Extended Travel Itinerary Datasets Towards Reproducibility

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Abstract

Recommending attractive travel itineraries to tourists is a promising application. A well-known drawback of existing research is the lack of public data for evaluating new recommendation methods and discussing the applicability of recommender systems in real-world applications. We aim to create reproducible environments for travel itinerary recommendation tasks. This paper demonstrates our re-implemented method for constructing travel log data based on Flickr metadata and predefined POI information. We also test our re-implemented baseline algorithms previously proposed and compare the results with existing work. Our results could contribute to the reproducibility of travel recommendation tasks.

Keywords

travel itinerary recommendation, reproducibility, data augmentation

1. Introduction

Recommender systems are ubiquitous in online platforms [1]. Among various target domains, tourism is a promising domain for the community (e.g., workshops [2], demonstrations [3, 4], industrial contributions [5]). In tourism, recommending an itinerary (a travel plan or trajectory in the literature) involves places to visit (e.g., points-of-interests, POIs), places to stay (i.e., accommodations), and how to travel between POIs (e.g., transportation and its mode); then the recommendation task remains complex. We can grasp representative research topics and concepts in the field through survey papers. Borràs et al. in [6] enumerated functions that support the tourism recommendation systems. Chen et al. clarified related recommendation tasks [7]. Lim et al. [8] discussed the taxonomy of touring-related research.

Using data-centric models (e.g., deep learning-based [9, 10, 11, 12] or customized optimization models [13]) are possible to provide personalized itineraries that match users' complex preferences. We need travel log data (log data that collects tourists' activities) to learn models from data and evaluate recommendation results. Lim et al. [8] mentioned that retrieving such data is important. In addition, collecting travel log data in different areas is valuable to evaluate recommender methods in various settings. If researchers are interested in how to deploy itinerary recommendation algorithms in some cities, they need travel log data in their target

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cities. When they need to customize existing algorithms for region-specific reasons, evaluating them using benchmark datasets is a common approach for validation.

Rich travel log data are available only in a few cities in the current status, which are adopted in previous work. We herein try to augment the rich travel log data, wherever we want to study and discuss. As a data source, we revisit geo-tagged photos like Flickr photos collected as a public dataset named YFCC100m [14]. Many researchers adopted this data source type due to the data availability issue. For example, Lim et al. [15] followed the protocol by Choudhury et al. [16] using geo-tagged photos to generate travel log data. They opened their datasets that consist of POI information, trajectories, and (travel) cost information in some selected cities¹. In contrast to such open datasets, we can access few datasets constructed from other data sources. For example, LBSN-based data collection was common before (Examples are in [17, 18, 19]); however, recent API updates made it difficult for researchers to collect check-in datasets in LBSN services, and researchers did not recently adopt this data source. Similarly, publicly available GPS trajectories are generally limited due to privacy issues. These backgrounds make us again focus on the geo-tagged media to extend travel log data as mentioned in [8].

Our contributions are summarized as below.

- We re-implement and release in public the mining procedure from geo-tagged photos by following existing studies [16, 15] to process the public Flickr dataset YFCC100m [14].
- We reproduce two existing baseline solvers (named Popularity and MarkovPath) from Chen et al. [7] as baseline solvers with utility tools related to extended travel log data.
- We provide computational experiments that (1) reproduce existing results to validate our approach, and (2) extend numerical evaluations to different cities for demonstration.

Note that the contributions and materials can be found at the public repository https://zenodo.org/record/8314376 (DOI: 10.5281/zenodo.8314376), which we will maintain and update incrementally for research purposes.

2. Travel Log Data: Review, Re-produce, and Argumentation

This section explains our re-implemented procedure to extend travel log datasets. Figure 1 illustrates our data flow. In preparing travel log data, we require the following components: (1) YFCC100m metadata ([14], top left side in Fig. 1), (2) YFCC100m metadata downloader (bottom left side in Fig. 1) and a procedure to preprocess downloaded metadata, (3) external POI information to design target area (top right in Fig. 1), and (4) travel log data generator based on (1)–(3) (right side in Fig. 1). We have various geo-tagged data sources (e.g., photos and tweets), and many researchers could start their studies following this methodology.

Here, we review public datasets in Sec. 2.1. We explain how to re-produce them in Sec. 2.2. We then try to generate existing data using our re-implemented procedure and extend travel log data for new cities in Sec. 2.3.

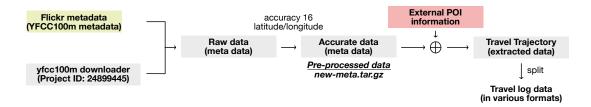


Figure 1: Data flow to generate extended travel trajectory datasets from YFCC100m dataset [14].

Table 1Summary of existing data (from [15, 20, 7, 21]).

City	# Photos	# Users	# POI	# Travel	Used			A	/ailabil	ity	
			Visits	Seqs.	[15]	[20]	[7]	[21]	I15	C16	T15
Toronto	157,505	1,395	39,419	6,057	✓	✓	✓		√	✓	
Osaka	392,420	450	7,747	1,115	✓	\checkmark	\checkmark		✓	\checkmark	
Glasgow	29,019	601	11,434	2,227	✓	\checkmark	\checkmark		✓	\checkmark	
Budapest	36,000	935	18,513	2,361		\checkmark			✓		
Perth	18,462	159	3,643	716		\checkmark			✓		
Vienna	85,149	1,155	34,515	3,193		\checkmark			✓		
Delhi	13,919	279	3,993	489		\checkmark			✓		
Edinburgh	82,060	1,454	3,3944	5,028	✓	\checkmark	\checkmark		✓	\checkmark	
Tokyo	55,364	979	15,622	3,798		\checkmark					
London	164,812	2,963	38,746	8,373		\checkmark					
Melbourne	94,142	1,000	23,995	5,106		\checkmark	\checkmark			\checkmark	
Pisa	18,170	1,825	7,176	3,446				\checkmark			\checkmark
Florence	102,888	7,049	44,746	16,863				\checkmark			\checkmark
Rome	234,616	13,772	89,090	35,602				\checkmark			\checkmark

2.1. Review on Existing Datasets

Table 1 summarizes details of existing datasets in 13 cities of different formats. These datasets are generated using Flickr metadata. As an example of public data, Lim et al. provided datasets on four cities (Toronto, Osaka, Glasgow, and Edinburgh) in [15], and they extended their datasets on ten cities (additional six cities; Budapest, Perth, Vienna, Delhi, Tokyo, and London) in [20], which we call I15 format. Some earlier work like [16] adopted Melbourne, and its data is also available. The same cities are adopted in Chen et al. [7] as a different format, which we call C16 format. Other cities in Italy were adopted in [21], which we call T15 format. Note that for I15, travel costs between POIs and benefits of POIs are also explicitly given. In contrast, for C16, travel costs between POIs are computed using the Haversine formula. The benefits of POIs are computed by the number of unique users who visit the POIs in their trajectories. We can convert data in I15 into those in C16, and datasets in C16 are less informative than those in I15. The data in T15 were independent, but the data source and the

¹https://sites.google.com/site/limkwanhui/datacode#ijcai15 (access confirmed on Feb 16, 2023).

process to generate the data seem to be similar to those in C16 and I15. All datasets contain POI information and travel logs (see also Sec. 2.2). The POI information is mandatory in the above formats, and trajectory information is stored in different formats.

2.2. Reproduce Existing Datasets for Validation

We review how to reproduce travel log data by following the procedure used in Choudhury et al. [16] and Lim et al. [15].

2.2.1. How existing data are produced

The public itinerary data is generated from YFCC100m [14] as shown in Fig. 1. In their procedure, we convert photo streams in YFCC100m [14] with the given POI information into travel log data. Therefore, our trial to reproduce the existing process is valuable to augment travel log data for a recommendation.

Each POI p in a given set \mathcal{P} of POIs has attributes representing its information (e.g., latitude, longitude, name, category, opening time, etc.). We assume that the set \mathcal{P} is prepared by researchers. In Lim et al. [15], the authors defined sets of POIs for each city by themselves after traversing Wikipedia links.

For a user u, let a photo stream recorded on the Flickr website (and collected as YFCC100m dataset) be $S_u := \langle (p_1, t_{p_1}^a, t_{p_1}^d), \dots (p_n, t_{p_n}^a, t_{p_n}^d) \rangle$, where $(p_j, t_{p_j}^a, t_{p_j}^d)$ for $1 \leq j \leq n$ means a user visited POI p_j with arriving time $t_{p_j}^a$ and departure time $t_{p_j}^d$. We first generate travel sequences from S_u for each user u by splitting S_u if $t_{p_x}^d - t_{p_x+1}^a > \tau$ with threshold τ . In existing work of [16] and [15], $\tau = 8$ hours. After getting travel sequences from all users in the target subset of YFCC100m, we can build historical data in 115.

2.2.2. Results of our re-implementation for public datasets

In this paper, we carefully re-implemented the above procedure, which could be the replication to generate the public travel log data. To assess our re-implementation, we here apply our procedure to YFCC100m using pre-defined POIs by Lim et al. [15] by selecting Toronto, Osaka, Glasgow, and Edinburgh from [15]. In our evaluation, we compare the re-produced datasets in four cities from [15] with those public datasets.

Table 2 shows the validation results. The above rows in each segment correspond to original data (public data by [15] and [7]) from Table 1, and the below rows show our re-produced data. Note that these results resemble each other. The results in Table 2 confirm the validity of our re-implemented procedure for trajectory mining using YFCC100m data.

2.3. Generate Extended Datasets

We can now apply our procedure to generate extended travel log datasets. To demonstrate how we researchers can generate their travel datasets for research purposes, we show how to prepare POI information in three ways.

Table 2Validation by comparing public and our data on four cities (above from [15] and [7], below by ours). Note that we fixed a spatial error in Osaka so that the reproduced dataset gets smaller than those reported in previous work, but we can confirm that the results are comparable.

City	# Photos	# Users	# POI Visits	# Travel Sequences
Toronto (public)	157,505	1,395	39,419	6,057
(ours)		1,397	39,479	6,066
Osaka (public)	392,420	450	7,747	1,115
(ours, bug fix)		394	7,400	981
Glasgow (public) (ours)	29,019	601 601	11,434 11,440	2,227 2,230
Edinburgh (public)	82,060	1,454	33,944	5,028
(ours)		1,454	33,952	5,029

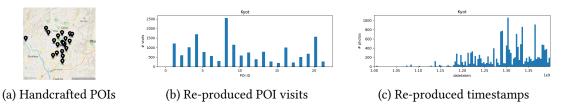


Figure 2: Handcrafted POI and histograms explain our generated datasets in Kyoto, Japan. The map figure in 2a is generated by Mapbox API (see also http://mapbox.com).

- **(POI Ext 1)** We handcraft POI information in the public datasets in Kyoto, Japan, next to Osaka. By comparing produced datasets in the two cities, we can evaluate how our implementation works and whether or not the method is applied to different cities. We explain this approach in Sec. 2.3.1.
- **(POI Ext 2)** We also try to demonstrate how to build POI information from Web sites. Following existing studies, we use LonelyPlanet and Google Maps API to collect POIs and their latitude/longitudes and use our re-implemented procedure to produce extended datasets for selected cities, which we explain in Sec. 2.3.2.

2.3.1. Extended Datasets Using Handcrafted POIs (POI Ext1)

We handcraft POI information in Kyoto, Japan, where unique identifiers and locations (i.e., latitudes and longitudes) are mandatory. Figure 2 illustrates re-produced results by our POIs (in Fig. 2a). By counting metrics corresponding to Table 2, the re-produced Kyoto dataset contains 631 users, 17,072 POI visits, and 1,670 travel sequences. These results are similar to those in Osaka and Glasgow, so we can confirm that the re-implemented procedure could apply to other cities with handcrafted POI information.

Table 3Statistics of new datasets on selected eleven cities in Japan. Column names abbreviations mean Attr (Attractions), Rest (Restaurants), Shop (Shopping), Night (Nightlife), and Ent (Entertainment). The three right columns are for generated travel log data.

City name	# POIs (# Top Choice)	Attr	Rest	Shop	Night	Ent	# Users	# POI Visits	# Travel Seqs.
Верри	30 (4)	11	10	5	4	0	44	701	146
Fukuoka	58 (7)	20	15	12	9	2	144	3211	733
Hiroshima	48 (8)	19	17	4	6	2	165	1600	587
Kanazawa	41 (5)	15	17	3	5	1	111	3315	590
Kumamoto	31 (7)	15	6	4	6	0	59	874	187
Kyoto	96 (48)	20	20	20	20	16	725	26136	4741
Matsumoto	22 (5)	8	7	2	5	0	68	1267	197
Nagasaki	41 (11)	20	12	5	4	0	77	2245	307
Naha	20 (9)	8	6	4	2	0	93	1875	323
Osaka	87 (24)	20	20	18	20	9	524	10007	2851
Tokyo	99 (82)	20	20	19	20	20	1745	56938	15161

2.3.2. Extended Datasets Using Collected POIs (POI Ext 2)

To generate extended datasets for our reproduced experiments in Sec. 3, we generate extended datasets in 11 selected cities sampled from Japan to show the reproducibility of travel itinerary recommendation tasks wherever we want to study.

We prepare POI information as follows. First, we manually extracted POI names of pages on cities in Japan from the website of LonelyPlanet². Second, we manually obtained categories of POIs and attached them to POIs. Third, we computed geodesic information (i.e., latitude and longitude) via Google Maps API³ for each POI. After filtering out outliers in terms of their locations, we completed POI information in selected 11 cities, which can be applied to generating extended travel log data. Table 3 explains the re-produced data. Throughout these results, we can confirm our procedure that extends travel log datasets for targeting areas.

3. Experiments and Evaluation

This section tries to reproduce existing experimental results using our re-implementations and to explore several extended datasets by providing additional experimental results on the performance of previously developed methods (Popularity and MarkovPath).

3.1. Re-implemented baselines

In this paper, we adopted the following baseline methods.

• Popularity: A solver recommending an itinerary with the largest popularity score.

²https://www.lonelyplanet.com/

³https://developers.google.com/maps?hl=en

• MarkovPath: A solver using a factorized transition matrix between POIs based on Chen et al. [7] to construct an itinerary, based on the public repository of Chen et al. [7].

Note that we do not include deep learning-based methods (e.g., [10, 11]) because (1) the details of architectures or learning parameters are not clearly explained, and (2) the ensuring reproducibility of deep learning-based methods in recommender systems is known to be challenging [22]. We want to resolve this issue in our future work.

3.2. Experimental Setups

In our re-produced experiments to assess reproducibility, we evaluate the following aspects using (A) re-produced public datasets and (B) extended datasets.

- **(Q1)** Whether or not our baseline procedures can generate itineraries whose results are similar to those reported using public and replicated data (A).
- **(Q2)** Whether or not our replicated data (A) in Table 2 on the existing four cities are similar enough to public data regarding generated itineraries by baselines.
- **(Q3)** Whether or not we can expect the generalization ability of previously reported results to other areas (i.e., 11 city datasets (B) in Japan from Sec. 2.3.2).

We herein adopt F1 and pairs F1 scores, used in Chen et al. [7] to evaluate itineraries.

3.3. Results and Discussions

Reproducing experimental results Table 4 and Table 5 answer (Q1) and (Q2) using F1 and pairs F1 scores, respectively. In Table 4, by comparing the first column block (Columns 3-4 from [7]) and second column block (Q1), we can confirm that our baseline solvers are implemented properly, and we can reproduce almost similar results in terms of F1 and pairs F1 scores. In Table 5, using the re-implemented baselines, we can confirm that our procedure for mining public data works reasonably to generate travel itinerary data, used in recommendation studies like [7]. Some results of MarkovPath show different results, but we conjecture that these differences are from the combinatorial solver used in experiments. In Chen et al. [7], the authors adopted a well-known commercial state-of-the-art solver Gurobi [23], but we only adopt non-commercial solver Cbc [24].

Extended experimental results Next, we apply our baseline methods to generate extended datasets in 11 cities for the question **(Q3)**. To evaluate generated itineraries, we again adopted the point-set-wise evaluation, which enables us to compare results in 11 cities with those in four public cities. Table 6 shows F1 and pairs F1 scores, and these results seem to be reasonable by comparing them with the previous results summarized in Table 4.

Table 4Validation of our baseline methods using public four cities: (Columns 3-4) already reported results in [7], (Columns 5-6) our baseline methods applied to public data used in [7] to answer (Q1).

City	Method	Fron	n [7]	(Q1) Our methods and public data i		
		F1	pairs F1	F1	pairs F1	
Toronto	Popularity	0.678 ± 0.121	0.384 ± 0.201	0.678 ± 0.121	0.384 ± 0.201	
	MarkovPath	0.688 ± 0.138	0.405 ± 0.231	0.688 ± 0.138	0.406 ± 0.230	
Osaka	Popularity	0.663 ± 0.125	0.365 ± 0.190	0.659 ± 0.130	0.360 ± 0.193	
	MarkovPath	0.706 ± 0.150	0.442 ± 0.260	0.706 ± 0.150	0.442 ± 0.260	
Glasgow	Popularity	0.745 ± 0.166	0.507 ± 0.298	0.744 ± 0.165	0.505 ± 0.297	
	MarkovPath	0.732 ± 0.168	0.485 ± 0.293	0.734 ± 0.169	0.489 ± 0.296	
Edinburgh	Popularity	0.701 ± 0.160	0.456 ± 0.259	0.701 ± 0.160	0.436 ± 0.258	
	MarkovPath	0.678 ± 0.149	0.400 ± 0.234	0.678 ± 0.149	0.399 ± 0.233	

Table 5Validation of our baseline methods using public four cities: (Columns 3-4) already reported results in [7], (Columns 5-6) our re-produced methods applied to our re-produced data to answer (Q2).

City	Method	Results in [7]		(Q2) Ours metho	ods and data in Table 2	
		F1	pairs F1	F1	pairs F1	
Toronto	Popularity	0.678 ± 0.121	0.384 ± 0.201	0.682 ± 0.121	0.390 ± 0.208	
	MarkovPath	0.688 ± 0.138	0.405 ± 0.231	0.684 ± 0.141	0.403 ± 0.240	
Osaka	Popularity	0.663 ± 0.125	0.365 ± 0.190	0.692 ± 0.113	0.399 ± 0.200	
	MarkovPath	0.706 ± 0.150	0.442 ± 0.260	0.705 ± 0.153	0.439 ± 0.273	
Glasgow	Popularity	0.745 ± 0.166	0.507 ± 0.298	0.749 ± 0.152	0.504 ± 0.288	
	MarkovPath	0.732 ± 0.168	0.485 ± 0.293	0.748 ± 0.148	0.502 ± 0.283	
Edinburgh	Popularity	0.701 ± 0.160	0.456 ± 0.259	0.708 ± 0.154	0.441 ± 0.261	
	MarkovPath	0.678 ± 0.149	0.400 ± 0.234	0.665 ± 0.133	0.373 ± 0.212	

Discussions The above two results for **(Q1)**, **(Q2)**, and **(Q3)** could validate both re-implemented procedures to generate extended data and re-implemented baselines. Our baselines are simple but effective. In our future work, as noted, we would like to prepare more baseline solvers (e.g., deep learning-based methods, and next POI prediction-based methods) for future discussions. In conclusion, we can use our re-implemented baseline solvers and procedure to generate extended datasets to start our travel itinerary recommendation studies wherever we want to commit.

4. Related Work

Several researchers have studied the itinerary recommendation tasks from a different perspective. For example, optimization-based [7, 15, 20, 8, 25] and learning-based [10, 11] methods have been proposed. In this paper, we do not dive into the details of existing methods and try to pursue state-of-the-art scores. Building our environment on a common framework like Recbole library [26] for travel itinerary recommendation tasks is one of our future works to accelerate

Table 6Extended experimental results using F1 scores (above) and pairs F1 scores (below) in each segment.

Method	Scores	Верри	Fukuoka	Hiroshima	Kanazawa
Popularity	F1 pairs F1	$ \begin{vmatrix} 0.667 \pm 0.147 \\ 0.391 \pm 0.211 \end{vmatrix}$	0.627 ± 0.100 0.310 ± 0.103	0.861 ± 0.167 0.712 ± 0.307	0.708 ± 0.143 0.438 ± 0.224
MarkovPath	F1 pairs F1	$\begin{array}{ c c c c c c c c c c c c c c c c c c c$	0.632 ± 0.145 0.334 ± 0.208	0.796 ± 0.196 0.612 ± 0.344	0.652 ± 0.162 0.365 ± 0.237
Method	Scores	Kumamoto	Kyoto	Matsumoto	Nagasaki
Popularity	F1 pairs F1	$ \begin{vmatrix} 0.777 \pm 0.131 \\ 0.515 \pm 0.233 \end{vmatrix}$	0.570 ± 0.140 0.262 ± 0.146	0.802 ± 0.147 0.564 ± 0.241	0.571 ± 0.120 0.265 ± 0.127
MarkovPath	F1 pairs F1	$\begin{array}{ c c c c c c c c c c c c c c c c c c c$	0.602 ± 0.166 0.314 ± 0.223	0.818 ± 0.154 0.588 ± 0.251	0.582 ± 0.160 0.307 ± 0.212
Method	Scores	Naha	Osaka	Tokyo	
Popularity	F1 pairs F1	$\begin{array}{ c c c c c c c c c c c c c c c c c c c$	0.676 ± 0.170 0.411 ± 0.273	0.626 ± 0.131 0.320 ± 0.182	
MarkovPath	F1 pairs F1	$\begin{array}{ c c c c c c }\hline 0.773 \pm 0.190 \\ 0.563 \pm 0.323\end{array}$	0.663 ± 0.155 0.243 ± 0.273	0.637 ± 0.138 0.336 ± 0.198	

research on this task. One possible issue for this direction is we need to carefully review the license of travel log data as they possibly have some private information to arrange such a public environment based on Recbole.

5. Conclusion

This paper focuses on the travel recommendation task and arranges the method to generate extended travel log data for future research. We also re-implement baseline methods to test our extended travel log data. Our validation confirms that our re-implemented procedure works as expected via re-produced and extended experimental results. We expect our re-implemented procedure could accelerate travel recommendation studies with extended data in various cities in future work.

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