typical publications, such as printed travel guides or personal blogs is often imprecise, biased or outdated.

In this paper we motivate a data-mining approach to improve destination recommender systems with learned travel patterns. Specifically, we propose a methodology to mine trips from location-based social networks to improve recommendations for the duration of stay at a destination. For this we propose a model for combining data from different sources and identify several metrics that are useful to ensure sufficient data quality, i.e., whether a traveler's check-in behavior is adequate to derive patterns from it.

We demonstrate the utility of our approach using a Foursquare data set from which we extract 23,418 trips in 77 countries. Analyzing these trips, we determine the travel durations per country, how many countries are typically visited in a given time span and which countries are often visited together in a composite trip.

Also, we discuss how this method can be generalized to other recommender systems domains.

KEYWORDS

recommender systems, tourism, data mining, item consumption duration, location-based social networks

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1 INTRODUCTION

Planning a composite trip, that is one spanning several destinations over a prolonged time, is quite a challenge even for expert travelers. Going on an independent trip to places which are off the beaten tourist track requires much preparation and involves many elements of uncertainty, such as the quality of the experience, precise costs, and the question how long one should stay in each region. A data-driven recommender system can be helpful to design a trip in such a complex domain, provided the underlying data is rich and up-to-date. Thus, it is not only important to recommend the

best items, i.e., destinations to travel to, but also how long. This can be generalized to the problem of determining the duration of item consumption in recommender systems. Building on [10, 25], this paper focuses on the problem of domain-specific durations of item consumption. Given a recommender system that solves a knapsack problem, i.e., returning k out of n possible items: What is an appropriate number for k and how long should the user consume each of the k chosen items? Concretely, the travel knapsack is constrained by time and money; the items are destinations the recommendation engine finds suitable for a specific traveler [10].

These questions can possibly be answered with an in-depth analysis of mobility patterns of travelers using location-based social networks (LBSNs). Users interact with SBSNs by checking-in at venues using mobile phones to indicate their presence at this location at a specific time. It is possible to reconstruct paths from check-ins and ultimately derive how the durations of stays at specific destinations are distributed.

The main contribution of this paper is a methodology to mine trips from user check-in data. We introduce a data model that allows combining data from various sources and metrics that inform the analyst whether the data quality is sufficient for generating satisfying trip recommendations. Applying our approach to a Foursquare data set, we produce preliminary results and discuss how they could be used in a destination recommender system.

The following related work describes approaches to tourist recommender systems, how they can be improved using LBSN data and human mobility in general. In section 3 we provide some definitions, describe our data model and data sources. The main section 4 describes the trip-mining approach with heuristics and metrics. We discuss our results and the applicability in recommender systems in section 5. Finally, we draw our conclusions and point out future work in section 6.

2 RELATED WORK

Research in tourist recommender systems has been around since over 15 years [21]. The success of recommender systems highly depends on the quality of the user model and the information about the items to be recommended. The increasing availability of data from SBSNs made it possible to learn about users' preferences [28], but also provides valuable insights to the relevancy of points of interests [11, 29]. While there are several approaches [9, 26] to solve variants of the Tourist Trip Design Problem [24], we aim to improve recommenders for composite trips.

Liu et al. [14] propose the TAST (Tourist-Area-Season Topic) Model to discover travelers' interests and identify the seasonal suitability of travel regions. In the follow-up paper [13] they both extensively evaluate this model and augment it with relationship information to recommend travel packages to groups. A similar approach introduced by Tan et al. [22] focuses on the feature selection

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to identify latent user interests. Using a framework of feature-value pairs for representing users and travel packages to calculate distance metrics they can employ collaborative filtering methods without any user ratings.

Herzog and Wörndl [10] develop a tourist recommender for composing personalized continental travels. The user is asked to specify her interests, e.g., nature & wildlife, beaches or winter sports along with potential travel regions and monetary and temporal limitations. Respecting these constraints, the recommendation consists of a set of regions that maximizes the user's preference score while taking the travel season and diversity of the regions into account. Determining the duration per region is done simultaneously, however, quite coarse grained by applying a static decrease in score of 5–10% per week. The underlying problem for picking the regions is a variant of the orienteering problem [23] using the Oregon Trail Knapsack Problem [5] as a scoring function. The destination information comes from several on- and offline information sources, which must be incorporated and updated manually.

Messaoud et al. [15] extend [10] by focusing on the diversity of activities [6] within a composite trip. Unlike Savir et al. [17], who use a simple mechanism to uphold a certain level for diversity of attractions, they use hierarchical clustering to improve the heterogeneity of activities. The underlying data set is the same as in [10], but extended with seasonal activities that have been rated in correspondence to specific regions and traveler types.

We propose to scale these approaches up and enhance the calculation of durations of stay using a data-driven approach. With nowadays' ubiquity of GPS modules in mobile phones a vast amount of spatial-temporal data is being collected. However, human mobility traces are privacy-sensitive information and most location trajectories are stashed by a handful corporations. Such data becomes publicly available if the users choose to publish them, as often done in LBSNs.

Song et al. [19] develop and evaluate mathematical models for human mobility and its predictability [20]. Further analysis of human mobility in LBSNs reveals that not only geographic and economic constraints affect mobility patterns, but also the individual social status [7]. However, an analysis of another LBSN, Gowalla, shows that the number of check-ins and the number of places a user has visited seem to follow log-normal distributions, while connecting to friends is better described by a Double-Pareto law [18].

LBSN data has also been used to capture cross-border movement [4]. The authors demonstrate how movement dynamics of people in a country can be analyzed, however, this study is not about tourists and is limited to one country, Kenya.

Noulas et al. [16] analyze activity patterns of Foursquare users, like the spatial and temporal distances between two check-ins. They discover place transitions that could well be used to predict or recommend future locations of users. We consider the mindset behind their approach quite similar to ours, however, their motivation was to uncover recurring patterns of human mobility, thus the resulting metrics go into a different direction.

Data from LBSNs have already been analyzed to improve recommender systems [2]. This is not surprising, since the user's locations and social graph tells much about individual preferences. For example, spatial co-occurrences can also be used to identify similar

users and generate implicit ratings for collaborative filtering algorithms [30]. In a more elaborate approach [1] travelers in a foreign city are matched to local experts based on their respective home behavior to recommend Foursquare venues.

Most similar to this work is [12]. The authors use past LBSN data to recommend traveling paths. For this they present solutions to derive the popularity, the proper time of day to visit, the transit time between venues and the best order to visit the places. In contrast to our work, the routes contain single points of interest in urban areas and they leave determining durations of stay at one place to future work.

To our knowledge, we are first to propose an approach to mine planet-scale tourist mobility patterns from LBSN data. Also, our underlying motivation, deriving domain-specific item consumption durations in recommender systems has not been investigated thoroughly.

3 DATA MODEL

We define tourist mobility patterns as the trajectories of users while performing leisure activities outside of their regular environment.

The trajectories can be seen as a continuous stream of check-ins: A check-in is a tuple of the unique identifier of a user (UUID), a location, and a timestamp. Note that the location must not necessarily be exact coordinates, but can also be indications of presence in a leaf of the region tree described in the next paragraph. Similarly, it is not required to have exact timestamps. It suffices if the dates of entering and leaving a specific region are known.

3.1 Destination Model

When recommending a set of destinations, it is worthwhile to discuss what a destination can be. From a user's perspective a destination should be a separate unit that contributes to the travel experience. This means that destinations are geographical areas whose touristic characteristics can be distinguished from others.

In the recommender system we adapt the idea of a hierarchical region tree (as in [10]), where destinations constitute the nodes. The advantage of such a model is that based on the query region the depth of the region tree can be adapted, in order to return destinations of a comprehensible size. For example, a query for North America should include not only the countries Canada, USA and Mexico, but also federal states. Conversely, when querying for destinations in Europe, it may be sufficient to recommend countries or even groups of countries as destinations.

There are several options for deriving a region tree. Wikitravel, a popular collaborative tourist guide, uses following hierarchy¹:

- Continents
 - Continental sections
 - Countries
 - Regions
 - More regions
 - Cities
 - Districts

¹https://wikitravel.org/en/Wikitravel:Geographical_hierarchy

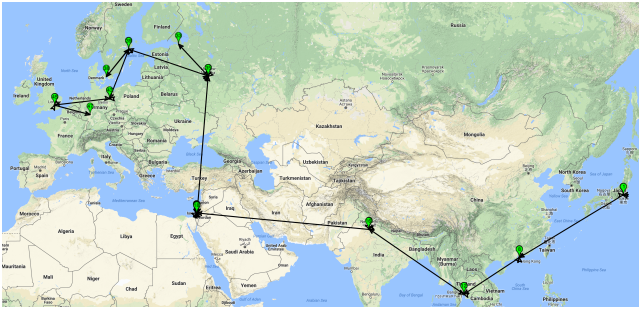


Figure 1: Visualization of a trip from the data set © 2017 Google

It should be noted that this hierarchy is not strict and the authors are encouraged to make exceptions when it serves the purpose of presenting travel information.

Another service, GeoTree² which is based on GeoNames³, offers a hierarchical region model. Querying the Place Hierarchy API⁴ from GeoNames, we obtained a four-level region tree with 250 countries in 7 continents with a total of 3874 regions (e.g., federal states) within these countries. Although this information corpus is sufficiently fine-grained and well-defined, it lacks the continental sections level which is quite relevant for tourists.

In the end, the region tree must balance specificity of destinations and the clustering of several regions into a larger geographic destination, e.g., New England or the Baltic States. Also, it must be able to map geographic coordinates (latitude, longitude pairs) to leaves in the tree.

At this stage of our research, we use countries as nodes of the region tree. With a richer region tree in place the concepts can be applied to any granularity.

3.2 Data Sets

Location data is inherently privacy-sensitive and valuable as it tells much about people's habits. Anonymizing it for research purposes is challenging, since correlating trajectories with single data points introduces many de-anonymization opportunities [8]. For this reason location-based social networks are usually quite restrictive towards querying user location and enforce more or less strict API limits. Nevertheless, Bao et al. [2] lists some data sets stemming from location-based social networks. To the best of our knowledge, Yang has published the largest data set about human mobility⁵ stemming from Foursquare [27]. It contains check-in data from 18 months (April 2012 to September 2013), 266,909 users at 3,680,126 venues in 77 countries. While these numbers are quite big, it should be noted that it only contains check-ins from 415 cities. Thus, it will not include travelers seeking recreation in the countryside.

Note that with our data model, it is possible to combine several data sources to create a larger stash of mobility data. However, this must be handled with care, as the data sets might be imbalanced regarding the population.

²<http://geotree.geonames.org>

³<http://www.geonames.org>

⁴<http://www.geonames.org/export/place-hierarchy.html>

⁵<https://sites.google.com/site/yangdingqi/home/foursquare-dataset>

Table 1: Characteristics of 65,745 travelers

Feature	max	mean	std. deviation
Countries visited	31	2.88	1.80
Days active	532	392.82	132.421
Check-ins	4284	141.50	157.89
Check-ins per day	49	0.42	0.69
Check-ins abroad	86.67%	12.23%	0.15

4 MINING TRIPS FROM CHECK-IN DATA

The overall goal is to collect tourist trips from non-tourism related mobility data. This section describes how we develop and evaluate heuristics using several metrics.

4.1 Data Processing

Our first step is to investigate the characteristics of the aforementioned Foursquare data set with regard to tourist mobility data. We remove 201,164 (75.37%) of the 266,909 users since they checked-in in a single country only.

Table 1 summarizes some basic characteristics of the remaining travelers. *Days active* is the time from the first to the last check-in of a user. The mean value of about 14 (out of 18) months of user activity is long enough to actually have the chance to observe prolonged travels. Furthermore, the mean value of one check-in per two days indicates that the users are quite active. In the end of section 4.2 we discuss whether the temporal resolution is actually high enough for analyzing travel patterns.

Since the data set does not include any user profiles, the travelers' home country must be determined from the check-in stream. The simplest heuristic assumes that a user's home country is the one with most check-ins. Applying this results in a mean value of 12.23% of foreign check-ins. This seems like a reasonable value to us, especially since the data stems from a prolonged time period. However, there are frequent travelers, who are abroad often or who simply don't check in frequently at home. To reduce such false positives, it would be possible to discard travelers who spend more time abroad than a predefined threshold, e.g., 50%. In this data set this would remove additional 1,762 travelers of uncertain home country. In the end we don't apply this additional heuristic, as we think that the data of such frequent travelers provides more benefit than the misclassification of the home country.

The users' check-in stream is segmented into trips by periods of being abroad before returning home. We require these trips to be at least seven days long, since short travels have a different character than the travels we design the recommender system for. Furthermore, this filters out weekend trips and business travels resulting in 34,892 trips from 23,218 distinct travelers. Figure 1 visualizes the itinerary of an exemplary long trip from the data set from Japan over South-East Asia, India, Israel and Europe.

4.2 Metrics

The further data processing is driven by metrics, which we now explain before analyzing the results.

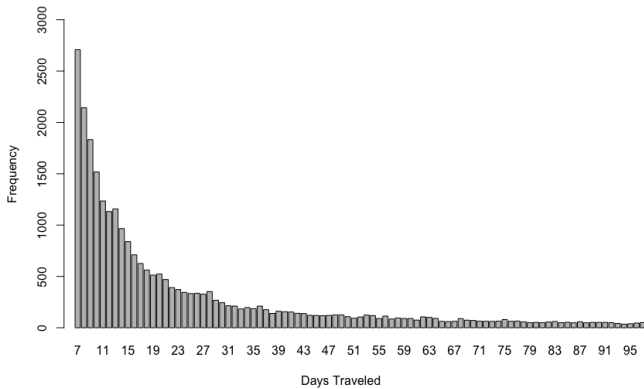


Figure 2: Trip durations, long tail ($max = 500$) omitted

Trip Duration. We define the duration of a trip as the number of calendar days from first to last check-in. Figure 2 shows the distribution of trip durations. One can see small spikes in the curve of the distribution at two, three and four weeks, which we attribute to the typical duration of holidays. This metric is useful to characterize the data set and identify weaknesses in the heuristics.

Check-in Rate. The check-in rate is the number of check-ins per day. It can be used to classify the activity of users.

$$\text{check-in rate} = \frac{\text{check-ins}}{\text{days}}$$

Check-in Density. For judging the quality of tourist mobility patterns, however, the check-in density is more important. This metric is central to us, because we rely on a constant stream of check-ins instead of check-ins occurring in bursts.

$$\text{check-in density} = \frac{\text{days with check-in}}{\text{days}}$$

Like the check-in rate, it can be calculated for single trips, or the the whole period under observation.

Transition Time. The transition time is the period between check-ins in different regions. It must be low for being able to correctly segment a check-in stream. The longer the transition time, the higher the uncertainty about the traveler’s location at a given point in time.

Sometimes, there are hints that ease the segmentation problem. For example, if the user’s first check-in in a country is at an airport or harbor, one can assume that she just arrived there, reducing the transition time to basically zero.

To verify that the mined trips are useful for our purposes, we calculate the mean transition time between two check-ins in different countries. The long mean duration of 9.80 days made us suspicious, given the mean of 0.42 check-ins per day (cf. Table 1). Our hypothesis is that the Foursquare app is not typically used at a constant rate, but check-ins occur in bursts. To verify this, we analyzed the check-in densities of the travelers. Indeed, some displayed a very small check-in density which inevitably leads to inaccurate results.

To come up with a suitable lower limit, we analyzed the consequences of enforcing a minimal check-in density. Figure 3 depicts

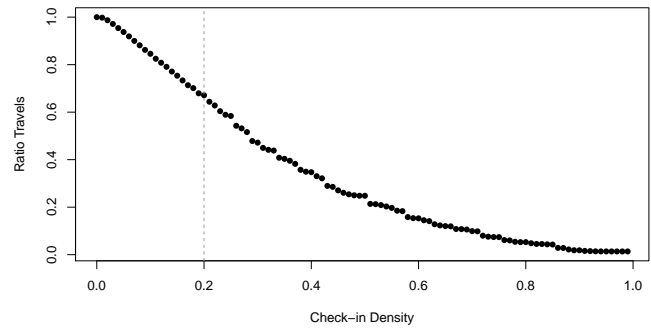


Figure 3: Check-in densities of travels

this trade-off. Since the curve is smooth and without an obvious ‘elbow’, we set the trade-off at 20%, which discards 32.88% of the trips. Recalling our initial goal with this heuristic, we reduced the mean transition time from 9.80 to 3.39 days while still keeping 23,418 trips.

5 RESULTS

Our two main findings are the durations of stay per region and the number of destinations per trip. The former bears quite convincing results, while for the analysis of destinations per trip more data of long travels would be required. Also, we find which are the countries visited most frequently together.

5.1 Duration of Stay per Region

Figure 4 shows the mean duration of stay for each country. Besides Kuwait, the top 20 countries are either travel destinations with warm maritime climate (especially islands) or countries with a very large area. We attribute that to beach holidays travels that usually take 2–3 weeks. The remoteness of islands and the size of the countries can be seen as factors that contribute to a long trip duration. Examining the trips to Kuwait, we find that most travelers stem from the US, Great Britain and the Arabic Emirates and typically don’t combine Kuwait with other countries in their trips. To us this indicates that these are business travelers who stay there for several weeks instead of returning home in the weekends.

Conversely, small, continental countries are the ones that are visited for very short periods. Open borders, as in the Schengen Area seem to contribute to smaller durations of stay, as opposed to countries with high visa fees, like Belarus or Kazakhstan, who charge about \$60 for a tourist visa.

5.2 Destinations per Trip

Figure 5 shows the mean number of visited countries given the travel duration. The low mean values are a consequence of the distribution: Most travelers typically only visit a small number of countries per trip. The curve is quite smooth in the beginning, however, after 50–100 days the variability increases (the shaded area depicts the standard deviation), since there are too few travels that contribute to the mean (cf. Figure 2). Long trips, like our example in Figure 1, with many countries are nevertheless interesting, as they can be analyzed regarding the sequence in which the countries are visited.

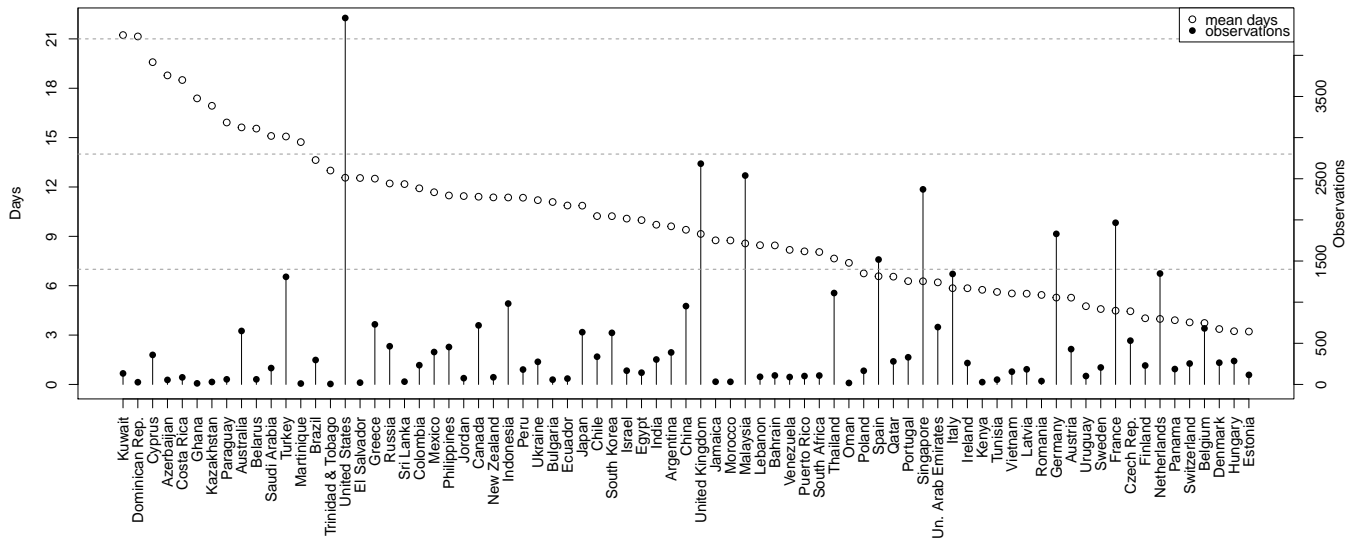


Figure 4: Durations of stay per regions

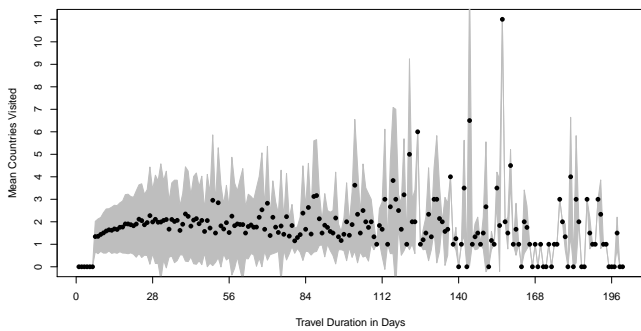


Figure 5: Countries per trip; duration < 200 days

Table 2: Country co-occurrences

n	Countries	Obs.
2	Malaysia, Singapore	269
	Canada, USA	162
	United Kingdom, France	156
	France, Italy	79
	United Kingdom, USA	79
3	France, Italy, Spain	50
	France, Belgium, Netherlands	38
	United Kingdom, France, Italy	34
	United Kingdom, France, Spain	29
	Thailand, Malaysia, Singapore	22
4	United Kingdom, France, Italy, Spain	21
	France, Belgium, Germany, Netherlands	17
	Austria, Czech Rep., Germany, Hungary	13
	France, Belgium, Italy, Netherlands	10
	France, Germany, Italy, Spain	10

5.3 Country Co-occurrences

Table 2 shows which trips are globally most frequent for a specific number of countries. When re-calculated for a specific query region these results can be used to determine the composition of countries in a recommendation. However, the small number of observations also shows the limitations of the data set.

5.4 Outlook: Item Consumption Duration from Mobility Patterns

We envision to use these metrics to improve recommendations for future travelers. Recall that our problem is to assign durations of stay to a set of regions.

In the basic case we can directly use the average durations of stay from Figure 4 as recommendations for how long a user should stay in the specific regions. If the user has completed a traveler type self-assessment or provides a check-in history, we can refine the recommendations based on the available mobility patterns. For example, if we know that our user is a *fast-mover*, i.e., one that spends little time per region, we could calculate the durations based on other travelers' habits that showed a similar behavior in the

past. Conversely, someone who prefers to spend holidays at one destination should be recommended a concise itinerary.

Generalizing this work is highly dependent on the problem domain. For example, one could transfer our approach to a fitness training scheduler, where the workout schedule of professional or semi-professional athletes is analyzed. Using data from sports watches it would be possible to automatically derive the amount of time they spend in their respective training type. The traveler type would correspond to the type of sports, while the countries would be the different training methods. Concretely, an triathlon athlete would practice swimming, running, biking, but also go to the gym to work out.

6 CONCLUSIONS AND FUTURE WORK

This paper marks a first step towards utilizing check-in data from LBSNs to derive durations of stay of individual destinations during a composite trip. With the proposed data model and approach it is possible to mine travel durations from trajectories of users and make informed decisions about the quality of data.

Since this research is at an early stage, several aspects can be improved in future. First and foremost, the granularity of the destination model must be refined to have federal states as leaves in the region tree. This would require much more traveler data, since with many more and smaller areas, the number of observations per region decreases. Other data sources besides LBSN user check-ins could be large corpora of images with location metadata such as Flickr⁶, 500px⁷, Photobucket⁸ or other image sharing platforms.

Incorporating information from tourist booking services for accommodation or transport would be a parallel avenue to pursue our goals. Again, this information is typically unavailable for research purposes. Combining several data sources with their own peculiarities and biases requires to analyze and potentially refine the metrics and heuristics proposed in this work.

Finally, we plan an in-depth analysis and clustering of characteristic traveler types to improve the personalization of recommended travel itineraries.

Further applications of this approach could be location prediction [3, 16] in general, but constructing destination n-grams can also contribute to determine the sequence in which the destinations are recommended.

REFERENCES

- [1] Jie Bao, Yu Zheng, and Mohamed F. Mokbel. 2012. Location-based and preference-aware recommendation using sparse geo-social networking data. In *Proceedings of the 20th International Conference on Advances in Geographic Information Systems (SIGSPATIAL '12)*. ACM, New York, NY, USA, 199–208. <https://doi.org/10.1145/2424321.2424348>
- [2] Jie Bao, Yu Zheng, David Wilkie, and Mohamed Mokbel. 2015. Recommendations in location-based social networks: a survey. *Geoinformatica* 19, 3 (feb 2015), 525–565. <https://doi.org/10.1007/s10707-014-0220-8> arXiv:1502.07526
- [3] Halgurt Bapierre. 2014. *Context Specific Next Location Prediction*. phdthesis. Technische Universität München, München.
- [4] Justine I. Blanford, Zhuojie Huang, Alexander Savelyev, and Alan M. MacEachren. 2015. Geo-Located Tweets. Enhancing Mobility Maps and Capturing Cross-Border Movement. *PLOS ONE* 10, 6 (jun 2015), 1–16. <https://doi.org/10.1371/journal.pone.0129202>
- [5] Jennifer J. Burg, John Ainsworth, Brian Casto, and Sheau-Dong Lang. 1999. Experiments with the “Oregon Trail Knapsack Problem”. *Electronic Notes in Discrete Mathematics* 1 (mar 1999), 26–35. [https://doi.org/10.1016/S1571-0653\(04\)00003-4](https://doi.org/10.1016/S1571-0653(04)00003-4)
- [6] Pablo Castells, Neil J. Hurley, and Saul Vargas. 2015. Novelty and Diversity in Recommender Systems. In *Recommender Systems Handbook*, Francesco Ricci, Lior Rokach, and Bracha Shapira (Eds.). Springer US, Boston, MA, Chapter Novelty and Diversity in Recommender Systems, 881–918. https://doi.org/10.1007/978-1-4899-7637-6_26
- [7] Zhiyuan Cheng, James Coverlee, Kyumin Lee, and Daniel Z. Sui. 2011. Exploring Millions of Footprints in Location Sharing Services. In *Proceedings of the Fifth International Conference on Weblogs and Social Media (ICWSM '11)*. AAAI, Palo Alto, CA, USA, 81–88.
- [8] Yves-Alexandre de Montjoye, César A. Hidalgo, Michel Verleysen, and Vincent D. Blondel. 2013. Unique in the Crowd: The privacy bounds of human mobility. *Scientific Reports* 3, 1 (March 2013), 1–5. <https://doi.org/10.1038/srep01376>
- [9] Damianos Gavalas, Charalampos Konstantopoulos, Konstantinos Mastakas, and Grammati Pantziou. 2014. A survey on algorithmic approaches for solving tourist trip design problems. *Journal of Heuristics* 20, 3 (01 Jun 2014), 291–328. <https://doi.org/10.1007/s10732-014-9242-5>
- [10] Daniel Herzog and Wolfgang Wörndl. 2014. A Travel Recommender System for Combining Multiple Travel Regions to a Composite Trip. In *CBRecSys@RecSys (CEUR Workshop Proceedings)*, Vol. 1245. CEUR-WS.org, Foster City, Silicon Valley, California, USA, 42–48.
- [11] Patrick Hiesel, Matthias Braunhofer, and Wolfgang Wörndl. 2016. Learning the Popularity of Items for Mobile Tourist Guides. In *RecTour@RecSys (CEUR Workshop Proceedings)*, Vol. 1685. CEUR-WS.org, New York, NY, USA, 8–15.
- [12] Hsun-Ping Hsieh, Cheng-Te Li, and Shou-De Lin. 2012. Exploiting Large-scale Check-in Data to Recommend Time-sensitive Routes. In *Proceedings of the ACM SIGKDD International Workshop on Urban Computing (UrbComp '12)*. ACM, New York, NY, USA, 55–62. <https://doi.org/10.1145/2346496.2346506>
- [13] Qi Liu, Enhong Chen, Hui Xiong, Yong Ge, Zhongmou Li, and Xiang Wu. 2014. A Cocktail Approach for Travel Package Recommendation. *IEEE Transactions on Knowledge and Data Engineering* 26, 2 (feb 2014), 278–293. <https://doi.org/10.1109/tkde.2012.233>
- [14] Qi Liu, Yong Ge, Zhongmou Li, Enhong Chen, and Hui Xiong. 2011. Personalized Travel Package Recommendation. In *Proceedings of the IEEE 11th International Conference on Data Mining (ICDM '11)*. IEEE, Vancouver, BC, Canada, 407–416. <https://doi.org/10.1109/icdm.2011.118>
- [15] Montassar Ben Messaoud, Ilyes Jenhani, Eya Garci, and Toon De Pessemier. 2017. SemCoTrip: A Variety-Seeking Model for Recommending Travel Activities in a Composite Trip. In *Advances in Artificial Intelligence: From Theory to Practice*. Springer International Publishing, Arras, France, 345–355. https://doi.org/10.1007/978-3-319-60042-0_40
- [16] Anastasios Noulas, Salvatore Scellato, Cecilia Mascolo, and Massimiliano Pontil. 2011. An empirical study of geographic user activity patterns in Foursquare. In *Proceedings of the Fifth International Conference on Weblogs and Social Media (ICWSM '11)*, Vol. 11. AAAI, Palo Alto, CA, USA, 70–573.
- [17] Amihai Savir, Ronen Brafman, and Guy Shani. 2013. Recommending Improved Configurations for Complex Objects with an Application in Travel Planning. In *Proceedings of the 7th ACM Conference on Recommender Systems (RecSys '13)*. ACM, New York, NY, USA, 391–394. <https://doi.org/10.1145/2507157.2507196>
- [18] Salvatore Scellato and Cecilia Mascolo. 2011. Measuring user activity on an online location-based social network. In *2011 IEEE Conference on Computer Communications Workshops*. IEEE, 918–923. <https://doi.org/10.1109/infocom.2011.5928943>
- [19] Chaoming Song, Tal Koren, Pu Wang, and Albert-László Barabási. 2010. Modelling the scaling properties of human mobility. *Nature Physics* 6, 10 (sep 2010), 818–823. <https://doi.org/10.1038/nphys1760> arXiv:1010.0436
- [20] Chaoming Song, Zehui Qu, Nicholas Blumm, and Albert-László Barabási. 2010. Limits of Predictability in Human Mobility. *Science* 327, 5968 (feb 2010), 1018–1021. <https://doi.org/10.1126/science.1177170>
- [21] Steffen Stabb, Hannes Werther, Francesco Ricci, Alexander Zipf, Ulrike Gretzel, Daniel R. Fesenmaier, Cécile Paris, and Craig Knoblock. 2002. Intelligent Systems for Tourism. *IEEE Intelligent Systems* 17 (Nov. 2002), 53–64. <https://doi.org/10.1109/mis.2002.1134362>
- [22] Chang Tan, Qi Liu, Enhong Chen, Hui Xiong, and Xiang Wu. 2014. Object-Oriented Travel Package Recommendation. *ACM Transactions on Intelligent Systems and Technology* 5, 3 (sep 2014), 1–26. <https://doi.org/10.1145/2542665>
- [23] Pieter Vansteenwegen, Wouter Souffriaau, and Dirk Van Oudheusden. 2011. The orienteering problem: A survey. *European Journal of Operational Research* 209, 1 (feb 2011), 1–10. <https://doi.org/10.1016/j.ejor.2010.03.045>
- [24] Pieter Vansteenwegen and Dirk Van Oudheusden. 2007. The Mobile Tourist Guide: An OR Opportunity. *OR Insight* 20, 3 (01 July 2007), 21–27. <https://doi.org/10.1057/ori.2007.17>
- [25] Wolfgang Wörndl. 2017. A Web-based Application for Recommending Travel Regions. In *Adjunct Publication of the 25th Conference on User Modeling, Adaptation and Personalization (UMAP '17)*. ACM, New York, NY, USA, 105–106. <https://doi.org/10.1145/3099023.3099031>
- [26] Wolfgang Wörndl, Alexander Hefe, and Daniel Herzog. 2017. Recommending a sequence of interesting places for tourist trips. *Information Technology & Tourism* 17, 1 (Feb. 2017), 31–54. <https://doi.org/10.1007/s40558-017-0076-5>
- [27] Dingqi Yang, Daqing Zhang, Longbiao Chen, and Bingqing Qu. 2015. Nation-Telescope: Monitoring and visualizing large-scale collective behavior in LBSNs. *Journal of Network and Computer Applications* 55 (sep 2015), 170–180. <https://doi.org/10.1016/j.jnca.2015.05.010>
- [28] Yang Ye, Yu Zheng, Yukun Chen, Jianhua Feng, and Xing Xie. 2009. Mining Individual Life Pattern Based on Location History. In *Tenth International Conference on Mobile Data Management: Systems, Services and Middleware (MDM '09)*. IEEE, 1–10. <https://doi.org/10.1109/mdm.2009.11>
- [29] Vincent W. Zheng, Yu Zheng, Xing Xie, and Qiang Yang. 2012. Towards mobile intelligence: Learning from GPS history data for collaborative recommendation. *Artificial Intelligence* 184-185, Supplement C (jun 2012), 17–37. <https://doi.org/10.1016/j.artint.2012.02.002>
- [30] Yu Zheng and Xing Xie. 2011. Learning travel recommendations from user-generated GPS traces. *ACM Transactions on Intelligent Systems and Technology* 2, 1, Article 2 (Jan. 2011), 29 pages. <https://doi.org/10.1145/1889681.1889683>

⁶<https://www.flickr.com>

⁷<https://500px.com>

⁸<http://photobucket.com>