Expanding the Boundaries: Recommender Systems and the Multifaceted World of Tourism

Alejandro Bellogin, Universidad Autónoma de Madrid

ACM RecSys Workshop on Recommenders in Tourism

Background

PhD at UAM, Spain

- Evaluating RecSys with an IR perspective
- Translating concepts from IR to RecSys

Postdoc at CWI, The Netherlands

- Reproducibility & benchmarking

Assistant/Associate professor at UAM, Spain

- Evaluation, sequences, POI, routes, …

My journey into tourism RecSys

- In 2017, we were contacted to create recommendations for “smart tourism”
  - Initial impression: “that is easy, we know many families of recommenders and one *should* work”

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- Data was quite difficult to obtain
  - Schedules and prices were important to be considered
  - Still no user profiles, histories, or similar available

- In 2017, we were contacted to create recommendations for "smart tourism"
  - Initial impression: "that is easy, we know many families of recommenders and one *should* work"
- Data was quite difficult to obtain
  - Schedules and prices were important to be considered
  - Still no user profiles, histories, or similar available
- Efficiency was critical, while the number of items increased daily
- Practical solution: focus on creating feasible routes, after filtering out unpreferred venues

Lessons learned

- Data is more important than the algorithm
  - At least, it should come first!
- It is possible to provide suggestions without user profiles
- There are several, slightly different tasks that can be defined
  - Each with different constraints, inputs, and outputs
  - In some of them, how to evaluate was not obvious
- We found related areas with similar problems but different vocabularies

Time for concrete examples

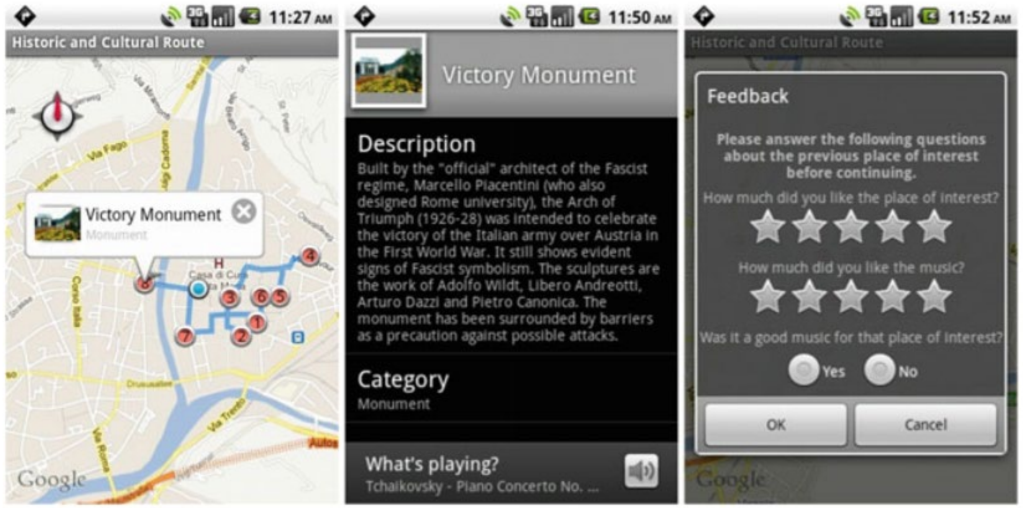
Data
Tasks
Evaluation

Time for concrete examples

Data
Tasks
Evaluation

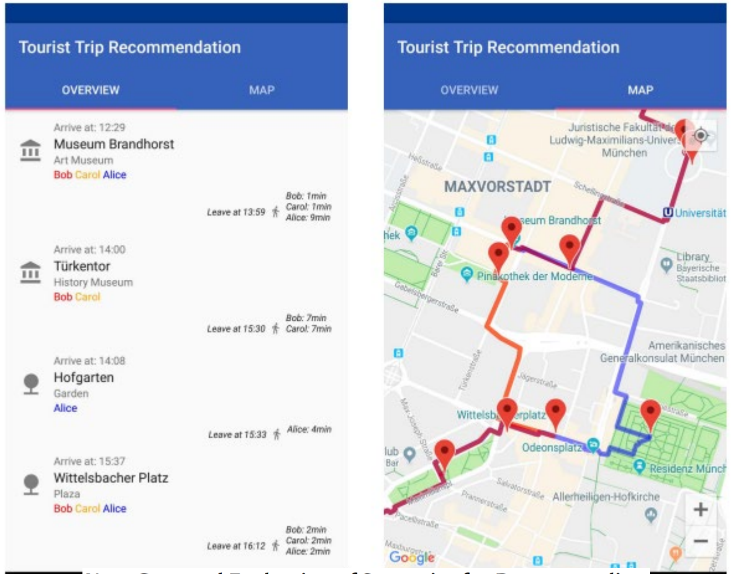
Data

- How data from tourism really looks like?
- In user studies:



Emotion-Based Matching of Music to Places

Marius Kaminskas and Francesco Ricci



User-Centered Evaluation of Strategies for Recommending Sequences of Points of Interest to Groups

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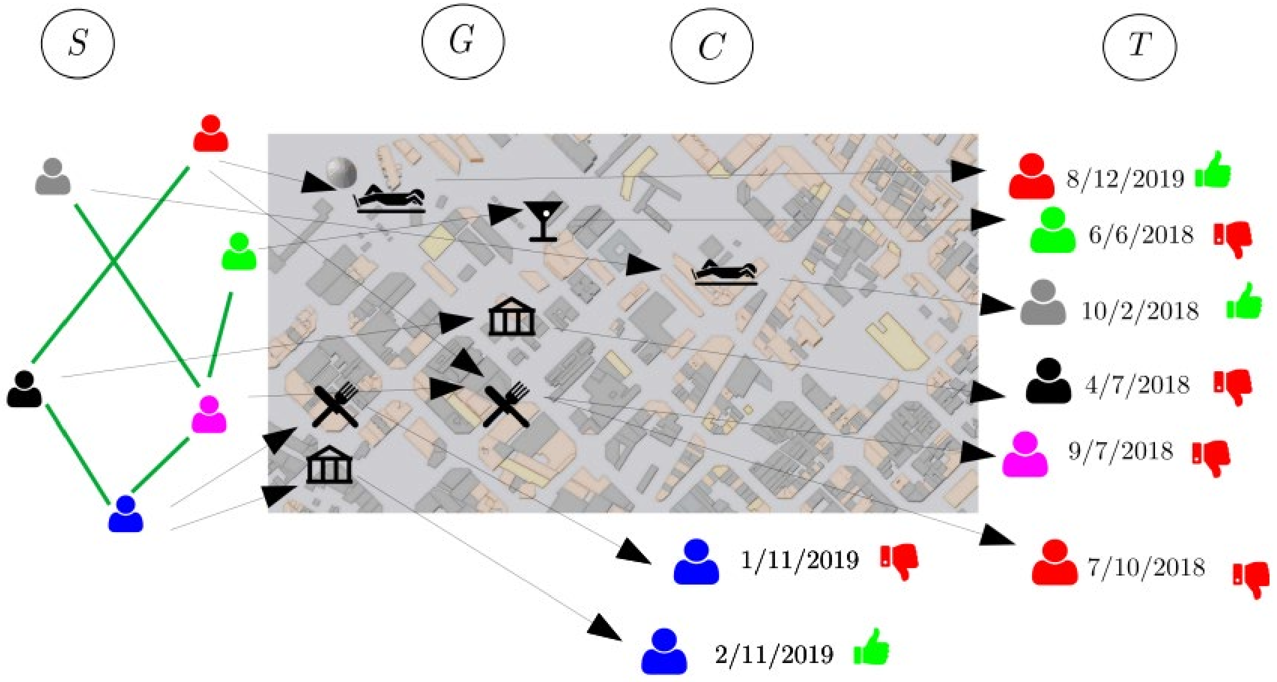
- Mobile applications
- Real users interacting with the recommender
- Feedback collected in "real-time"

Data

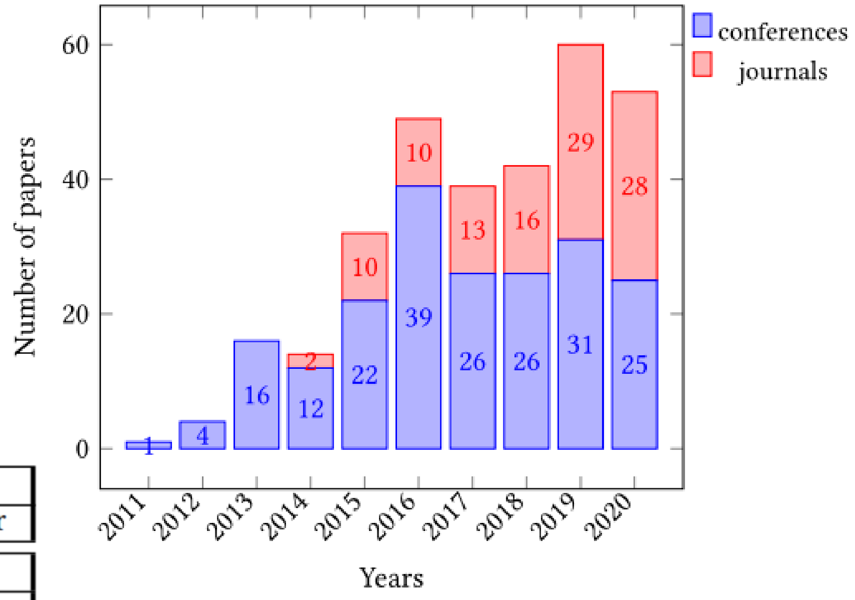
- How data from tourism really looks like?
- In offline evaluation, Location-Based Social Networks (LBSN) dominate the literature
  - Interactions = check-ins
  - Social connections
  - Geographical information
  - Categorical attributes (e.g., food, museum)
  - Time



Data

- How data from tourism really looks like?
- In offline evaluation, Location-Based Social Networks (LBSN) dominate the literature
- In our study, between 2011 and 2020 we found:

Source	Papers retrieved	Valid papers
Scopus	404	302
ScienceDirect	50	30
ACM	71	43
Unique papers	**431**	**310**



Number of Papers	LBSN				
	Gowalla	Foursquare	Yelp	Brightkite	Other
Most Representatives	30	34	4	6	8
Total	156	199	54	40	43

Point-of-Interest Recommender Systems Based on Location-Based Social Networks: A Survey from an Experimental Perspective

PABLO SÁNCHEZ and ALEJANDRO BELLOGÍN, Universidad Autónoma de Madrid, Spain

Data

- How data from tourism really looks like?
- In offline evaluation, Location-Based Social Networks (LBSN) dominate the literature
- But, how are these datasets collected? Let's take Foursquare, the most popular LBSN
- The largest dataset (by Yang et al., 2016) describes the process as

> Hence, we capture check-ins by crawling Foursquare-tagged tweets from the Twitter Public Stream.[6] Using this approach, we collected a Foursquare check-in dataset over about 18 months (from April 2012 to September 2013).

Participatory Cultural Mapping Based on Collective Behavior Data in Location-Based Social Networks

DINGQI YANG, eXascale Infolab, University of Fribourg
DAQING ZHANG, Institut Mines-Télécom/Télécom SudParis Peking University
BINGQING QU, University of Rennes 1 - IRISA &INRIA Rennes

  - Why using a third-party API like Twitter? Because check-ins are not public

- For other datasets (like Gowalla and Brightkite), check-ins were collected when they were public

Data

- How data from tourism really looks like?
- In offline evaluation, Location-Based Social Networks (LBSN) dominate the literature

- Are check-ins representative of tourists?
  - They can be used by *anyone* on the LBSN

5. IDENTIFICATION OF LOCAL USERS

Cultural mapping suggests that only local users' activities in a city are eligible to characterize the culture of the city. To identify local users in a city, we need to know the home location of each user. However, due to privacy protection, such information cannot be accessed from Foursquare. Moreover, although Twitter gives users the option to register a home location for their accounts, only a limited number of users provide valid information. Therefore, it is necessary to algorithmically identify the home location for each user.

Participatory Cultural Mapping Based on Collective Behavior Data in Location-Based Social Networks

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- Using these datasets may require extra work:
  - Identification of local users
  - Tourists vs locals: recommenders behave differently
  - Different categories of tourists: varied number of clusters depending on dataset
  - Data cleaning: removal of "private" residencies or other categories to *actually work* with Points-of-Interest (POI)
  - Route or trip identification

Travelers vs. Locals: The Effect of Cluster Analysis in Point-of-Interest Recommendation

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Mining trips from location-based social networks for clustering travelers and destinations

Linus W. Dietz[1] · Avradip Sen[1] · Rinita Roy[1] · Wolfgang Wörndl[1]

Applying reranking strategies to route recommendation using sequence-aware evaluation

Pablo Sánchez[1] · Alejandro Bellogín[1]

Data

- How data from tourism really looks like?
- In other areas, data is more fine-grained: coordinates taken from sensors like GPS, WiFi, or Bluetooth
  - This requires *inferring the venues* that were actually visited

Dataset	Collection / Publication	#Participants	Duration	#Events	Sampling	Location	GPS	Check-ins	GSM	Wifi	Bluetooth	Annotation
GeoLife (Zheng et al. [25])	2007-2012 / 2012	182	5.5 years	25M	5 sec	Beijing, CN	✓	✗	✗	✗	✗	✗
MDC (Kiukkonen et al. [13])	2009-2011 / 2012	185	3 years	11M	-	Lausanne, CH	✓	✗	✓	✓	✓	relationships
Privamov (Mokhtar et al. [16])	2014-2016 / 2017	100	15 months	15M	-	Lyon, FR	✓	✗	✓	✓	✗	✗
Reality Mining (Pentland [17])	2004 / 2009	100	9 months	5M	-	Boston, US	✗	✗	✗	✗	✓	relationships
FourSquare (Yang et al. [23])	2011-2012 / 2013	3112	10 months	9M	-	New York, US	✗	✓	✗	✗	✗	relationships
blebeacon (Sikeridis et al. [20])	2016 / 2018	46	1 month	5M	-	California, US	✗	✗	✗	✗	✓	✗
hyccups (Ciobanu and Dobre [8])	2012 / 2016	72	63 days	-	-	Bucharest, RO	✗	✗	✗	✓	✗	relationships
sigcomm2009 (Pietilainen and Diot [18])	2009 / 2012	76	2 days	-	120 sec	Barcelona, ES	✗	✗	✗	✓	✓	✗
telefonica (Bogomolov et al. [3])	2013 / 2014	342	4 weeks	-	-	ES	✗	✗	✓	✗	✗	✗
ParticipAct (Chessa et al. [6])	2013-2015 / 2017	300	1 year	-	-	Bologna, IT	✓	✗	✗	✓	✓	✗
Nodobo (Bell et al. [2])	? / 2011	27	4 months	5M	-	Glasgow, GB	✗	✗	✓	✓	✗	✗
d4d challenge (Furletti et al. [11])	2016 / 2016	9M	1 year	-	-	SN	✗	✗	✓	✗	✗	✗
Gowalla (Cho et al. [7])	2008-2010 / 2011	196,591	1.5 years	6M	-	Worldwide	✗	✓	✗	✗	✗	relationships
Brightkite (Chessa et al. [6])	2008-2010 / 2010	58,228	1.5 years	4M	-	Worldwide	✗	✓	✗	✗	✗	relationships
Breadcrumbs	2018 / 2019	81	12 weeks	14M	50 sec	Lausanne, CH	✓	✗	✗	✓	✓	ground-truth semantic labels relationships

Table 1: Comparative summary of popular mobility datasets available to the community (: GPS / : Check-ins / : GSM / : Wifi / : Bluetooth).

- Tripbuilder and YFCC100M exploit coordinates from geo-located Flickr photos

Breadcrumbs: A Rich Mobility Dataset with Point-of-Interest Annotations

Arielle Moro, University of Lausanne, Switzerland, Arielle.Moro@unil.ch
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Pierre-Adrien Ghiringhelli, University of Lausanne, Switzerland, Pierre-Adrien.Ghiringhelli@unil.ch
Bertil Chapuis, University of Lausanne, Switzerland, Bertil.Chapuis@unil.ch
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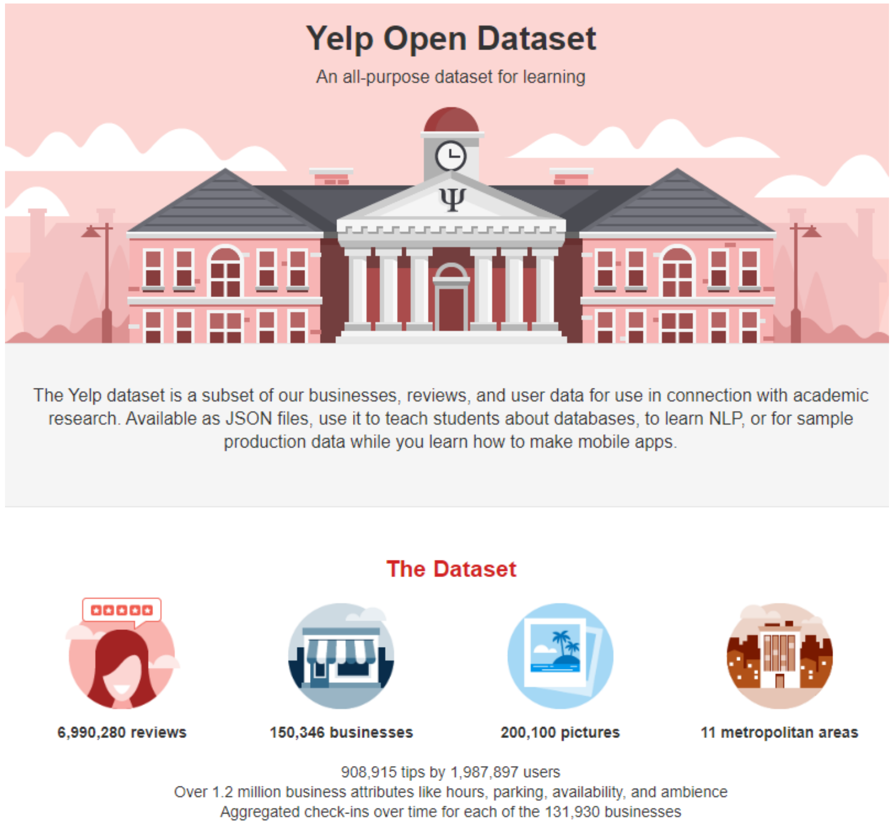
Benoît Garbinato, University of Lausanne, Switzerland, Benoit.Garbinato@unil.ch

Data

- How data from tourism really looks like?
- How do we decide if a point is **interesting enough** to be considered a POI?

- There are datasets focused on specific categories or tourism product – they may be useful, depending on the task:
  - **Restaurants**
  - Hotels
  - Destinations
  - Reviews



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ACM RecSys Challenge 2019

About Publications Participation Timeline Program Organizers RecSys 2019

About

The RecSys Challenge 2019 will be organized by trivago, TU Wien, Polytechnic University of Bari, and Karlsruhe Institute of Technology. trivago is a global hotel search platform focused on reshaping the way travelers search for and compare hotels, while enabling advertisers of hotels to grow their businesses by providing access to a broad audience of travelers via our websites and apps. trivago has established 55 localized platforms in over 190 countries and provides access to over two million hotels, including alternative accommodations, with prices and availability from over 400+ booking sites and hotel chains.

This year's challenge focuses on travel metasearch. The goal of this challenge is to develop a session-based and context-aware recommender system using various input data to provide a list of accommodations that will match the needs of the user.

Data

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- How do we decide if a point is **interesting enough** to be considered a POI?

- There are datasets focused on specific categories or tourism product – they may be useful, depending on the task:
  - Restaurants
  - Hotels
  - **Destinations**
  - Reviews

WebTour 2021 Challenge by Booking.com

As a part of the WebTour workshop, the WebTour 2021 Challenge organized by Booking.com will take place. It focuses on a multi-destinations trip planning problem, which is a popular scenario in the travel domain. The goal of this challenge is to make the best recommendation of an additional in-trip destination. To do so, Booking.com provides a unique dataset based on millions of real anonymized bookings. Top performing teams will receive prizes sponsored by Booking.com and be invited to submit short papers to the workshop about their solution approach. For more information, the dataset and submission guidelines please visit https://www.bookingchallenge.com.

Data

- How data from tourism really looks like?
- How do we decide if a point is **interesting enough** to be considered a POI?

- There are datasets focused on specific categories or tourism product – they may be useful, depending on the task:
  - Restaurants
  - Hotels
  - Destinations
  - **Reviews**

RecTour 2024 Challenge

Description:

As a part of the RecTour workshop, the **RecTour 2024 Challenge** organized by Booking.com will take place.

It focuses on ranking reviews, which is an important aspect that influences users' decision-making. The most trivial way to rank reviews would be according to review scores or time-based.

An alternative approach would be to rank the reviews with the most "helpfulness" votes. However, the main problem with this approach is that most of the reviews do not get this helpfulness votes thus suffering from presentation bias.

In this challenge, the task is to match given accommodations and users to their respective review IDs. The concept is that when a new user interacts with the booking system, we can analyze the accommodation they are viewing along with available user features (e.g., couple, country, etc.). This enables us to display reviews in an order that considers the review content with respect to the user and accommodation characteristics.

To do so, Booking.com provides a unique training dataset containing 1.6 million reviews based on real anonymized bookings.

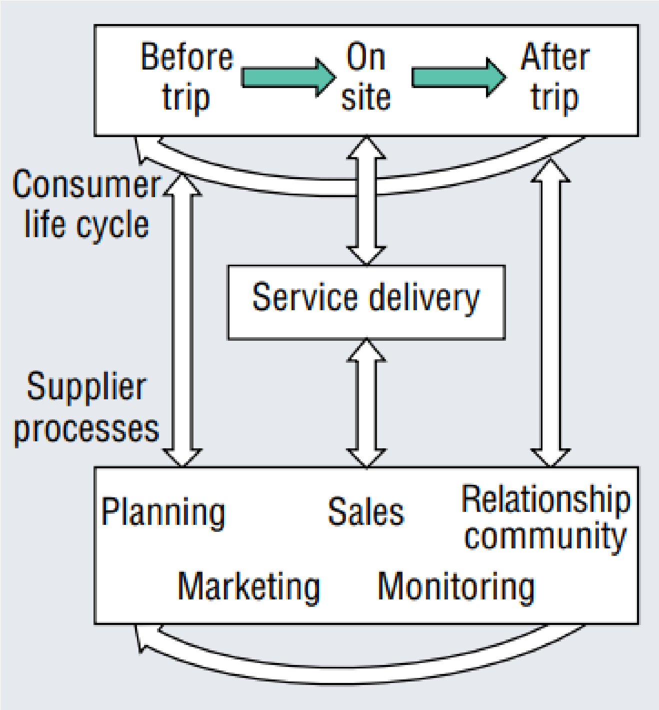
Data

- How data from tourism really looks like?
- Are any of these representations realistic?

- Back in 2002 the tourist life cycle was represented like this

- The distinction between before trip / on site / after trip is not frequently made

- Besides, tourism is a group experience, none of these datasets capture this
  - See RecTour 2016 keynote by H. Werthner



Intelligent Systems for Tourism

Steffen Staab, University of Karlsruhe, sst@aifb.uni-karlsruhe.de
Hannes Werthner, ITC-irst Research Center, werthner@itc.it.

NOVEMBER/DECEMBER 2002

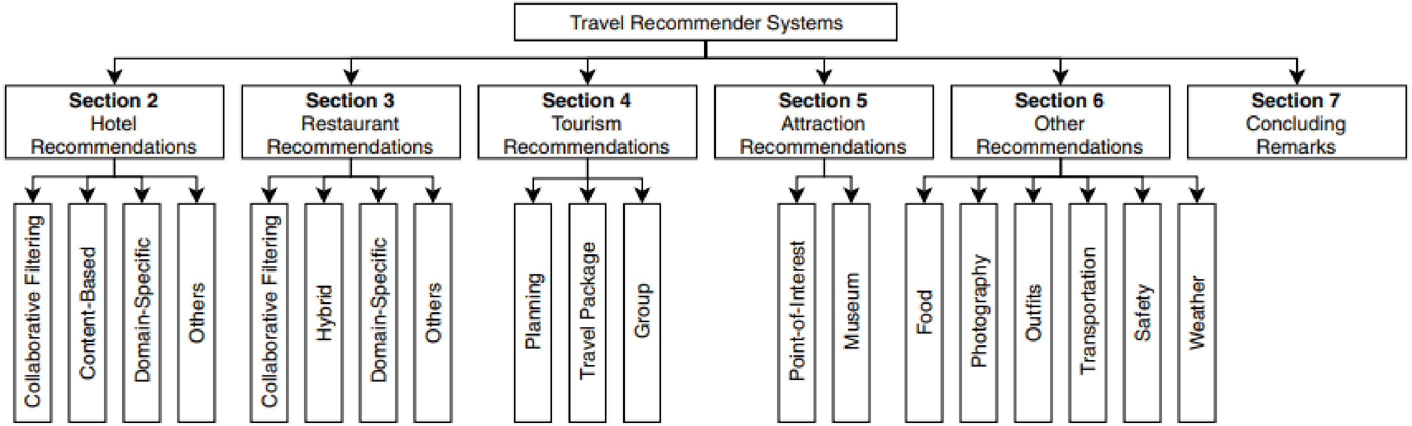
Time for concrete examples

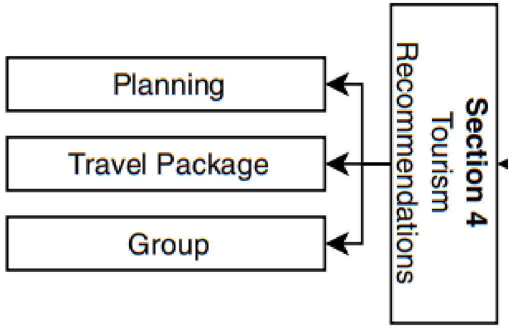
Data
Tasks
Evaluation

Tasks

- How do we define tourism recommendation? Which tasks are we trying to solve?

- It is a very complex area, with several sub-tasks, not all of them equally considered in the literature



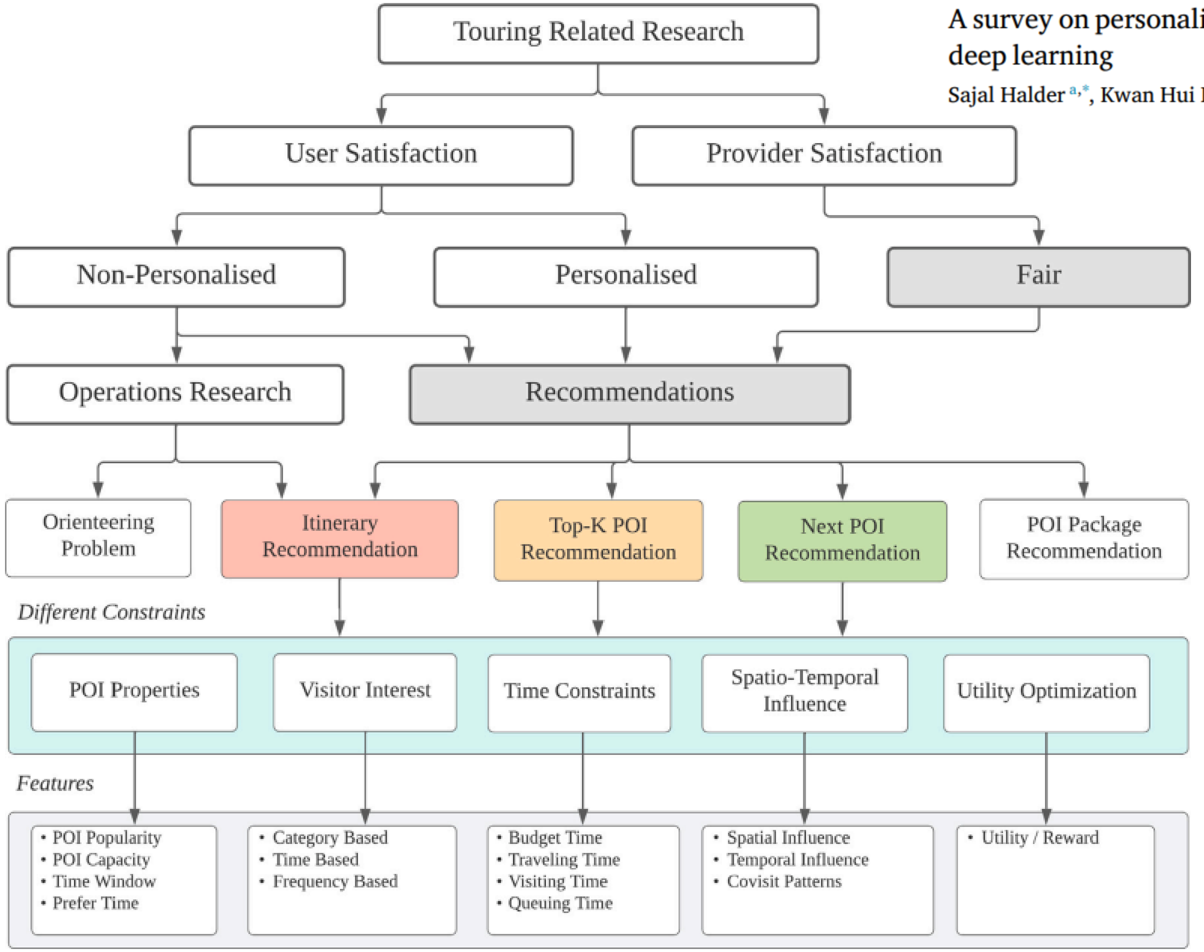


A Comprehensive Survey on Travel Recommender Systems

Kinjal Chaudhari[1] · Ankit Thakkar[1]

Tasks

- How do we define tourism recommendation? Which tasks are we trying to solve?



A survey on personalized itinerary recommendation: From optimisation to deep learning

Sajal Halder[a,*], Kwan Hui Lim[b], Jeffrey Chan[a], Xiuzhen Zhang[a]

Tasks

- How do we define tourism recommendation? Which tasks are we trying to solve?

- It seems the most popular ones are:
  - Top-N POI recommendation
  - Next-POI recommendation
  - Itinerary/tour/route recommendation
  - Others:
    - Package recommendation
    - Recommend music, clothes, or photos for a tour
    - Personalisation of museum guides
    - …

Tasks

- How do we define tourism recommendation? Which tasks are we trying to solve?

- Some of these tasks may benefit from techniques or concepts from other areas:
  - **Operational research**: find routes while satisfying given constraints
  - Trajectory mining
  - Urban computing

- Successful examples:

The Vacation Planning Problem: A multi-level clustering-based metaheuristic approach

Nikolaos Vathis [a,d,*], Charalampos Konstantopoulos [b,d], Grammati Pantziou [a,d], Damianos Gavalas [c,d]

Heuristics for the time dependent team orienteering problem: Application to tourist route planning ☆, ☆☆

Damianos Gavalas [a,f,*], Charalampos Konstantopoulos [b,f], Konstantinos Mastakas [c,f], Grammati Pantziou [d,f], Nikolaos Vathis [e,f]

A Delay-Robust Touristic Plan Recommendation Using Real-World Public Transportation Information

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CompRec-Trip: a Composite Recommendation System for Travel Planning

Min Xie †, Laks V.S. Lakshmanan †, Peter T. Wood ‡
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Tasks

- How do we define tourism recommendation? Which tasks are we trying to solve?

- Some of these tasks may benefit from techniques or concepts from other areas:
  - Operational research
  - Trajectory mining: understanding routes as trajectories allow to apply several data mining techniques and analyses
  - Urban computing

- Successful examples:

User Oriented Trajectory Search for Trip Recommendation

Shuo Shang [†] Ruogu Ding [§] Bo Yuan [‡] Kexin Xie[†] Kai Zheng[†] Panos Kalnis [§]

Discovering Related Users in Location-Based Social Networks

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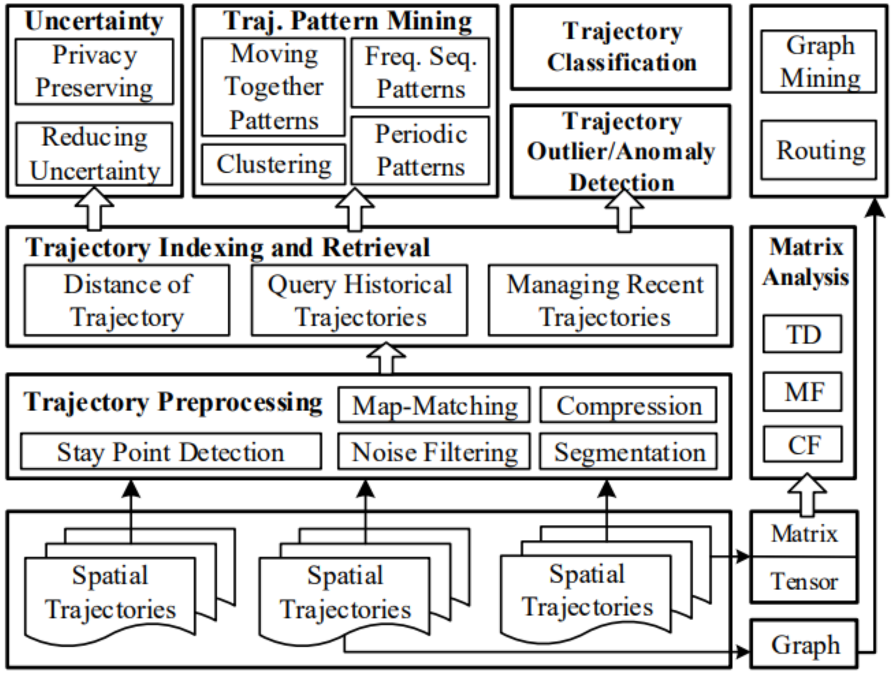


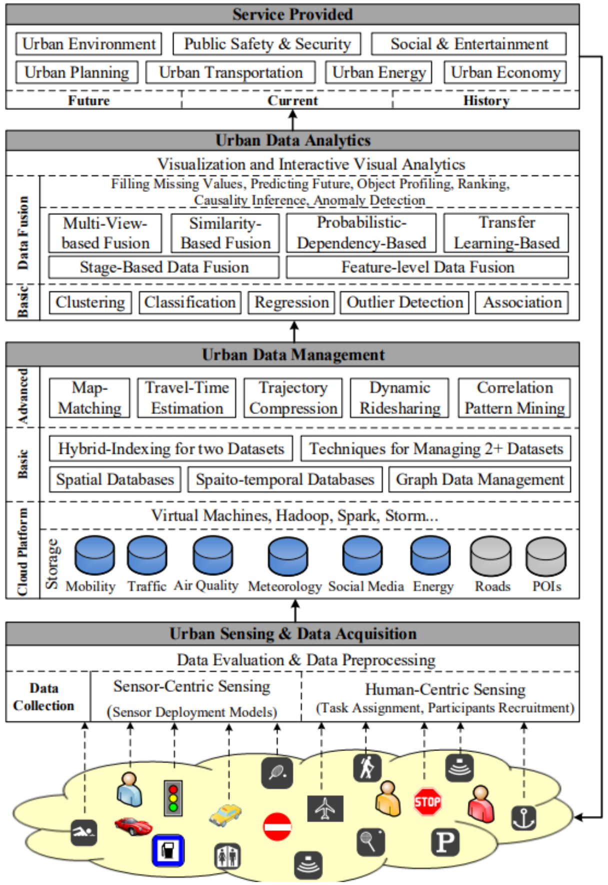
Trajectory Data Mining: An Overview

YU ZHENG
Microsoft Research

Alejandro Bellogin – RecTour 2024

Tasks

- How do we define tourism recommendation? Which tasks are we trying to solve?
- Some of these tasks may benefit from techniques or concepts from other areas:
  - Operational research
  - Trajectory mining
  - **Urban computing**: exploits data generated in cities
- Successful examples:



An Agent-Based Traffic Recommendation System: Revisiting and Revising Urban Traffic Management Strategies

Junchen Jin, *Member, IEEE*, Dingding Rong, Yuqi Pang, Peijun Ye, Qingyuan Ji, Xiao Wang, *Senior Member, IEEE*, Ge Wang, and Fei-Yue Wang, *Fellow, IEEE*

Democratizing Urban Mobility Through an Open-Source, Multi-Criteria Route Recommendation System

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Alejandro Bellogín – RecTour 2024

Alejandro Bellogin – RecTour 2024

Time for concrete examples

Data
Tasks
Evaluation

Evaluation

- The proper evaluation method depends on the task
- Classical ranking evaluation is tied to one specific task: top-N POI recommendation
- If we consider **sequentiality** (next-POI/route recommendation), this aspect should be evaluated

- Ad-hoc metrics: inspired by F_1, measuring whether a pair of POIs are adjacent

$$\text{pairs-F}_1 = \frac{2P_{\text{PAIR}}R_{\text{PAIR}}}{P_{\text{PAIR}} + R_{\text{PAIR}}}$$

Learning Points and Routes to Recommend Trajectories

Dawei Chen Cheng Soon Ong Lexing Xie

- Metrics from trajectory mining: trajectory distance measures
  - Based on alignment: Dynamic Time Warping, Longest Common SubSequence
  - Based on sub-trajectories: Hausdorff distance, segment distance

Trajectory Pattern Mining

Hoyoung Jeung, Man Lung Yiu, and Christian S. Jensen

Evaluation

- The proper evaluation method depends on the task
- There are two problems typically considered when evaluating recommenders in this domain:
  - Sparsity: to address this, some works consider similarities between items, through categories usually

Recall (on PoIs and Categories). This is the popular recall metrics that in the Information Retrieval domain measures the fraction of the documents that are relevant to the query that are successfully retrieved. In our case it is computed for a user and a suggested itinerary as the fraction of PoIs (or Categories) in the user PoI history which occurs in the suggested itinerary.

Where Shall We Go Today?
Planning Touristic Tours with TripBuilder

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Franco Maria Nardini,
Raffaele Perego, Chiara Renso
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Tour Interest: $T^u_{Int}(I)$**.** The overall interest of all POIs in the recommended itinerary I to a user u, defined as: $T^u_{Int}(I) = \sum_{p \in I} Int_u(Cat_p)$.

Personalized Tour Recommendation Based on
User Interests and Points of Interest Visit Durations

Kwan Hui Lim[*†], **Jeffrey Chan**[*], **Christopher Leckie**[*†] and **Shanika Karunasekera**[*]
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[†]Victoria Research Laboratory, National ICT Australia, Australia
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Evaluation

- The proper evaluation method depends on the task

- There are two problems typically considered when evaluating recommenders in this domain:
  - Sparsity: to address this, some works consider similarities between items, through categories usually
  - **Repetitions** – related to the task (recommend new venues or next venue even if it is not new for user)
    - Algorithms may have very different behaviour depending on this configuration

Recommender	Test with new venues P	R	NDCG	MAP	LCS	LCSP	LCSR	Test with known venues P	R	NDCG	MAP	LCS	LCSP	LCSR
Rnd	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Pop	0.039	0.076	0.063	0.030	0.008	0.034	0.071	0.054	0.082	0.079	0.036	0.009	0.046	0.075
Training	0.000	0.000	0.000	0.000	0.000	0.000	0.000	†**0.120**	†**0.190**	0.186	0.100	†**0.034**	0.090	†**0.157**
AvgDis	0.001	0.001	0.001	0.001	0.000	0.001	0.001	0.003	0.006	0.007	0.005	0.001	0.002	0.006
AvgDisFreq	0.001	0.002	0.001	0.001	0.000	0.001	0.001	0.003	0.007	0.008	0.005	0.001	0.003	0.006
PGN	0.041	0.082	0.073	0.036	0.009	0.037	0.077	0.070	0.112	0.124	0.065	0.013	0.059	0.101
UB	0.045	0.088	0.078	0.039	0.009	0.039	0.081	0.110	0.167	0.178	0.098	0.021	0.086	0.142
IB	0.036	0.069	0.063	0.032	0.008	0.032	0.064	0.108	0.156	0.175	0.098	0.019	0.082	0.130
HKV	0.043	0.087	0.076	0.039	0.009	0.038	0.080	0.105	0.158	0.170	0.093	0.019	0.082	0.135
IRenMF	0.044	0.089	0.077	0.039	0.010	0.039	0.083	0.100	0.151	0.164	0.090	0.018	0.079	0.130
IRenMFFreq	†**0.047**	†**0.094**	†**0.082**	†**0.042**	†**0.010**	†**0.041**	†**0.087**	**0.117**	**0.181**	†**0.194**	†**0.109**	**0.023**	†**0.092**	**0.154**

Challenges on evaluating venue recommendation approaches

Position paper

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- This was also observed in trajectory recommendation, where it is better to avoid including revisits within the trajectory

How important is it to remove loops? Having confirmed that loops in the top-scoring sequence are an issue, it is now of interest to establish that removing such loops during prediction is in fact important. This is confirmed in Tables 2 – 3, where we see that there can be as much as a **17%** improvement in performance over the VITERBI baseline. These improvements are over all queries, including those where the VITERBI algorithm does not have loops. Restricting to those queries where there are loops, Tables 4b – 5b show that the improvements are dramatic, being as high as **50%**.

Revisiting revisits in trajectory recommendation

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Evaluation

- The proper evaluation method depends on the task

- Of course, other dimensions should be considered:
  - Bias
  - Exposure
  - Novelty
  - Distance
  - Sustainability

	Accuracy		Novelty	Diversity	Popularity		Exposure		Distance		Coverage
Recommender	**P**	**nDCG**	**EPC**	**Gini**	**PopI**	**PopC**	**ExpP**	**ExpR**	**DistT**	**DistU**	**UC**
Rnd	0.000	0.000	**0.999**	**0.551**	**0.303**	*0.760*	**0.000**	**0.001**	37.2	34.7	**7,253**
Pop	**0.071**	*0.087*	0.746	0.000	0.000	0.960	0.131	0.121	*24.9*	*26.4*	**7,253**
UB	*0.070*	*0.087*	0.769	0.001	0.002	0.968	0.103	0.093	26.0	25.8	*6,931*
IB	0.063	0.080	0.819	*0.025*	*0.026*	*0.911*	0.064	0.057	23.2	25.0	*6,931*
HKV	0.064	0.078	*0.845*	0.002	0.003	0.921	*0.038*	*0.031*	*22.0*	*21.7*	*6,931*
BPR	0.066	0.081	0.754	0.000	0.003	0.955	0.123	0.112	25.6	27.7	*6,931*
TD	**0.071**	**0.088**	0.776	0.001	0.003	0.965	0.097	0.087	25.9	25.4	*6,931*
MC	0.051	0.062	0.804	0.001	0.003	*0.939*	0.107	0.098	26.5	30.9	6,879
FPMC	0.053	0.064	0.807	0.001	0.001	0.943	0.103	0.096	31.0	30.1	6,884
Fossil	0.058	0.074	*0.851*	*0.003*	*0.006*	0.878	*0.046*	*0.040*	*22.0*	*21.7*	6,879
KDE	*0.004*	*0.005*	**0.999**	*0.318*	*0.212*	0.753	**0.000**	**0.001**	**0.4**	15.5	6,879
AvgDis	0.001	0.001	**0.999**	0.202	0.187	**0.719**	**0.000**	**0.001**	0.6	**4.2**	*6,931*
FMFMGM	0.063	0.079	0.772	0.001	0.002	0.979	0.105	0.095	23.7	22.7	6,931
GeoBPR	0.065	0.081	0.756	0.000	0.001	0.957	0.120	0.110	23.7	24.2	6,931
IRenMF	*0.069*	0.083	*0.799*	0.003	0.008	0.951	*0.072*	*0.063*	23.9	23.8	6,931
PGN	0.068	*0.086*	0.777	*0.014*	*0.023*	*0.932*	0.110	0.100	*23.6*	*20.9*	**7,253**
Skyline	0.784	0.996	0.982	0.231	0.087	0.796	0.000	0.000	17.5	18.8	7,241

Bias characterization, assessment, and mitigation in location-based recommender systems

Pablo Sánchez[1,2] · Alejandro Bellogín[2] · Ludovico Boratto[3]

Evaluation

- The proper evaluation method depends on the task

- Of course, other dimensions should be considered:
  - Bias
  - Exposure
  - Novelty
  - Distance
  - Sustainability

Sustainability of the tourism ecosystem needs to be seen from several perspectives:

- Environmental sustainability with respect to resource consumption for building and maintaining the tourism infrastructure and transportation;
- Economic sustainability (including regulation to avoid oligopolistic and monopolistic structures).
- Democratic, participatory development;
- Social sustainability, also with respect to the wealth gap between tourists and employees in tourism and the involvement of local business actors in tourism destinations;
- Cultural sustainability, i.e. to preserve and respect different cultures.

Future research issues in IT and tourism

A manifesto as a result of the JITT workshop in June 2014, Vienna

Hannes Werthner · Aurkene Alzua-Sorzabal · Lorenzo Cantoni · Astrid Dickinger · Ulrike Gretzel · Dietmar Jannach · Julia Neidhardt · Birgit Pröll · Francesco Ricci · Miriam Scaglione · Brigitte Stangl · Oliviero Stock · Markus Zanker

Besides recent works on this topic, do not forget it was already mentioned in 2014 manifesto

Evaluation

- The proper evaluation method depends on the task
- Are these evaluation metrics and methodologies capturing what is expected in tourism RecSys?

	Q-BASE	Q-POP PUSH				SKNN	s-SKNN	POP
		$\alpha = 0.009$	$\alpha = 0.1$	$\alpha = 0.5$	$\alpha = 0.8$			
Reward	**0.032***	0.020	-0.001	-0.009	-0.009	-0.010	-0.010	-0.015
Precision	0.045	0.062	0.063	0.060	0.060	**0.068**	0.063	0.050
Popularity	**0.319***	0.517	0.634	0.643	0.643	0.528	0.570	0.733
SimKNN	0.061	0.307	0.441	0.451	0.450	-	**0.530**	0.352

The results of our experiments seem to confirm that RSs that precisely predict the user choices (offline) are also liked most by real users. In our case, this means that Q-POP PUSH and SKNN are better RSs than Q-BASE. Our explanation of this result is that both high offline precision and large probability of liked recommendations (online) are influenced by the popularity of the recommended items. In fact, these popular items are often in the users' test sets, and users are likely to be familiar with them.

Despite its lower offline precision performance and a lower extent of liked recommendations in the user study, Q-BASE is the RS that may better accomplish the true goal of a tourism RS: it suggests more next-POIs that are both liked and novel. So, by optimising the reward Q-BASE is capable of discovering novel items that are also appreciated (when users are able to assess them).

Recommender System	*Visited*	*Novel*	*Liked*	*Liked & Novel*
Q-BASE	0.165*	0.517*	0.361*	0.091
Q-POP PUSH	0.245	0.376	0.464	0.076
SKNN	0.238	0.371	0.466	0.082

Hence, apparently a more precise RS, based on an offline test, also recommends online items that the user will like more. Besides, the obtained results falsify our hypothesis that optimising the reward of a recommendation, as Q-BASE do, will produce recommendations that the user will like more. However, Q-BASE suggests more novel POIs and, interestingly, more recommendations that are both liked and novel (last column in Table 2).

Inverse Reinforcement Learning and Point of Interest Recommendations*

Discussion Paper

David Massimo, Francesco Ricci

Alejandro Bellogin – RecTour 2024

Key takeaways

- Tourism is a rich domain, with several opportunities and use cases
- There are still many challenges ahead
- We should explore related areas and embrace their perspectives and methodologies

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Expanding the Boundaries: Recommender Systems and the Multifaceted World of Tourism

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Thank you

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