Context Trails: A Dataset to Study Contextual and Route Recommendation

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MOTIVATION

Lack of datasets with routes AND context

Dataset	Domain	Users	Items	Interactions	Contexts	Used in
Adom	Movie	0.1K	0.2K	1.5K	Companion, Location	[15, 26]
Comoda	Movie	0.1K	1.2K	2.3K	Mood, Social, Time, Weather	[32, 13]
DePaulMovie	Movie	0.1K	0.1K	5K	Companion, Location, Time	[47, 25]
In Car	Music	0.01K	0.2K	4K	Driving style, Mood, Road type, Weather	[1]
Food	Food	0.2K	0.01K	6.4K	Hunger level, Real/virtual	[15, 26, 28, 22]
Foursquare	POI	0.2K-51K	0.3K-500K	0.5K-3.5M	Demographic, Location, Time, Weather	[21, 10, 20, 29]
Frappe	Apps	1K	4K	95K	Location, Time	[28, 36, 22]
HyperCars-Gowalla	POI	24K	40K	1M	Location, Time, Weather	[2]
HyperCars-Yelp	POI	312K	12.6K	1.1M	Location, Time, Weather	[2]
LastFM	Music	0.01K-3K	1.8K-174K	93K-19M	Last interactions, Order, Tag, Time	[11, 27, 41, 7, 38, 6, 34, 12]
MovieLens	Movie	0.7K-140K	1.6K-19K	31K-20M	Age, Time	[45, 50, 16, 9, 38, 43, 6, 13, 14, 50, 12, 43, 7]
STS	POI	0.3K	0.3K	2.5K	Budget, Companion, Goal, Mood, Time, Weather	[3]
TripAdvisor	POI	1.2K-2.6K	1.5K-1.9K	4.7K-9.3K	Trip type	[46, 32]
Weeplaces NY	POI	4.5K	16.1K	864K	Weather	[8]
Yelp	POI	5K-96K	13K-49K	144K-2.3M	Last purchase, Location, Time	[22, 21, 9, 12, 33, 33]

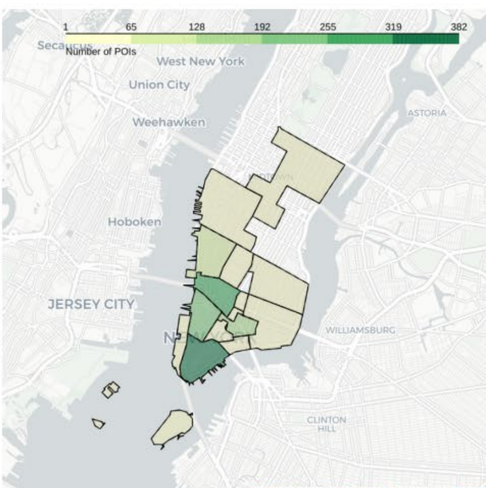
Lack of datasets with routes AND context

Dataset	Cities	Users	Items	Check-ins	Routes	Used in
Foursquare Global Scale	415	267K	3.7M	33.3M	NA	[40]
GeoLife	1	0.2K	≈17K	28M	17.6K	[48, 35]
Gowalla	50	1.6K-107K	3.5K-1.3M	116K-6.4M	NA	[42, 17, 37, 39, 30, 44]
Semantic Trails 2013	10K	256K	2.8M	18.6M	6.1M	[24]
Semantic Trails 2018	52K	400K	1.9M	11.9M	4M	[24]
Trip builder	3	22.6K	1.3K	133K	55.5K	[5, 4]
VeronaCard	1	(unk)	0.1K	1.2M	250K	[23]
YFCC100M	1-7	0.9-6.5K	0.1K	17K-130K	4K-20K	[18, 19, 31, 49]

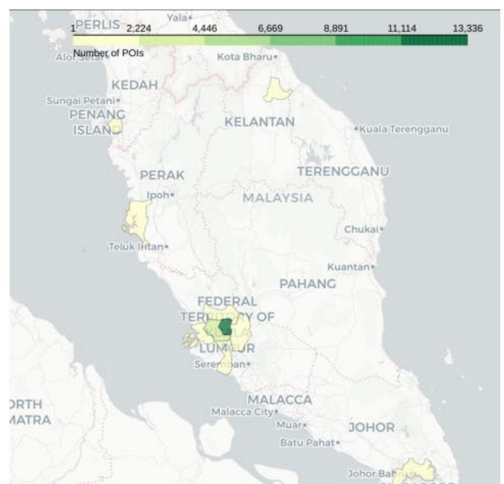
CONTRIBUTION

Main contribution

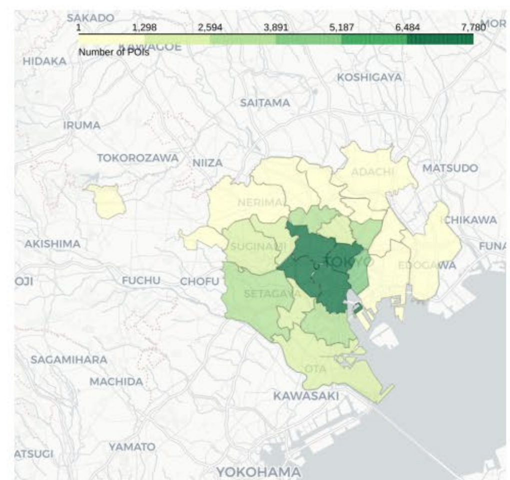
- A new **dataset** with user-POI interactions grouped as routes for 3 cities and POI <u>schedules</u>, categories, and <u>weather</u> conditions



(a) New York City



(b) Petaling Jaya



(c) Tokyo

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Context Trails	POI	85K	84K	1.3M	Location, Schedule, Time, Weather	

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Context Trails	3	85K	84K	1.3M	580K	

Other contributions

- A comprehensive **analysis** through detailed statistics and various visualizations

- **Benchmarking** experiments across 3 recommendation tasks:
  - Classic POI recommendation
  - Route recommendation
  - Context-aware recommendation

WHAT

Data content

- **POI** information: Foursquare id, coordinates, categories, schedule

- **Route** information: check-ins grouped by route

- **Weather** context: temperature, precipitation levels, wind speed, sky conditions, …

- Splits: to facilitate **replicating** our experiments

Statistics and visualizations

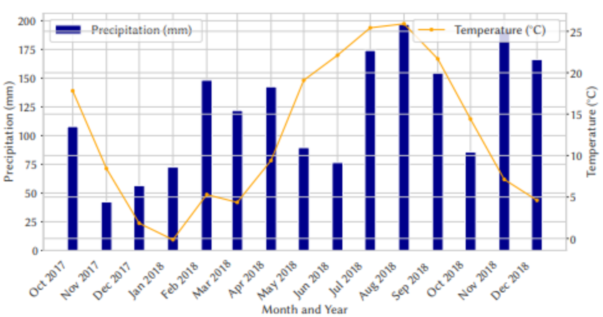
- We selected 3 cities from different cultures and data size

Statistics of the data collected for the three cities, including its Wikidata ID (WikID), number of users (|U|), POIs (|P|) and POIs with schedule ($|P_s|$), check-ins (|C|), and unique number of contexts as weather conditions (CT_w), temperature values (CT_t), and schedules (CT_s).

City	WikID	|U|	|P|	|C|	CT_w	CT_t	CT_s	$\|P_s\|$
NYC	Q60	1,649	1,461	4,849	10	430	53	1,177
PTJ	Q864965	18,346	18,618	153,543	4	122	153	17,207
TOK	Q308891	66,125	64,086	1,178,663	8	385	333	57,192

Statistics and visualizations

- These cities exhibit varying precipitation volumes and average temperatures



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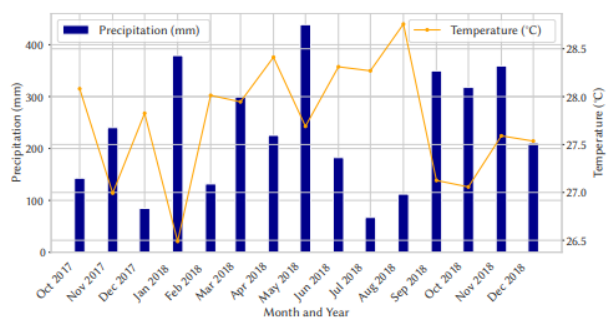
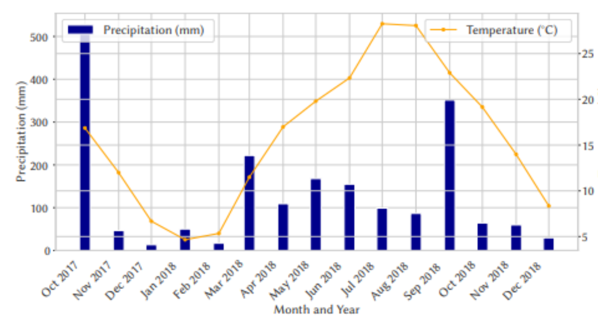


(b) Petaling Jaya



(c) Tokyo

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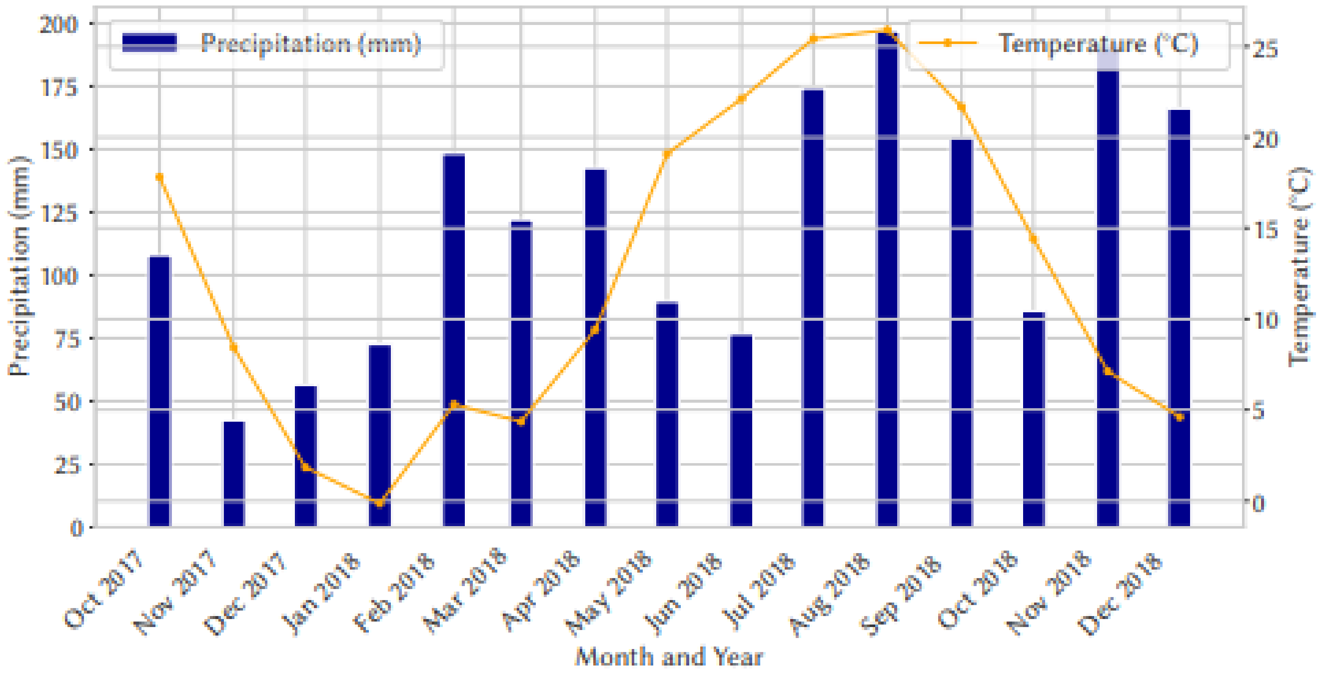

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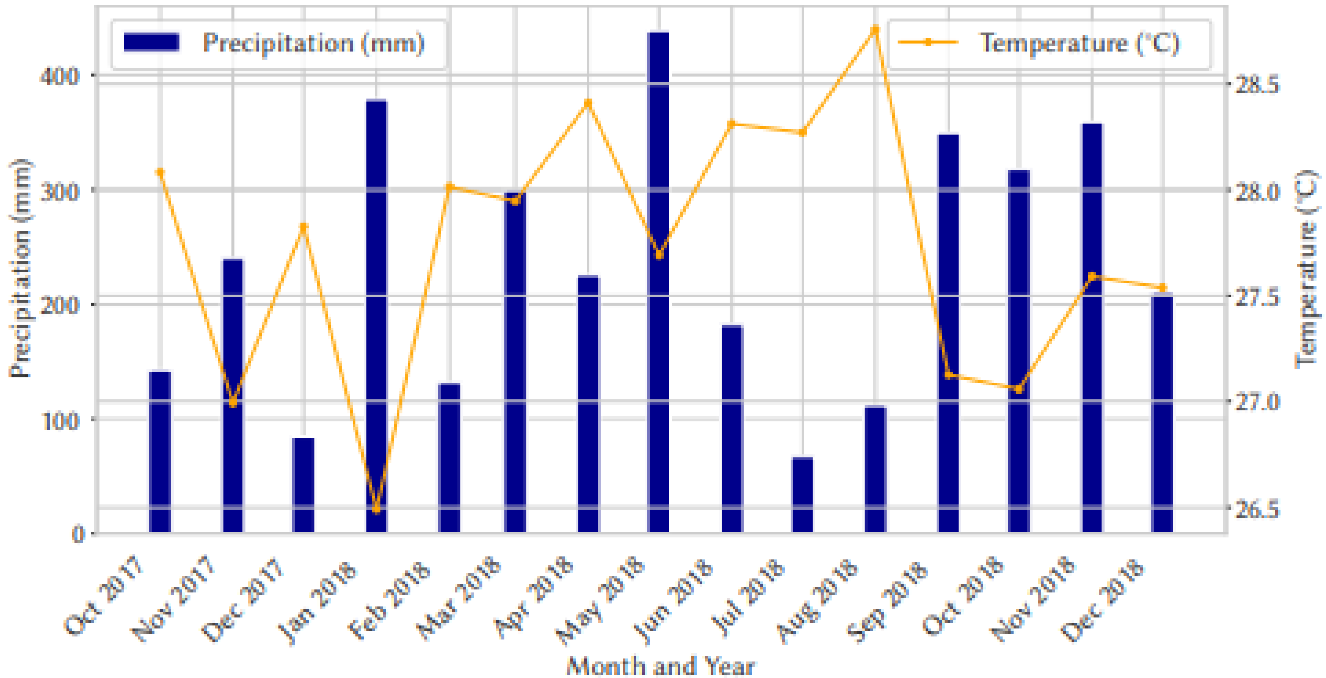

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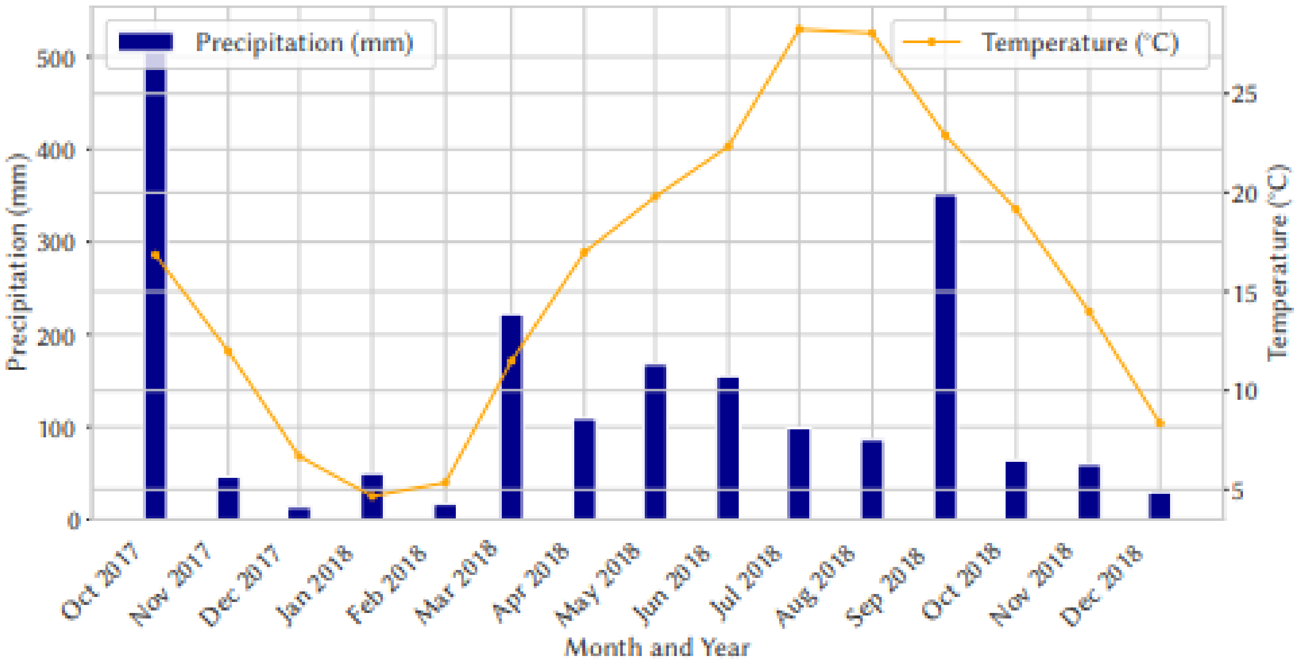
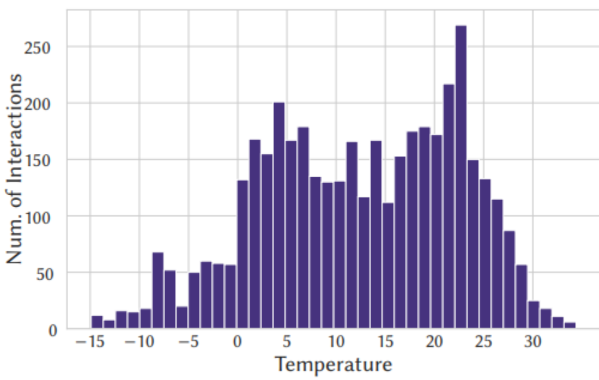


(c) Tokyo

Statistics and visualizations

- When comparing conditions **happening** when interacting, NYC and Tokyo are *not so different*



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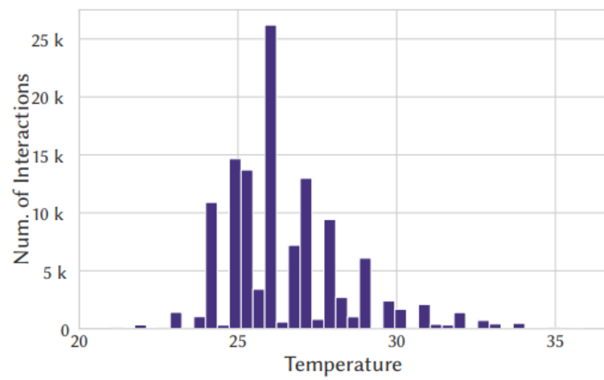

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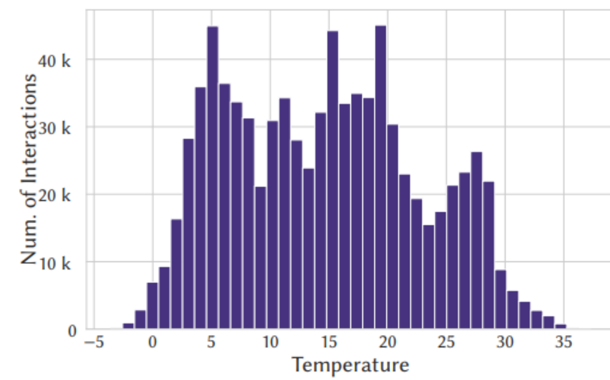

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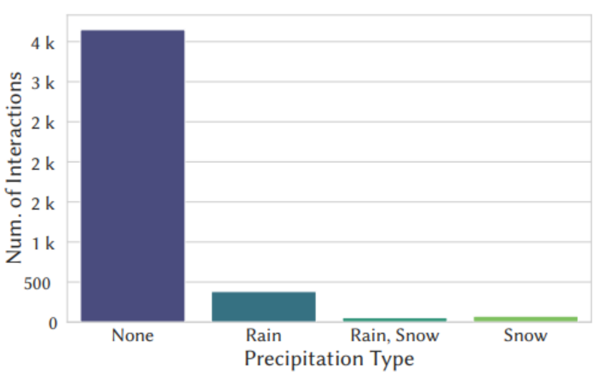

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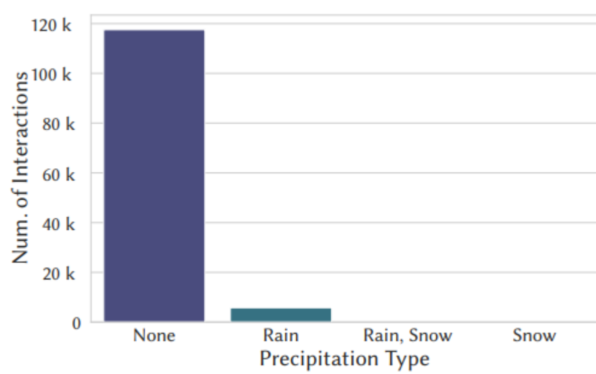

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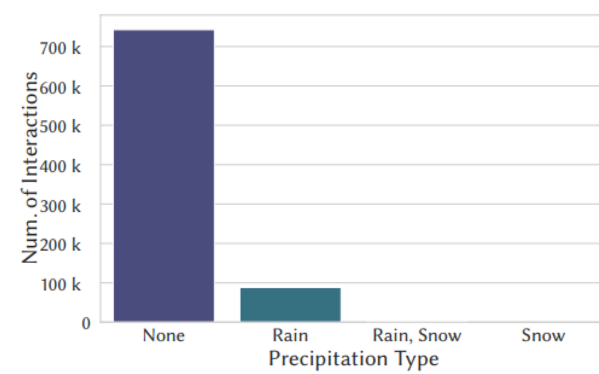

(c) Tokyo

Statistics and visualizations

- Types of POIs **open** depending on the time of the day evidences differences between cities

(a) New York City (b) Petaling Jaya (c) Tokyo

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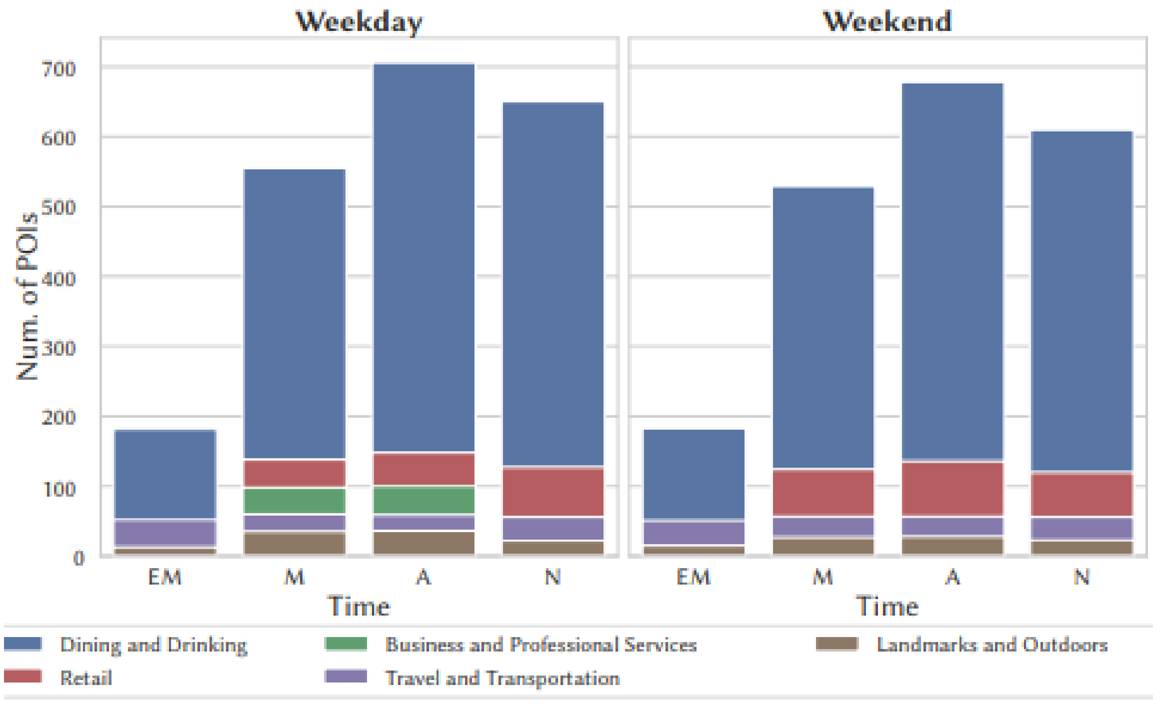

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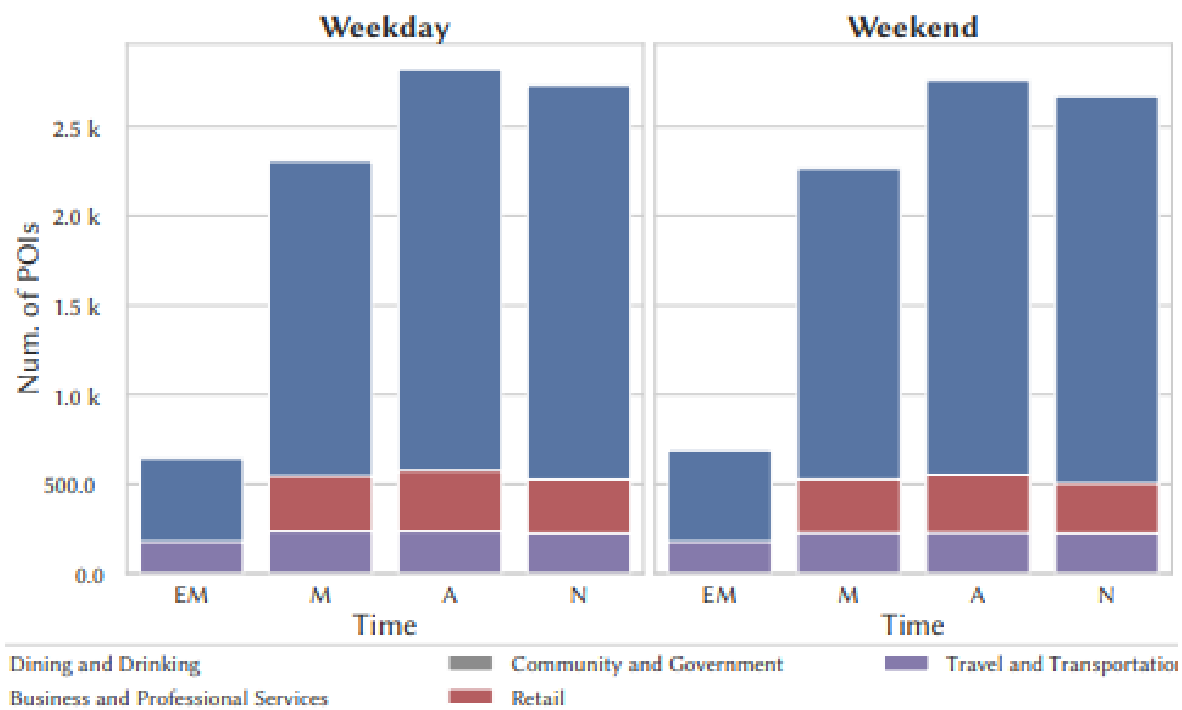

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Statistics and visualizations

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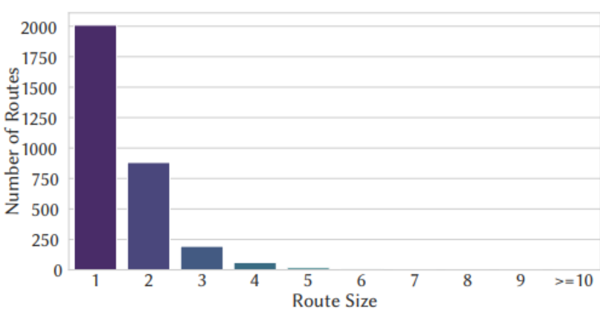
(c) Tokyo

Statistics and visualizations

- An important difference between cities is the length of the routes, although most of them are quite short



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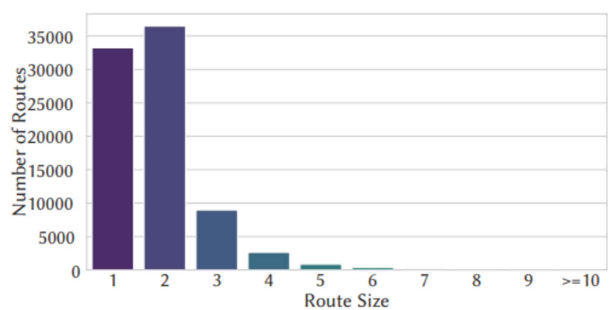

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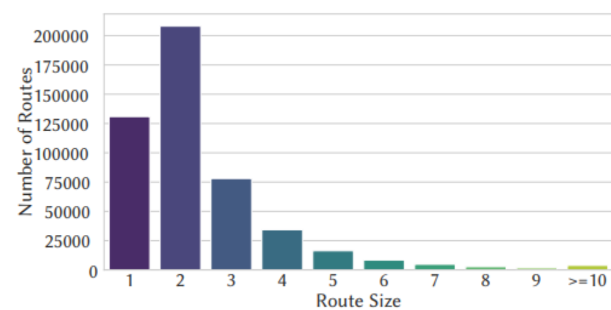

(c) Tokyo

WHY

Potential uses

- Analyze how weather conditions influence human mobility patterns or POI visiting behaviors
- Adaptive models that adjust to external factors
- Weather-aware route recommendations
- …

Considered recommendation tasks

- POI recommendation: propose relevant POI users may want to visit

- Route recommendation: suggesting an ordered sequence of POIs to visit in a single time frame

- Context-aware recommendation: context is considered before, after, or when producing the recommendations

Benchmarking recommendation tasks

- Coverage issues for many methods
- Popularity bias
- Geographical or hybrid methods outperform standard CF methods

City	NYC				PTJ				TOK			
Method	**nDCG**	**EPC**	**Gini**	**UC**	**nDCG**	**EPC**	**Gini**	**UC**	**nDCG**	**EPC**	**Gini**	**UC**
Rnd	0.0000	**0.9981**	**0.4772**	**397**	0.0002	**0.9996**	**0.4960**	**5593**	0.0001	**0.9998**	**0.5710**	**26523**
Pop	**0.1096**	0.9385	0.0028	**397**	0.0612	0.9060	0.0002	**5593**	0.2260	0.8418	0.0001	**26523**
UB	0.0133	0.9927	0.1173	75	0.0798	0.9423	0.0074	3473	0.2343	0.8854	0.0024	19059
IB	0.0130	0.9945	0.1474	85	0.0495	0.9733	0.1206	3542	0.1422	0.9325	0.0674	19716
EASEr	0.0105	0.9890	0.0689	95	0.0800	0.9339	0.0037	3563	0.2081	0.8969	0.0014	19759
$RP^3\beta$	0.0106	0.9973	0.1639	95	0.0033	0.9994	0.1808	3563	0.0596	0.9794	0.1147	19759
BPR	0.0485	0.9425	0.0040	95	0.0746	0.9089	0.0003	3563	0.2350	0.8462	0.0001	19759
GeoBPR	0.0530	0.9670	0.0121	95	**0.0912**	0.9162	0.0004	3563	0.2323	0.8517	0.0001	19759
IRenMF	0.0327	0.9884	0.0949	95	0.0888	0.9263	0.0006	3563	**0.2390**	0.8487	0.0001	19759
H-PUM	0.1069	0.9437	0.0137	**397**	0.0686	0.9163	0.0054	**5593**	0.2188	0.8687	0.0170	**26523**
Skyline	0.8949	0.9826	0.0985	350	0.8537	0.9834	0.0766	5427	0.7707	0.9597	0.0623	26327

Benchmarking recommendation tasks

- Markov Chains or hybrid obtain best results
- In this task, not only accuracy is important: **distance** indicates how realistic a route may be

City	Recommender	nDCG	EPC	Gini	Dist (km)	UC
NYC	Baseline-T	0.3584	0.9737	0.0078	0	16
	ClosestNN-T	0.4162	**0.9913**	**0.0385**	**0.544**	16
	MC-T	0.4285	0.9746	0.0138	0.905	16
	FMC-T	0.4130	0.9682	0.0070	5.637	16
	kNN-T	0.4253	0.9845	0.0131	1.226	16
	WG-T	**0.4332**	0.9880	0.0345	1.012	16
PTJ	Baseline-T	0.3777	0.9681	0.0092	0	390
	ClosestNN-T	0.3879	**0.9873**	**0.0386**	**0.103**	390
	MC-T	**0.4225**	0.9624	0.0072	4.433	390
	FMC-T	0.3833	0.9784	0.0022	41.486	390
	kNN-T	0.4002	0.9768	0.0144	3.133	390
	WG-T	0.4191	0.9767	0.0244	2.493	390
TOK	Baseline-T	0.3696	0.8555	0.0109	0	5870
	ClosestNN-T	0.3729	**0.9669**	**0.0392**	**0.053**	5870
	MC-T	**0.4250**	0.6954	0.0066	5.757	5870
	FMC-T	0.4110	0.7661	0.0024	15.939	5870
	kNN-T	0.4158	0.8683	0.0104	5.725	5870
	WG-T	0.4210	0.8076	0.0273	6.016	5870

Benchmarking recommendation tasks

- We apply a **post-filter** to POI rankings so there is a match with the target context
- Both the method and the context **depend on the city**, because of their inherent characteristics

City	Recommender	Time	Weather	Full
NYC	C-Rnd	0.0018	0.0005	0.0005
	C-Pop	**0.0375**	0.0060	0.0050
	C-H-PUM	0.0254	0.0048	0.0045
PTJ	C-Rnd	0.0003	0.0001	0.0004
	C-Pop	0.0146	0.0088	0.0116
	C-H-PUM	**0.0148**	0.0026	0.0115
TOK	C-Rnd	0.0000	0.0000	0.0000
	C-Pop	0.0057	**0.0113**	0.0053
	C-H-PUM	0.0048	0.0033	0.0031

HOW

Data collection

- The dataset is based on 3 data sources:

- SemanticTrails: user-POI interactions with **routes**
- VisualCrossing: historical **weather** data with hourly resolution
- Foursquare: coordinates and opening/closing hours (**schedules**)

WHERE

Resources

- Dataset available as a Zenodo record:

  https://zenodo.org/records/15855966

- Source code to use it and reproduce our benchmarking experiments:

  https://github.com/pablosanchezp/ContextTrailsExperiments

NEXT

Limitations and future work

- Routes and interactions limited to those in SemanticTrails (from 2018)
  - Link dataset with related sources like Yelp or Gowalla
- Not all types of POIs might be interesting
  - Filter out based on categories (provided in data)
- Only 3 cities collected
  - Already working on extending dataset with more cities

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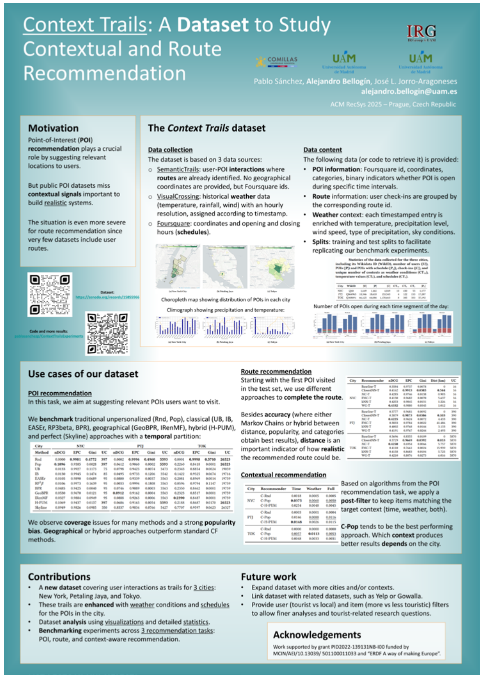
Thursday @ poster session



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